

# Ovarian cancer serum biomarker discovery using proteomics

Musarat Kabir

Department of Gynaecological Oncology,  
University College London (UCL),  
Gower Street, London

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I [Musarat Kabir] confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

### **Abstract**

Ovarian cancer is a lethal gynaecological malignancy which is known as the silent killer. It has a poor prognosis due to the lack of major symptoms in early stage disease and hence its late detection. Cancer antigen-125, the most widely used biomarker for ovarian cancer detection, lacks appropriate sensitivity and specificity. Thus, early biomarkers of the disease are urgently required. Proteomic analysis of human serum promises to be a valuable approach for the discovery of putative biomarkers for human malignancies like ovarian cancer, which could be developed into non-invasive blood tests. In this study, serum samples from a pilot study for ovarian cancer screening which were collected prior to diagnosis were processed at Memorial Sloan Kettering Cancer Research Centre, in collaboration with Prof. Tempst's group, who had developed a novel mass spectrometry (MS)-based technology platform for the high-throughput extraction and measurement of serum peptides. Several marker peaks were identified, which when used in combination with the ovarian cancer biomarker CA-125, assisted in the discrimination of case versus healthy samples at an earlier point prior to diagnosis. Work then involved the establishment and optimisation of a similar serum profiling platform at UCL. This involved the optimisation of a liquid-handling robot to provide semi-automated high-throughput sample purification and spotting, and optimisation of spectral acquisition and processing. The reproducibility of the platform was tested and the effects of different sample handling conditions on peptide profiles examined. The method was then used to search for putative markers of ovarian cancer, using identically processed samples from women diagnosed with malignant or benign ovarian cancer and healthy controls. Finally, as a complementary approach to discover protein biomarkers, the same samples were profiled using 2D Difference Gel Electrophoresis, employing different fractionation strategies to overcome the very large dynamic range of protein expression in serum. Mass spectrometry was used to identify several previously reported and some novel putative biomarkers of ovarian cancer, which warrant further validation.

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Allahumma infa'nii bimaa 'allamtanii wa'allimnii maa yanfa' unii.

Allahumma ijil leesanee 'amiran bi thikrika wa qalbi bi khashyatika. Ameen.

مسرتٌ كَبِيرٌ

### Abbreviations

The abbreviations that are used throughout this thesis are listed below. The abbreviations are subdivided into four categories: General; Chemicals; Mass spectrometry and separation techniques and Proteins. The meaning of the abbreviation is also given the first time used.

#### **General**

AJCC	American Joint Committee on Cancer
CA-125	Cancer antigen 125
CEA	Carcinoembryonic antigen
Da	Dalton
FIGO	International Federation of Gynaecology and Obstetrics
HMR	High Mass Range 4–15 kDa m/z
HNPPCC	Hereditary non-polyposis colorectal cancer syndrome
k-NN	K-nearest neighbours classification algorithm
Laser	Light Amplification by Stimulated Emission of Radiation
LMR	Low Mass Range 700-4000Da m/z
MARS	Multiple Affinity Removal System
Mw	Molecular Weight
mmu	Millimass units
pI	Isoelectric point
ppm	parts per million
PSA	Prostate-specific antigen
RPM	Revolution Per Minute
RT	Room Temperature
SVM	Support Vector Machine
TNM	Classification of Malignant Tumours cancer staging system
UKCTOCS	United Kingdom Collaborative Trial of Ovarian Cancer Screening
UKOPS	United Kingdom Ovarian cancer Population Study
UV	Ultra Violet

#### **Chemicals**

$\alpha$ -CCA	Alpha cyano 4-hydroxy-cinnamic acid
AmBic	Ammonium bicarbonate ( $\text{NH}_4\text{HCO}_3$ )
ACN	Acetonitrile
APS	Ammonium Persulphate
BPB	Bromophenol Blue
C8	Octyl silane material
C18	Octadecyl silane material
CCB	Colloidal Coomassie Blue
CHAPS	(3-[(3-cholamidopropyl)dimethylammonio]-1-propanesulfonate)
Cy2	3-(4-carboxymethyl)phenylmethyl)-3'-ethyloxacarbocyanine halide N-hydroxy-succinimidyl ester
Cy3	1-(5-carboxypentyl)-1'-propylindocarbocyanine halide N-hydroxy-succinimidyl ester

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Cy5	1-(5-carboxypentyl)-1'-methylindodicarbocyanine halide N-hydroxysuccinimidyl
DTT	dithiothreitol
IAM	Iodoacetamide
SDS	Sodium Dodecyl Sulphate
TEMED	N,N,N',N'-Tetramethylethylenediamine
TFA	Trifluoroacetic Acid
Tris	Tris-(hydroxymethyl) aminomethane
NHS-ester	N-hydroxy-succinimidyl
PBS	Phosphate-buffered saline

### Mass spectrometry and separation techniques

1DE	One-Dimensional Gel Electrophoresis
2DE	Two-Dimensional Gel Electrophoresis
2D-LC	Two-Dimensional Liquid Chromatography
BVA	Biological Variation Analysis
DE	Delayed Extraction
DIA	Differential In-gel Analysis
DIGE	Difference gel electrophoresis
ESI	Electrospray Ionisation
HPLC	High Performance Liquid Chromatography
IEF	Isoelectrical focusing
IPG	Immobilised pH Gradient
LC	Liquid Chromatography
LC-MS	Liquid Chromatography coupled online with Mass Spectrometry
MALDI	Matrix-Assisted-Laser-Desorption/Ionisation
m/z	mass-to-charge ratio
MS	Mass spectrometry
MS/MS	Tandem mass spectrometry
TOF	Time of Flight
PAGE	Polyacrylamide gel electrophoresis
RP	Reverse phase

### Proteins

ALB	Albumin
APO	Apolipoproteins
HP	Haptoglobin
IgA	Immunoglobulin A
IgG	Immunoglobulin G
SERPIN	Serine protease inhibitor (Antitrypsin)
TF	Transferrin

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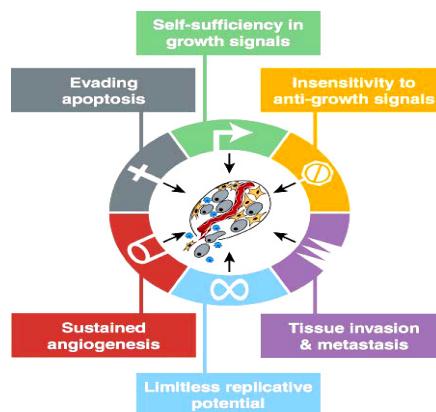
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## Chapter 1 Introduction

### 1.1 Overview of cancer

Cancer is a disease which can affect people of all nationalities and age groups. A number of cancer types are sex specific, such as cervical, uterine sarcoma and ovarian cancer in females and prostate cancer in males. More than 100 distinct types of human cancer have been described, and subtypes of tumours can be found within specific organs [Grizzi and Chiriva-Internati, 2006]. It is theorised that all cancers start with a mutation in a single cell in the body. Although in rare cases a single mutation may be enough, cancer is typically an accumulation of mutations that irreversibly transforms a normal cell into a cancerous one over a prolonged period of time.

Human cancer is predominately a disease of the various cell surface and glandular epithelia [Cairns, 1975; Grizzi and Chiriva-Internati, 2006; Grizzi et al., 2006]. It is a multistage process involving dynamic changes in the genome with alterations in different families of the cell cycle regulatory mechanisms. For example, the production of oncogenes with dominant gain of function and tumour suppressor genes with recessive loss of function as shown in Figure 1.1 [Hanahan and Weinberg, 2000]. Essentially, cancers arise through clonal selection, an evolutionary process promoting proliferation of mutated cells as a result of gene expression changes which also confer a survival advantage. These gene expression changes may manifest as the appearance of new proteins, differences in the amount of expressed proteins, and/or changes in post-translational modifications [Bell, 2005; Hanahan and Weinberg, 2000].



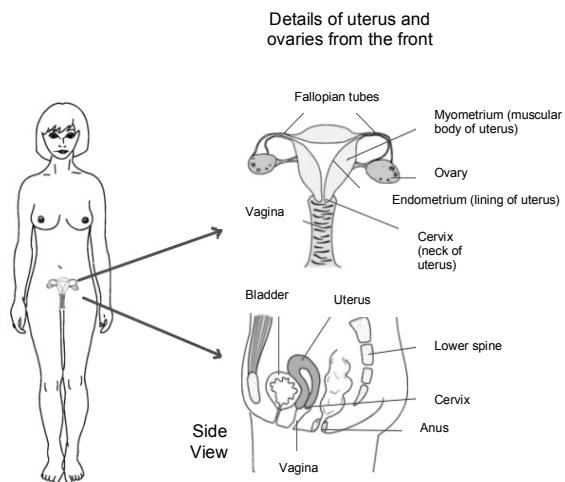
**Figure 1.1 The acquired capabilities of cancer cells.** Adapted from Hanahan & Weinberg (2000).

The majority of cancer cell genotypes are believed to be a manifestation of six essential alterations in the cell physiology that collectively dictate malignant growth. These alterations include evading apoptosis, self-sufficiency in growth signals, insensitivity to anti-growth signals, limitless replicative potential, sustained angiogenesis, and tissue invasion and metastasis [Hanahan and Weinberg, 2000]. Only 10% of cancers are the result of inherited genetic susceptibility. Thus, a 90% risk of developing cancer is attributed to a combination of environment, diet, cultural and lifestyle factors [Bell, 2005; Hanahan and Weinberg, 2000].

A diagnosis of cancer can be a very stressful event for the patients and their families. Patients, partners and other family members can suffer from clinical levels of depression and severe levels of anxiety and stress reactions [Steck et al., 2007]. However, cancer does not have to be terminal and treatment can be very successful for example treatment of prostate and some breast cancers. Successful treatment is invariably dependent on early detection. In the case of late detection where advanced metastatic disease has already developed, there is an extremely poor prognosis. For example, pancreatic and ovarian cancers, while relatively uncommon, have extremely poor prognoses which are directly attributable to their late diagnosis. Thus, early stage disease biomarkers are urgently needed.

### **1.1.1 Overview of ovarian cancer**

Ovarian cancers are one of the most lethal gynaecological malignancies worldwide. The tumours range from benign to aggressive malignant including an intermediate class referred to as borderline carcinomas. Ovarian cancers arise in the ovaries which are responsible for hormone and egg production. As Figure 1.2 shows they lie in the pelvis either side of the uterus. Like other cancers, ovarian tumours are believed to arise through clonal selection of a mutated cell.



**Figure 1.2 Schematic illustration of the female reproductive system and position of the ovaries**

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There are three types of ovarian cancer named according to the cell type from which the tumour originates. The most common are epithelial cancers (carcinomas), which arise in the ovarian surface epithelium (OSE) and account for 90% of diagnosed cases. Epithelial carcinomas can be histologically classified depending on their microscopic appearance and site; namely, endometrioid, mucinous, serous, clear cell, and undifferentiated carcinomas, [Rosenthal et al., 2006].

The second type is malignant germ cell tumours that form in the part of the ovary responsible for egg production; overall they account for approximately 5% of ovarian cancers. The third type comprises malignant sex-cord/stromal tumours. These arise in the connective tissue and hormone producing parts of the ovary and also account for 5% of malignant ovarian tumours.

### 1.1.2 Ovarian cancer aetiology and risk factors

In around 90% of ovarian cancer cases, there is no identifiable cause. However, family history plays an important role in ovarian cancer. Ovarian cancer has been linked with several hereditary syndromes including: breast-ovarian cancer syndrome, hereditary non-polyposis colorectal cancer syndrome, site-specific ovarian cancer

syndrome, Li-Fraumeni syndrome and Cowden's syndrome. All of these are within the 10% of cases that have known identifiable hereditary causes of ovarian cancer.

Breast-ovarian cancer syndrome is characterised by a hereditary mutation in the BRCA1 gene, which has been linked to increased risk of both breast and ovarian cancer. About 30-40% of women who have this mutation develop ovarian cancer. A mutation of the BRCA2 gene also increases the risk of ovarian cancer, but to a lesser degree. Clues that may indicate the presence of these mutations include family members who have ovarian cancer or breast cancer or both, especially those who are diagnosed with breast cancer when younger than 50 years. Ashkenazi Jews demonstrate increased frequency of BRCA1 and BRCA2 gene mutations [Ramus et al., 2007; King et al., 2003].

Hereditary non-polyposis colorectal cancer (HNPCC) syndrome (also known as Lynch syndrome II) is a genetic syndrome that is also caused by inherited gene mutations that reduce the body's ability to repair damage to its DNA. This results in a greatly increased risk for colorectal, endometrial and ovarian cancer. HNPCC is predominately associated with colon cancer developing in people younger than 50 years. The risk for ovarian cancer with HNPCC syndrome is much less than that associated with BRCA1 or BRCA2 and probably causes about 1% of all ovarian epithelial cancers. Other organs that can be involved include the breast, stomach, and pancreas. Germline mutations in one of five mismatch repair genes are responsible for this syndrome. These are MSH2 (chromosome 2q), MLH1 (chromosome 3p), PMS1 (chromosome 2q) PMS2 (chromosome 7p) and MSH6 (chromosome 2p) [Zweemer, 2002].

Li-Fraumeni syndrome is a rare, hereditary cancer syndrome that is linked to an inherited mutation in the p53 gene, which normally prevents cells with DNA damage from replicating. Cancers in Li-Fraumeni families typically occur between the ages of 15 and 44 [Fallows et al., 2001]. Cowden's syndrome or multiple hamartoma syndrome is an inherited genetic disease caused again by mutations in the PTEN tumour suppressor gene. These mutations prevent the PTEN protein from effectively regulating cell survival and division, which can lead to the formation of tumours.

Cowden syndrome is one of several inherited diseases caused by mutations in the PTEN gene. This syndrome primarily affects women, causing skin rashes, tiny wart-like bumps, thyroid disease, and severe benign fibrocystic disease. By age 40, 50-75% of women with Cowden's syndrome develop breast or ovarian cancer. Cowden's syndrome can also be associated with kidney, Merkel cell skin and thyroid cancers [Wright and Whitney, 2006; 2005].

Other factors that increase ovarian cancer risk include age greater than 50 years; 50% of all ovarian cancers are found in women over the age of 63. Studies have indicated a relationship between the number of menstrual cycles in a woman's lifetime and her risk of developing ovarian cancer. Nulliparity (no pregnancies) can also contribute to the risk of developing ovarian cancer. Some studies have shown that the use of fertility drugs also increases the risk of ovarian cancer, such as the prolonged use of the fertility drug clomiphene citrate, especially without achieving pregnancy, may increase the risk for developing ovarian tumours, particularly a type known as low malignant potential or borderline tumours. However, results have not been consistent [Ayhan et al., 2004]. Furthermore, Ashkenazi Jewish heritage (by virtue of an increased frequency of BRCA1 and BRCA2 gene mutations) or European heritage also increases ovarian cancer risk. As some studies have shown that white women are much more likely to have ovarian cancer than African American women, although this may be due to better detection in more developed countries [Ness et al., 2000]. In addition, some studies suggest that the use of estrogen replacement therapy may promote ovarian cancer in women who have been through menopause [Moorman et al., 2005]. The risk among women who used ERT for longer than 10 years was almost double that of women who had never used it and the risk among those who used it for 20 years or more was tripled. For normal healthy women the average lifetime risk for developing ovarian cancer is about 2% [Moorman et al., 2005].

In contrast, factors that inhibit ovulation seem to protect against the development of ovarian cancer. This may be because ovulation disrupts the epithelial layer of the ovary. As cells divide to repair the damage, mutations may occur, increasing the risk of developing cancer (the "incessant ovulation theory") [Purdie et al., 2003; Holschneider and Berek, 2000]. For example, higher numbers of full-term

pregnancies (>37 weeks gestation) also significantly reduces the risk of ovarian cancer as does the use of oral contraceptives. This may be through a combination of ovulation suppression and induction of apoptosis by progestagens [Holschneider and Berek, 2000]. Furthermore, surgery involving tubal ligation to prevent pregnancy, or having a hysterectomy, also lowers the risk of ovarian cancer as does breastfeeding [Tung et al., 2005]. Finally, the removal of the ovaries before cancer occurs reduces the risk to zero. This may be an option for women with a strong family history of the disease, a known mutation in BRCA1 or 2, or in women over 45 years old undergoing abdominal surgery for other reasons.

### 1.1.3 Staging of ovarian cancers

All ovarian cancers are classified according to the terms of the staging scheme developed by the International Federation of Gynecology and Obstetrics (FIGO system) and the classification system developed by the American Joint Committee on Cancer (AJCC, TNM system), which indicate likely prognosis and help to define treatment (Table 1.1). Once an ovarian cancer is assigned a stage, the classification does not change, even if the cancer recurs or metastasizes to other sites within the body. Ovarian cancer treatment ultimately depends upon such staging. In general, the lower the stage, the more favourable is the prognosis.

Stage	Criteria
I	Confined to one (IA) or both (IB) ovaries. The tumour may be on the surface of the ovaries, the tumour may have ruptured, or malignant cells are found in peritoneal fluid or washings (IC).
II	Found outside the ovary and has spread to the uterus or fallopian tubes (IIA) or other areas in the pelvis (IIB). A stage II tumour may involve the capsule of the ovary, or peritoneal fluid or washings contain malignant cells (IIC).
III	Spread to abdominal organs and/or lymph nodes. Microscopic deposits of tumour are on abdominal peritoneal surfaces (IIIA), or small (<2cm) implants of tumour on abdominal peritoneal surfaces (IIIB). Abdominal implants may be larger (>2cm) or pelvic or retroperitoneal abdominal lymph nodes may be involved (IIIC).
IV	Spread outside the abdominal cavity (e.g. malignant cells are found in the fluid surrounding the lungs), or cancer has spread within the intra-abdominal organs (e.g. liver, spleen)

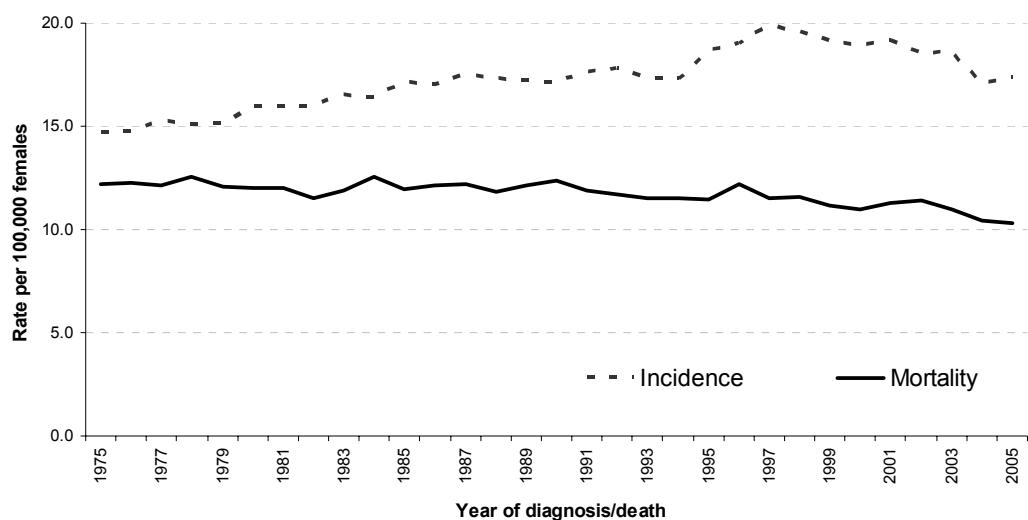
**Table 1.1 Staging in ovarian cancer according to the International Federation of Gynaecology and Obstetrics (FIGO) staging system.**

Ovarian cancers are typically diagnosed at a late stage. This probably reflects the absence of major symptoms in early stage disease, due to the anatomic position of the ovaries, which results in minimal interference with surrounding structures until the ovarian enlargement is considerable, or metastatic disease supervenes. When symptoms do occur, they are frequently nonspecific, often requiring multiple consultations with a primary care physician before further investigation is prompted. Thus, the prognosis is typically poor [Rosenthal et al., 2006].

There are three main forms of treatment for ovarian cancer which include surgery to remove cancerous tissue, chemotherapy to destroy cancer cells using strong anti-cancer drugs and radiotherapy to destroy cancer cells by high-energy radiation exposure. There are also many combinations of these treatment methods. The success of the treatment depends upon a number of factors (e.g., stage and grade of the disease, the histopathologic type, and the patient's age and overall health). Surgery usually is required to treat ovarian cancer. Most patients undergo surgery in addition to another form of treatment (e.g., chemotherapy and/or radiotherapy). Surgery helps the physician to accurately stage the tumour, make a diagnosis, and perform debulking (removal of as much tumour mass as possible). Debulking surgery is especially important in ovarian cancer because aggressive removal of cancerous tissue is associated with improved survival. Once ovarian cancer is confirmed, a total hysterectomy (removal of the uterus), bilateral salpingo-oophorectomy (removal of the fallopian tubes and ovaries on both sides), omentectomy (removal of the fatty tissue that covers the bowels), lymphadenectomy (removal of one or more lymph nodes) may be performed. Tissue removed during debulking is sent for histopathological examination. Patients with no residual tumour mass or tumour masses that measure less than 1 cm have the best survival rate. Modified ("conservative") surgery that leaves tumour-free reproductive organs intact may be conducted in women who still wish to still have children if (a) the tumour is confined (usually not serous or endometriotic in type, which tend to be bilateral tumours), and (b) wedge biopsy of the opposite ovary shows no evidence for disease involvement. Such a procedure carries an increased risk of relapse, therefore, total hysterectomy and salpingo-oophorectomy is recommended immediately after childbearing is complete.

### 1.1.4 The rationale for ovarian cancer screening & novel biomarker discovery

In developed countries, ovarian cancer remains a highly lethal disease. The American Cancer Society estimates that about 22,430 new cases of ovarian cancer were diagnosed in the United States during 2007. In the UK nearly 7,000 cases of ovarian cancer are diagnosed resulting in more than 4,400 deaths each year. Ovarian cancer accounts for about 3% of all cancers in women. The ovarian cancer incidence rate has increased by about 0.5% per year since 1975 (Figure 1.3). Ovarian cancer is predominantly a disease of older, post-menopausal women with almost 85% of cases being diagnosed in women over 50 years. There is a steep increase in incidence after the usual age of the menopause [Breedlove and Busenhart, 2005]. As a result of the advances in surgical management and chemotherapeutic options over the last few decades, the medium term survival for ovarian cancer patients has improved. However, overall long-term survival has not been significantly improved. Poor survival rates are mainly attributable to late diagnosis of the disease as most sufferers of ovarian cancer do not show specific symptoms until the later stages of disease [Rosenthal et al., 2006].



**Figure 1.3 Age-standardised (to only include women over the age of 50) ovarian cancer incidence and mortality rates, Great Britain (1975-2005).**

(Reproduced with permission from Cancer Research UK, May 2008  
<http://info.cancerresearchuk.org/cancerstats/types/ovary/incidence/>)

The overall 5-year survival rate for ovarian cancer is 15% to 30%, whereas the 5-year survival rate of women with stage I at the time of diagnosis can be as high as 95%. However, there is no recommended screening method for women considered to be at low risk of ovarian cancer due to a lack of evidence of a long-term survival benefit, the lack of accurate and sensitive markers and the risks of false positive screening results i.e. unnecessary anxiety and surgery [Breedlove and Busenhart, 2005].

Current screening techniques such as transvaginal sonography and the serum cancer antigen 125 (CA-125) assay are only recommended for women with known strong risk factors. However, both transvaginal sonography and serum CA-125 are currently of unproven diagnostic use. CA-125, the most widely used biomarker for ovarian cancer detection, is a celomic epithelium-related glycoprotein protein that is secreted into the bloodstream by ovarian cells. A CA-125 test result of greater than 35 U/ml is generally accepted as being elevated. The CA-125 test has an 80% chance of returning true positive results from stage II, III, and IV ovarian cancer patients. The other 20% of ovarian cancer patients do not show any increase in CA-125 concentrations. The CA-125 test only returns true positive results for about 50% of stage I ovarian cancer patients. Thus, the CA-125 test is not an adequate early detection tool when used alone [Bosse et al., 2006]. CA-125 is also produced by other mesothelium-derived tissues (e.g. the peritoneum) and consequently may be elevated in many benign gynaecologic diseases and other types of cancer, leading to false positive results. For example, 70% of people with cirrhosis, 60% of people with pancreatic cancer and 20%-25% of people with other malignancies have elevated levels of CA-125. The CA-125 test also has a lower specificity in pre-menopausal women than post-menopausal women [Bosse et al., 2006]. Furthermore, because ultrasound cannot determine the histology of any mass detected, an ovary that looks suspicious on ultrasound may need to be removed surgically in order to exclude the diagnosis of cancer, creating a burden on the health service.

Although a large randomised trial of ovarian cancer screening in the general population is already underway to evaluate the use of an algorithm incorporating rate of change of CA-125 over time, to increase sensitivity and specificity, there is still

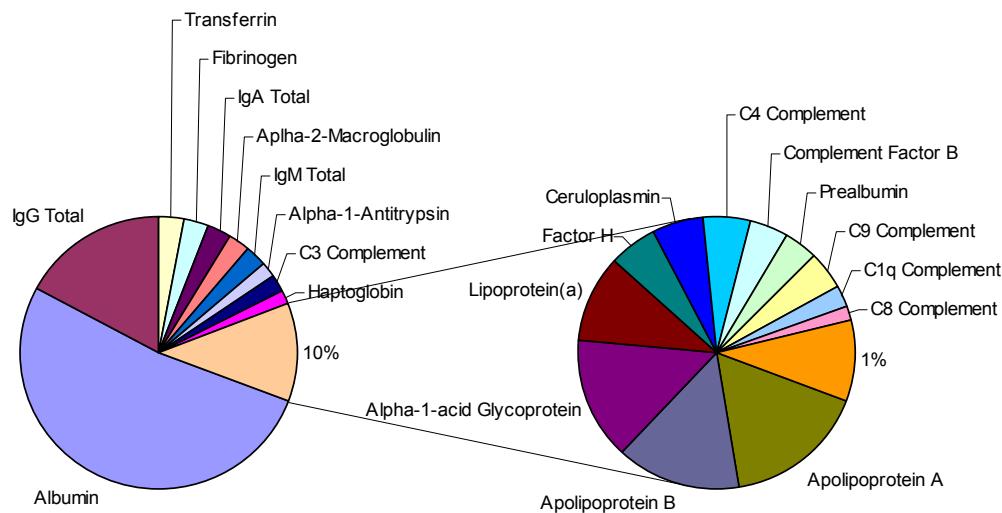
only preliminary evidence that such a screening technique will reduce the mortality from ovarian cancer [Jacobs et al., 1999; Rosenthal et al., 2006].

There is thus an urgent need to find new biomarkers of ovarian cancer amenable to mass screening with high sensitivity and specificity for early-stage ovarian cancer detection and diagnosis that would enable early diagnosis, so that surgical therapy can be offered to all patients rather than a select few. This would ultimately decrease the morbidity and mortality rates from this disease [Bast, Jr. et al., 1998; 2002]. Ideally, for large-scale screening biomarkers would be detectable in the blood, facilitating the development of relatively non-invasive collection and assays.

## 1.2 Human Serum

Human serum is the clear yellowish fluid obtained upon separating whole blood into its solid and liquid components after it has been allowed to clot. Serum is a complex bodily fluid that contains approximately 60 to 80 mg of protein per mL in addition to various small molecules including salts, lipids, amino acids and sugars. The major protein constituents of serum include albumin (ALB), immunoglobulins (IgG, IgA), transferrin (TF), antitrypsin (SERPIN), haptoglobin (HP), complement proteins and lipoproteins (APO). Twenty-two of these abundant proteins make up 99% of the total protein content (Figure 1.4). It is estimated that 1000s of relatively low abundances proteins and peptides may be commonly present in serum [Fusaro and Stone, 2003]. In addition to the major protein constituents, serum contains any other proteins that are actively synthesized and secreted, or shed from cells and tissues throughout the body. As serum constantly perfuses tissues in their microenvironment, it potentially holds an archive of histological information. Therefore, the background matrix of serum represents a complex milieu in which unique disease-specific biomarkers may be found in extremely low abundance.

However, while the easily obtainable nature and the high protein content of serum deem it a valuable specimen for biomarker determination, human serum is one of the most complex proteomes known and there are still numerous hurdles to overcome when analysing it. For example, albumin is the most abundant protein in serum and may be 10 or more orders of magnitude higher in concentration than the rarest of proteins [Fusaro and Stone, 2003]. In addition, many serum proteins have similar molecular weight and overall charge, making protein separation difficult. Therefore, biomarkers for disease at low concentrations in serum may be hidden by more abundant proteins with similar biophysical characteristics. As such, the reliable proteomic characterisation of serum and identification of biomarkers could be dramatically improved by reducing the complexity of the serum proteome through additional fractionation.



**Figure 1.4 The relative contribution of proteins within serum.** It is hypothesized that putative biomarkers will be found in the 1% portion of serum proteins [Fusaro and Stone, 2003].

### 1.2.1 Serum protein biomarkers

A biomarker can be broadly defined as any characteristic that can be objectively measured and evaluated as an indicator of normal biological or pathological processes. Serum protein biomarkers are produced by tissues or tumours. When detected in higher or lower amounts in blood, they can be suggestive of the presence of a tumour.

Tests based on biomarkers have been around for more than half a century, but interest in their application for diagnostics and for clinical screening has increased remarkably since the beginning of the 21<sup>st</sup> century [Baker, 2005]. Biomarkers have the potential to have a tremendous impact in clinical oncology by facilitating the identification of individuals at risk for developing cancer, assisting in the preclinical detection of cancer and ultimately allowing real-time monitoring of therapeutic responses. Several serological markers are already routinely used for a number of cancers (Table 1.2).

One example of a serum biomarker is cancer antigen 125 (CA-125). As previously mentioned, CA-125 is used as a biomarker for measuring the risk of ovarian cancer or as an indicator of malignancy. However, evidence suggests CA-125 lacks the sensitivity and specificity for general screening as it can be elevated in other malignant cancers, including those originating in the endometrium, fallopian tubes, lungs, breast and gastrointestinal tract. CA-125 may also be elevated in a number of relatively benign conditions, such as endometriosis, several diseases of the ovary, and pregnancy. Hence, there is a need to find putative markers for ovarian cancer which can be used in combination with CA-125 levels to offer non-invasive screening which is robust, highly sensitive and disease-specific. Examples of existing serum markers for ovarian cancer include carcinoembryonic antigen, ovarian cystadenocarcinoma antigen, lipid-associated sialic acid, NB/70K, TAG 72.3 as well as CA-125.

Biomarker	Cancer type	Specificity	Example of non-cancer pathology	Primary clinical use
$\alpha$ -fetoprotein	Hepatocellular, non-seminomatous testicular	Moderate	Prostatitis	Staging
Human chorionic gonadotropin- $\beta$	Testicular, ovarian	Low	Pregnancy	Staging
CA-15-3	Breast	Poor	Cirrhosis, benign diseases of ovaries and breast	Disease monitoring
CA19-9	Gastro, pancreatic, stomach	Poor	Gastritis	Disease monitoring
CA-125	Ovarian, cervical, uterine, fallopian tube	Moderate	Pancreatitis, kidney or liver disease	Disease monitoring
CA27-29	Breast	Not known	Not known	Disease monitoring
CEA	Colorectal, pancreas, lung, breast, medullary thyroid	Low	Non-malignant disorders	Disease monitoring
Epidermal growth factor receptor	Colon, non-small cell lung cancer	Low	Non-malignant disorders e.g. benign prostatic hyperplasia	Selection of therapy
Her2/Neu	Breast, ovarian	Moderate	Benign breast disease	Disease monitoring; selection of therapy
PSA	Prostate	High	Benign prostatic hyperplasia	Screening; disease monitoring
Thyroglobulin	Thyroid	Poor	Grave's disease thyroiditis	Disease monitoring

CA: Cancer antigen; CEA Carcinoembryonic antigen; PSA: Prostate-specific antigen

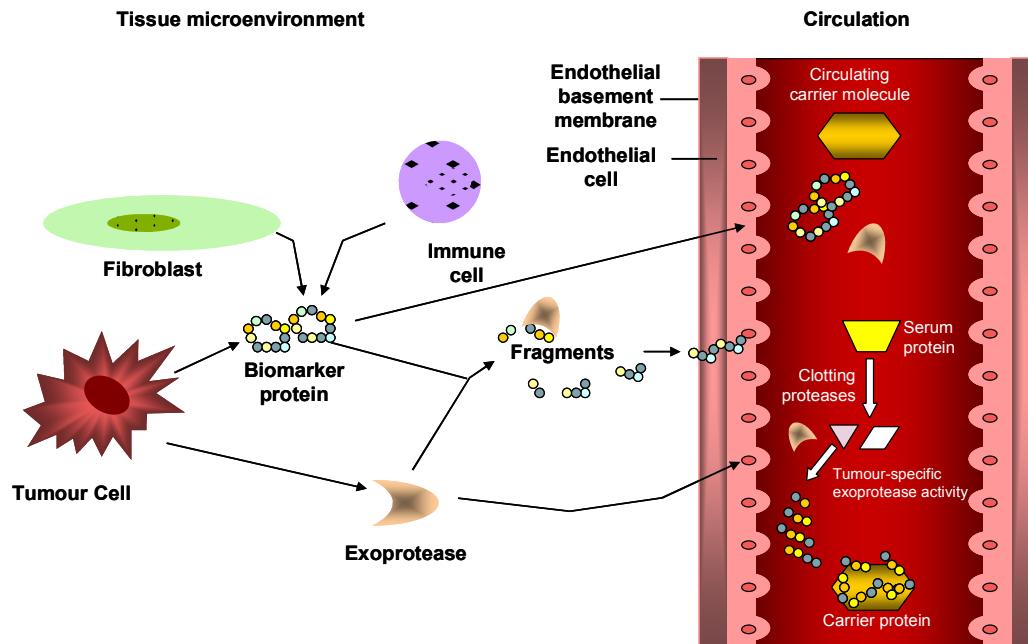
**Table 1.2 Common serum cancer markers used in primary care.** Adapted from aoui-Jamali & Xu (2006).

### 1.2.2 Serum proteomics in cancer biomarker discovery

In recent years there has been immense interest in applying proteomics to the development of new serological biomarker platforms for early diagnosis of chronic diseases such as cancer. Proteomics can be defined as the qualitative and quantitative comparison of proteomes (PROTEin complement of a genOME) under different conditions to further unravel biological processes. Since at least the 1950s there has been support for the idea that plasma/serum protein patterns might provide important insight into the presence and activity of disease. Undeniably, extracellular fluids such as serum represent a major link among all cells, tissues and organs of an organism and contain a complex collection of peptides, proteins and protein fragments that are produced in the entire body. Thus, the analysis of human serum has great potential for novel putative biomarker discovery. Indeed assays to measure  $> 100$  different proteins in blood have been developed and are in routine use in clinical chemistry laboratories today. The fibrinogen functional turbidimetric assay is an example of a blood-based assay which has a diagnostic value in pathology-disseminated intravascular coagulation and in assessing risk for atherothrombosis [Stief, 2008].

Conventionally, differential two-dimensional polyacrylamide gel electrophoresis (2D-PAGE) was the mainstay of proteomic biomarker discovery [Anderson and Anderson, 2002; Anderson et al., 2004]. However, as a result of improvements in the sensitivity and accuracy of mass spectrometry (MS), proteomics has become increasingly popular for the analysis of complex protein samples such as human plasma and serum. This has led to the identification of more than 1500 different gene products in the serum/plasma of healthy donors [Villanueva et al., 2006]. In addition to proteomic studies looking for biomarkers of cancer in serum [Villanueva et al., 2006; Zimmerman et al., 2005; Zhang et al., 2004], several cancer specific proteins have been identified in the urine of patients with visceral cancers, such as lung [Tantipaiboonwong et al., 2005], ovarian cancer [Chambers and Vanderhyden, 2006] and breast cancer [Roy et al., 2004]. These studies support the view that bodily fluids like plasma, serum and urine have the potential to be a valuable source of diagnostic and prognostic markers of disease [Mor et al., 2005; Liotta and Petricoin, 2006].

It has been hypothesised that proteolysis activity within the tissue microenvironment generates protein fragments that passively diffuse into the circulation. Diagnostic peptides can also be generated *ex vivo* by circulating enzymes derived from the diseased tissue microenvironment acting on exogenously derived protein fragments produced by during the clotting process as shown in Figure 1.5 [Villanueva et al., 2006].



**Figure 1.5 Proteases generate surrogate biomarker fragments.** Circulating proteins generated in the diseased tissue microenvironment may serve as diagnostic protein markers. [Villanueva et al., 2006].

Numerous groups have identified a number of putative cancer biomarkers using mass spectrometry-based proteomics tools which could be potentially useful for diagnosis (Table 1.3) [aoui-Jamali and Xu, 2006]. This may have the added benefit of increasing our understanding of the pathways involved in the initiation and progression of cancer as well as for identifying key cancer biomarkers [Ransohoff, 2005; Robbins et al., 2005].

Biomarker	Cancer type	References
Apolipoprotein A1	Ovarian, pancreatic	Zhang et al., 2004; Kozak et al., 2005
Haptoglobin $\alpha$ -subunit	Ovarian, pancreatic, lung	Ye et al., 2003
Transthyretin fragment	Ovarian	Kozak et al., 2005
Inter-alpha-trypsin inhibitor fragment	Ovarian, pancreatic	Zhang et al., 2004
Vitamin D-binding protein	Prostate, breast	Corder et al., 1993; Pawlik et al., 2006
Serum amyloid A	Nasopharyngeal, pancreatic, ovarian	Orchekowski et al., 2005; Moshkovskii et al., 2005; Hellerman et al., 2007
$\alpha$ 1-antitrypsin and $\alpha$ 1-antichymotrypsin	Pancreatic	Orchekowski et al., 2005; Yu et al., 2005
Haemoglobin-alpha & -beta subunits	Ovarian	Woong-Shick et al., 2005
EPCA-2	Prostate	Leman et al., 2007
Afamin	Ovarian	Jackson et al., 2007

**Table 1.3 Examples of putative serum biomarkers.** Adapted from aoui-Jamali et al. (2006).

The use of mass spectrometry for the direct analysis of proteins and peptides from biological fluids, i.e. human serum, for putative disease biomarker discovery was first reported in 2002. Using peak pattern discrimination several groups reported on the correct classification of (a) ovarian cancer [Petricoin et al., 2002] (b) prostate cancer [Adam et al., 2002; Qu et al., 2002] and (c) breast cancer [Li et al., 2002]. As such, proposals for a blood test-based on MS pattern-recognition of human serum proteins for detecting cancer were put to the U.S. Food and Drug Administration. Subsequent to this commercial laboratories planned to market a blood test for ovarian cancer in late 2003 or early 2004 [Pan et al., 2005; Petricoin and Liotta, 2002; Petricoin et al., 2002; Petricoin, III et al., 2002; Rodland, 2004; Villanueva et al., 2006; Yu et al., 2003; Zhang et al., 2004; Zimmerman et al., 2005]. However, questions were raised about whether the technology's results were reproducible and reliable enough for application in practice [Baggerly et al., 2004; Baggerly et al., 2005]. Important limitations were found in the design of serum proteomics analysis by MS. Bias and chance (or overfitting of data) were considered as probable explanations of the misinterpretation of data. Hence, plans for the blood test were delayed by the U.S. Food and Drug Administration.

While serum proteomics may offer a non-invasive method for population-based screening programmes, the technology has several draw backs and is highly sensitive to pre- and post-analytical variations. Bias is encountered from inherent properties of the samples studied. Many intrinsic specimen characteristics may have no

relationship with the disease in question, but are introduced by any number of factors dependent on logistics of sample collection or selection of subjects included in the study [Drake et al., 2004; Timms et al., 2007; Villanueva et al., 2005]. Strict adherence to standard operating protocols of specimen collection and appropriate matching of case versus control subjects are essential to minimise such sources of error. Collection of case and control specimens by the same site(s) is preferred as each collection site will unavoidably introduce its own bias into how samples are collected [Villanueva et al., 2005; Rai et al., 2005; Drake et al., 2004; Timms et al., 2007; West-Nielsen et al., 2005]. The controversy sparked by the reports in 2002 stimulated improvements in many areas of serum proteomics, from sample collection and serum preparation to the development of new bioinformatics tools to analyse and compare large numbers of data points that are typical of mass spectrometry.

However, another major drawback to MS-based serum profiling is the limitation of this technology to effectively analyse highly complex protein mixtures. Detection of ionized molecules using time-of-flight platforms is inversely related to molecular size such that peptides and small proteins are more readily detected by MS. This places a significant limitation on MS proteomic profiling. Blood protein levels range from nearly millimolar down to femtomolar concentrations. Typical cancer biomarkers are found in the pico- to subnanomolar range. Although MS is highly sensitive, its application to serum profiling has demonstrated the ability to identify proteins at low to submicromolar concentrations. As a result of the complexity of the serum proteome and the limited detection range of MS-based platforms several pre-fractionation techniques have become popular. Another drawback to using MS profiling of the serum proteome is the difficulty of standardising and calibrating instrumentation across multiple sites in order to directly compare findings from different laboratories.

Furthermore, most proteomic studies published to date have identified relatively abundant host response (acute-phase) proteins as candidate biomarkers [Fung et al., 2005]. Host response proteins, e.g. haptoglobin, serum amyloid A,  $\alpha$ -1-antitrypsin,  $\alpha$ -1-antichymotrypsin, inter- $\alpha$ -trypsin inhibitor and the apolipoproteins, are often dismissed because of an apparent lack of specificity. However, it is hypothesized that

the peptide/protein changes comprising the diagnostic patterns in MS based analysis are derived (directly or indirectly) from the molecular state of the tumour–host microenvironment. The proteomic pattern that originates from this microenvironment may signal the presence of an early-stage lesion. Under this hypothesis, the discriminatory markers are likely to be metabolic products, enzymatic fragments, modified proteins, peptides, or cytokines that could be highly specific for the microenvironment of the lesion [Liotta and Petricoin, 2006].

There are several examples of host response proteins which have been identified as markers for ovarian cancer. Recently, three ‘host-response’ proteins, apolipoprotein A1 (down-regulated in cancer), a truncated form of transthyretin (down-regulated) and a cleavage fragment of inter- $\alpha$ -trypsin inhibitor heavy chain H4 (up-regulated) were also identified as putative markers for ovarian cancer using a proteomics based approach [Zhang et al., 2004]. Furthermore, apolipoprotein A1 (Apo A1), transferrin (TF) and transthyretin (TTR) are also reported as a panel of markers for ovarian cancer [Nosssov et al., 2008]. However, attempts to independently validate these proteins were unsuccessful. Furthermore, these proteins may not be specific for ovarian cancer.

### 1.3 Sample fractionation and protein separation methods

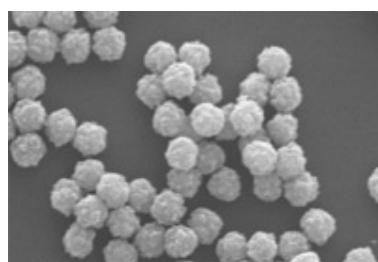
To overcome the problems posed by the large dynamic range of the serum proteome and the interference of the abundant proteins, sample fractionation has become a prerequisite for MS-based serum profiling. Extensive fractionation is thought to improve protein coverage, but adds to the cost of throughput and affects method reproducibility.

#### 1.3.1 Magnetic bead-based peptide extraction

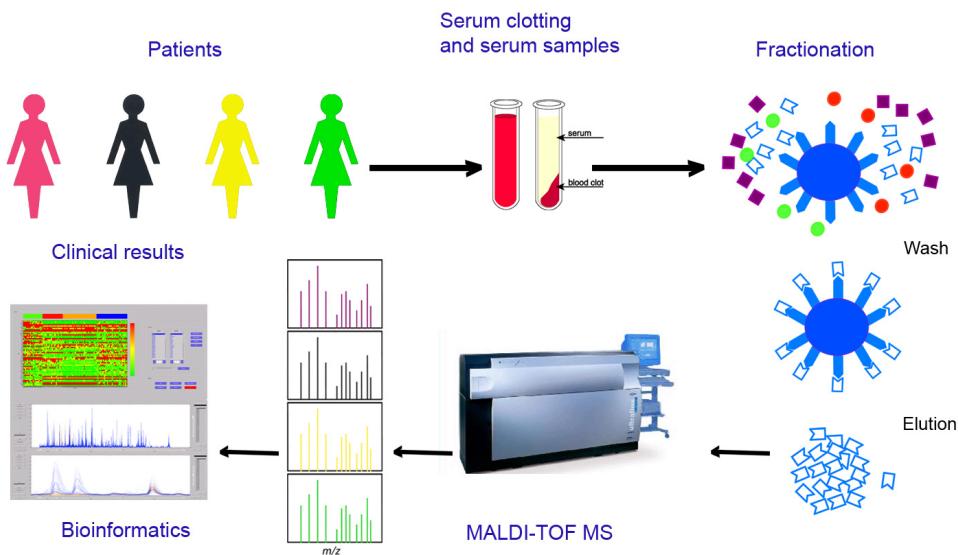
As a result of the complexity of serum and the presence of salts a polypeptide extraction and desalting step is almost always necessary prior to MS-based protein profiling. Methods such as magnetic bead extraction have been combined with MALDI-TOF MS for mass spectral profiling of serum peptides and proteins, often using automated extraction to improve sample throughput and reproducibility [Villanueva et al., 2004; Villanueva, 2006]. Fractionation simplifies complex samples and separates peptides and proteins from non-protein species hence removing contaminants and improving the detection limits for serum peptide ions. The high sensitivity of modern mass spectrometers, combined with advanced bioinformatics makes this technique ideally suited for proteome profiling and protein identification. Other available techniques for serum profiling include Surface-enhanced laser desorption/ionization (SELDI) MS. SELDI is a variation of matrix-assisted laser desorption/ionization (MALDI) MS that uses a target modified to achieve biochemical affinity with the analyte compound. In MALDI-MS, a protein or peptide sample is mixed with the matrix molecule in solution and small amounts of the mixture are deposited on a surface and allowed to co-crystallize as the solvent evaporates. While in SELDI-MS the protein mixture is spotted on a surface modified with a chemical functionality. Binding to the SELDI surface acts as a separation step and the subset of proteins that bind to the surface are easier to analyse. Common surfaces include CM10 (weak-positive ion exchange), H50 (hydrophobic surface, similar to C6-C12 reverse phase columns), IMAC30 (metal-binding surface), and Q10 (strong anion exchanger). Surfaces can also be functionalized with antibodies, other proteins, or DNA.

Within the published literature there is an overall lack of consensus over the optimal method for serum peptide extraction. Different papers detail the use of different types of stationary phases and co-ordinating ligands and employ different conditions for polypeptide binding, washing and elution. The lack of agreement between published protocols, combined with the widespread reports of low inter-laboratory reproducibility highlights the need for method development of a generalised protocol targeted at mass spectrometry [Baumann et al., 2005; de Noo et al., 2005; Martorella and Robbins, 2007; Villanueva et al., 2004].

The most commonly used resins for serum extraction are reverse phase (RP) beads that have modified alkyl groups and can be made of a polymer shell with an iron core. These beads are superparamagnetic, which means that the beads exhibit magnetic properties in a magnetic field, with no residual magnetism once removed (Figure 1.6). The beads separate gently and no columns or centrifugation steps are necessary. They are spherical in shape and have defined surface chemistry minimising chemical agglutination and non-specific binding. This allows uniformity (co-efficient of variance (CV)  $<3\%$ ) of size, shape and surface area provides optimal accessibility and reaction kinetics, for rapid and efficient binding, batch-to-batch consistency (typically within 5%) improving the reproducibility across different runs. A typical MS-based serum profiling workflow is shown in Figure 1.7.



**Figure 1.6 Superparamagnetic beads used for serum extraction**



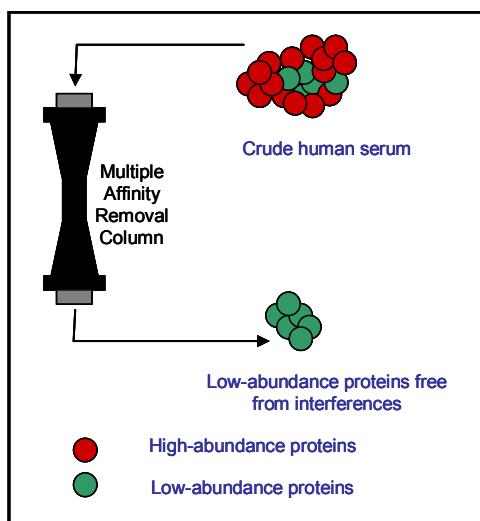
**Figure 1.7 Basic principles of proteomics-based serum profiling.** Blood samples from volunteers are collected and processed using a standardised protocol. Samples are then fractionated to extract peptide and proteins for analysis by mass spectrometry coupled with bioinformatics tools to mine for differentially expressed peaks between cases and controls.

### 1.3.2 Serum Depletion

Albumin constitutes anywhere from 55% to 75% of the total protein content of human serum and consequently, is an overwhelming signal in separation and detection assays. Even following albumin removal, serum still contains other high-abundance proteins, the most abundant being IgG, IgA, transferrin, haptoglobin, fibrinogen and antitrypsin. Collectively, these seven proteins constitute ~90% of the total protein in serum. Therefore, their removal represents a fundamental improvement toward characterisation of the lower abundant serum proteins. Classically, Cibacron Blue and protein A/G chromatography methods have been used to deplete serum of albumin and the immunoglobulins. However, an increasing number of methods for the removal of high-abundance proteins from serum are becoming commercially available, making serum analysis a more routine laboratory procedure. The work presented in this thesis has involved the use of two recently commercialised enrichment strategies including the Multiple Affinity Removal System (MARS, Agilent) and the ProteoMiner protein enrichment kit (BioRad).

### 1.3.3 The Multiple Affinity Removal System (MARS)

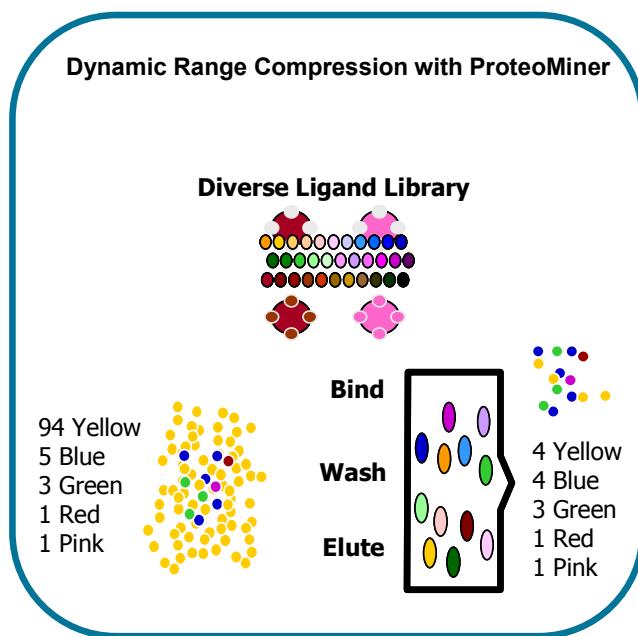
MARS consists of a reusable high-capacity affinity liquid chromatography column containing polyclonal antibodies for the removal of the top seven abundant proteins from human serum. It is designed to bind and remove 85-90% of albumin, IgG, transferrin, haptoglobin, IgA, antitrypsin & fibrinogen which constitutes 90% of the total protein amount in serum. Thus, it facilitates the downstream expression profiling of lower abundant protein species in the flow through (Figure 1.8).



**Figure 1.8 Schematic illustration of the MARS column.** The “top-seven” abundant proteins are captured by affinity binding to antibodies and removed from serum. This facilitates the analysis of the lower abundant protein fraction for putative biomarker discovery.

### 1.3.4 ProteoMiner technology

The ProteoMiner technology is a sample preparation tool used for the compression of the dynamic range of protein concentrations. It is based on treatment of complex protein samples with a large, highly diverse library of hexa-peptides bound to chromatographic supports in a spin column. In theory, the library contains binding sites for all protein sequences in the sample. Since the bead capacity limits binding capacity, high-abundance proteins quickly saturate their binding sites and excess protein is washed out during the procedure. In contrast, low-abundance proteins are concentrated on their specific ligands, thereby decreasing the dynamic range of protein expression in the sample. When analysed in downstream applications, the number of proteins detected dramatically increases (Figure 1.9) [Guerrier et al. 2006; Guerrier et al. 2008; Boschetti et al. 2008].



**Figure 1.9 Schematic illustration of the ProteoMiner protein enrichment strategy.** An ‘equalised’ amount of all serum proteins are captured by the combinatorial peptide ligands.

### 1.3.5 High performance two-dimensional gel electrophoresis

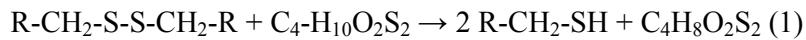
In 1975 O'Farrell, Klose, and Scheele almost simultaneously published methods based on isoelectrical focusing (IEF) of proteins in the first dimension and SDS-polyacrylamide gel electrophoresis (SDS-PAGE) in the second. This marked the introduction of two-dimensional electrophoresis (2-DE) for proteins separation and the beginning of the proteomics era [Scheele, 1975; O'Farrell, 1975; Klose, 1975].

In general, 2-DE sorts proteins in two dimensions based on protein charge and molecular weight. In the first dimension, proteins are separated by IEF in a pH gradient, where proteins become focused at their isoelectric points (pI) when they reach zero net charge [Righetti, 1989; Righetti et al., 1988]. The three dimensional configuration of the proteins does not play a role as the protein is assumed to be completely denatured because of the chaotropic chemicals used in the solubilisation buffer. Post-translational modifications (PTMs), such as phosphorylation or glycosylation may influence the net charge of a protein, and can be visualised as spot trains on the gel. Isoelectric focusing is in principle an end point method.

Furthermore, a major development to overcome the problems of pH gradient instability and irreproducibility was the introduction of immobilized pH gradients (IPG) for IEF [Bjellqvist et al., 1982]. IPGs are based on the principle that the pH gradient is generated by a limited number (6-8) of well-defined chemicals (the 'Immobilines') which are co-polymerized with the acrylamide matrix. Thus cathodic drift is eliminated, reproducibility enhanced and pattern matching and inter-laboratory comparisons were simplified. IPGs allow the generation of pH gradients of any desired range (broad, narrow or ultra-narrow) between pH 3 and 12. Since the sample loading capacity of IPG-IEF is also higher than with CA-IEF, especially in combination with narrow (1 pH unit) or ultra-narrow (0.1 pH unit) IPGs, 2D-PAGE with IPGs is the method of choice for micropreparative separation and spot identification.

Following IEF, IPG strips are equilibrated for the second dimension. This treatment has three functions; reduction and alkylation of disulfide bonds, acetylation and SDS

treatment. In order to maintain solubilisation in the second dimension, disulphide bonds are once more reduced with dithiothreitol (DTT) according to reaction (1) and alkylated with iodoacetamide according to reaction (2). Alkylation prevents the formation of new disulfide bonds.



In the second dimension, proteins are separated according to their relative molecular weight (Mw) by conventional SDS-PAGE. The detergent SDS binds to the proteins at a ratio of about one SDS molecule per two amino acid residues in such a way that all proteins have the same net negative charge density and thus migrate in an electrical field according to their relative molecular mass. The strips are transferred to second dimension polyacrylamide gels. An electric field is applied and the proteins migrate towards the anode due to their negative charge and the sieving effects of cross-linked gels.

The 2D electrophoretic mobility of a protein is reasonably specific thus allowing accurate comparison of protein amounts in different samples analysed on distinct gels. Usually each spot on the resolving 2D gel corresponds to a single protein species of the sample, however, in certain cases more than one protein can be found in a single spot on a gel. This happens when proteins present in the same spot have the same pI and Mw. 2-DE allows separation of thousands of different proteins as well as providing protein information such as the protein pI, Mw, PTM and the amount of each protein. At present, there are no other techniques that are capable of simultaneously resolving thousands of proteins in one separation procedure. However, there are some drawbacks of 2-DE (i.e. poor resolution of high and low molecular weight proteins and hydrophobic and basic proteins, low gel-to-gel reproducibility in different experimental runs; it is also a labour intensive and expensive technique) that have limited its application in some proteomics studies.

An important step made in the 2-DE strategy for protein study was the introduction of protein labelling and detection in order to further define quantitative and qualitative

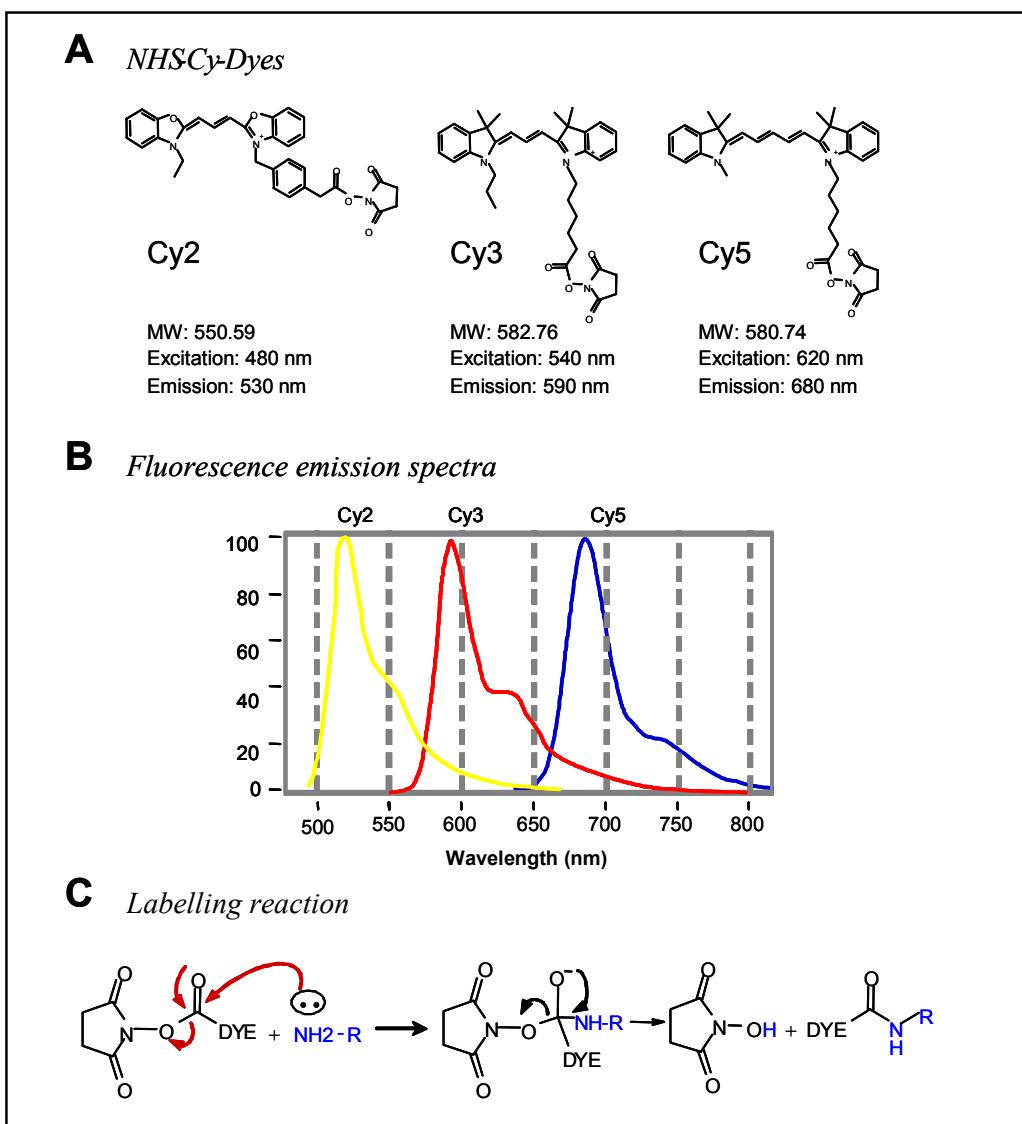
profiles of complex protein samples. The sensitivity and specificity of protein stains has always been the major factor influencing the amount of information that can be extracted from 2D gels. In addition, the most significant breakthrough in proteomics has been the mass spectrometric identification of gel-separated proteins, which has extended analyses beyond the mere display of proteins. Mass spectrometry is very sensitive, can deal with a mixture of proteins and is amenable to high-throughput operation. In the last decade, the sensitivity of analysis and accuracy of results for protein identification by MS have increased by several orders of magnitude, and nowadays it is estimated that proteins in the femtomolar range can be identified from complex samples if appropriate fractionation strategies are applied.

Several reviews have outlined the different methods of choice for detection of gel separated proteins [Patton, 2000; Rabilloud, 2002]. Most strategies for protein detection in 2D gels use post-electrophoretic protein staining and a multitude of different methods have been described which differ in their sensitivity, specificity, linear dynamic range and compatibility with downstream identification mainly by mass spectrometry. Common post-electrophoretic protein stains employed for protein detection before MS include: i) Colloidal Coomassie Blue G-250, which has a linear detection range of 100ng-10 $\mu$ g, is simple to use and is compatible with MS [Neuhoff et al., 1988]; ii) Silver stains have a higher sensitive range of detection, typically 2-4 ng of protein per spot. Some silver-staining methods are incompatible with MS, because the aldehyde-based cross-linkers used in the sensitisation steps can cross-link proteins, and because the silver ions can interfere with mass spectrometric data analysis. Silver staining is only linear over a small dynamic range and can also stain differently based on the protein post-translational modifications and amino acid composition. This makes silver staining a poor choice for quantitation of protein expression. iii) fluorescent stains, such as the ruthenium-based fluorescent dyes SYPRO Ruby SYPRO Orange and Deep purple (Molecular Probes). SYPRO Ruby is a transition metal organic complex that binds directly to proteins by electrostatic interactions. It provides sensitivity similar to that of classical silver staining (1-2 ng of protein/spot) but without the complex methodology, limitation on linear dynamic range, or the problems with MS compatibility. However, fluorescent dyes are expensive and require fluorescent scanners for analysis. v) Phosphoprotein stains are

becoming increasingly important because of the growing interest in studying phosphorylation, an important post-translational modification that influences and determines the function of proteins. Pro-Q Diamond (Molecular Probes, Eugene, OR, USA) has been introduced as a fluorescence detection method for gel separated phosphoproteins with a detection limit of 1-2 ng. However, it was shown that this dye is not highly specific and it can label non phosphorylated proteins. Several reviews have outlined the different methods of choice for detection of gel separated proteins [Schulenberg et al., 2003; Steinberg et al., 2003].

### 1.3.6 Two-dimensional Difference Gel Electrophoresis (2D-DIGE)

Fluorescence two-dimensional difference gel electrophoresis (2D-DIGE) is a 2-DE gel-based proteomics technique that provides a sensitive, rapid and quantitative analysis of differential protein expression between two or more biological samples. Developed by Unlu et al. in 1997, the technique utilizes charge- and mass- matched chemical derivatives of spectrally distinct fluorescent cyanine dyes which are used to covalently label lysine residues in different samples prior to mixing and separating on the same 2-DE gel [Unlu et al., 1997]. In this way, the labelled samples would be subjected to identical electrophoretic conditions to generate directly superimposable images for relative quantification. Cyanine dyes were first described by Mujumdar et al. [Mujumdar et al., 1989; Mujumdar et al., 1993]. These fluorophors have a structure which can be modified to create a panel of reactive fluorescent tags. Unlu et al., (1997) developed the N-hydroxy-succinimidyl (NHS)-ester derivatives of the fluorescent cyanines 3 and 5 (NHS-propyl-Cy3 and NHS-methyl-Cy5). These dyes and a third cyanine dye, NHS-Cy2, are now commercially available from GE Healthcare (Figure 1.10). All 3 dyes possess a single net charge of +1, thus maintaining the charge of the lysine residue which they modify.



**Figure 1.10 Characteristics of the NHS-Cy-dyes.** A) Structure of the NHS-Cyanine dyes. Cy2, 3-(4-carboxymethyl-phenylmethyl)-3'-ethyloxacarbocyanine halide N-hydroxysuccinimidyl ester; Cy3, 1-(5-carboxypentyl)-1'-propylindocarbocyanine halide N-hydroxysuccinimidyl ester; Cy5; 1-(5-carboxypentyl)-1'-methylindodicarbocyanine halide N-hydroxysuccinimidyl. Each dye has a similar molecular weight and single positive charge matching the charge of the modified primary amino group. B) Each dye displays distinct emission spectra enabling the individual detection of differentially labelled proteins at the appropriate wavelength without overlap of signals. C) The dyes have an N-hydroxysuccinimidyl ester reactive group triggering covalent interaction with the primary amine groups of lysine residues or the N-terminus.

Initially, the NHS Cy3 and Cy5 dyes were used to label different protein samples prior to mixing and running them on the same 2-DE [Unlu et al., 1997]. This allowed the samples to run under identical electrophoretic conditions in a type of differential display format. Theoretically, to compare the same proteins derived from two differently labelled samples, the dyes should be mass and charge matched and the dye modifications should not perturb the electrophoretic mobility of labelled proteins. For this reason, the size of the aliphatic chain (Figure 1.10A) was originally modulated to maintain a similar molecular weight between each dye and the dyes possess a positive charge which matches the positively charged amino groups they modify.

The advantage of using lysine labelling is that almost all proteins contain at least one lysine residue and it contains a reactive amino group. For expression profiling the dyes are typically used under conditions of minimal stoichiometrical labelling. Ideally, just a single lysine residue is labelled in around 5% of the molecules of a particular protein. This helps to keep protein soluble and limits the shift in Mw of the labelled versus unlabelled population of proteins during SDS-PAGE run, whilst keeping the sensitivity of detection high. The reported sensitivity of DIGE labelling is ~1ng protein per spot. The method of using the three Cy dyes was originally evaluated and applied by Tonge et al. and Gharbi et al. [Tonge et al., 2001; Gharbi et al., 2002] and further optimised and commercialised by GE Healthcare.

For quantification, one of the dyes (usually Cy2) is used to label an internal standard sample which is run on all gels and usually comprises an equal pool of proteins from all samples under investigation [Gharbi et al., 2002]. Thus, the Cy2 labelled pool is used for normalisation of data across gels, thereby reducing experimental variation and increasing the accuracy of quantitation and statistical confidence of protein expression differences. Since fluorescence detection also provides a superior linear dynamic range of detection and sensitivity compared to visible staining methods [Patton, 2000], this technology is suited to the analysis of biological samples with their large dynamic ranges of protein abundance. As shown in Figure 1.11 this labelling strategy is also compatible with downstream identification of gel spots by mass spectrometry (MS) [Tonge et al., 2001; Gharbi et al., 2002].

For protein expression profiling, gels are converted to digital images using scanning devices and these are processed to detect the protein features. Spot volumes are quantified and spot patterns matched across different gels. Statistical methods are then employed to detect protein spots with statistically significant changes in expression. This kind of image analysis is usually performed with dedicated software programmes.

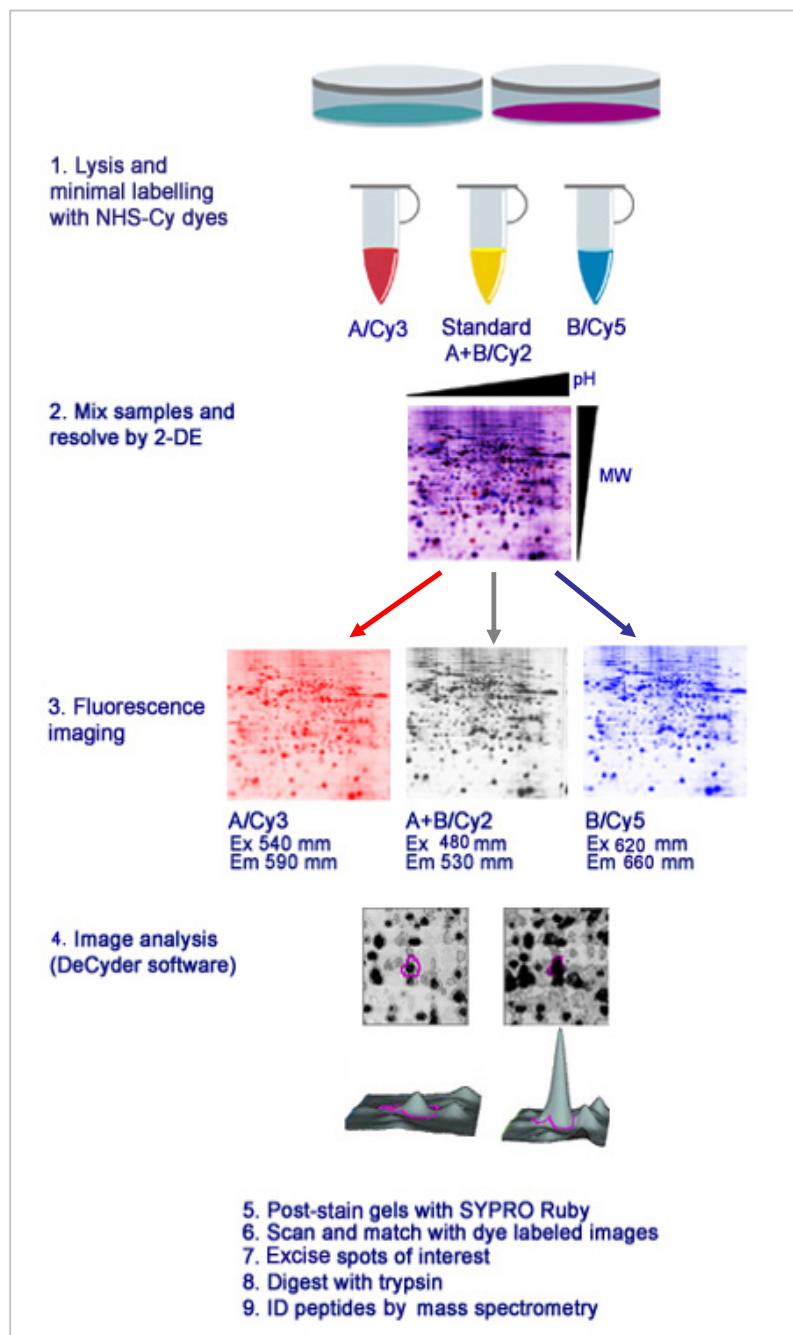


Figure 1.11 Schematic representation of 2D-DIGE protocol for minimal lysine labelling and using an internal standard for normalization.

## 1.4 Mass Spectrometry

### 1.4.1 Biological Mass Spectrometry

Mass spectrometry (MS) is a powerful analytical technique used for the accurate measurement of the mass-to-charge ratio ( $m/z$ ) of molecules. The development of the first mass spectrometer is attributed to J.J. Thomson, who at the beginning of the 20<sup>th</sup> century measured the  $m/z$  ratios of several atoms and small molecules. In the first half of the 20<sup>th</sup> century, developments in ionisation methods and analysers occurred with the parallel application of mass spectrometry in the field of organic chemistry for the elucidation of chemical structures. It was not until the beginning of the 1990's however, that the field of biological mass spectrometry became significant. This was due to the introduction of soft ionisation methods, e.g. Matrix-Assisted-Laser-Desorption/Ionisation (MALDI) by Tanaka, and Karas and Hillenkamp, and Electron Spray Ionisation (ESI) by Fenn that allowed for the ionisation of macromolecules such as proteins and peptides [Lin et al., 2003; Zhang et al., 2004]. In recognition of the development of ESI and for the development of soft laser desorption (SLD) Fenn and Tanaka received the Nobel Prize for Chemistry in 2002.

A mass spectrometer can be defined as an instrument capable of measuring the mass-to-charge ratio of molecules. Mass spectrometers generally couple three devices, namely i) an ionisation device, ii) a mass analyser and iii) a detector. In addition, sample inlet and data output recorders are needed, but they are not part of the mass spectrometer as such. There are many different kinds of mass spectrometers described generally by the types of ionisation sources, mass analysers, and detectors that are used. In all MS methods, analyte molecules must be converted into gaseous ions using an ionisation source. The most commonly used ionisation sources for biological molecules are MALDI. The other most used ionisation source is ESI. Other ionisation methods include Fast Atom Bombardment (FAB), Chemical Ionisation (CI), Thermal Ionisation (TIMS), Secondary Ionisation (SIMS) and Plasma Desorption (PD).

An electric or magnetic field can deflect charged particles, and since the kinetic energy imparted by motion through an electric field gives the particles an inertia

dependent on the particle's mass, the mass analyser can use this to steer certain ions to a detector based on their  $m/z$  ratio by varying the electrical or magnetic field. It can be used to select a narrow mass range (i.e. to select peptides of interest for tandem mass spectrometry (MS/MS)) or to scan through a range of masses to catalogue the ions present (survey scan). Examples of mass analysers are quadrupole mass analysers, time-of-flight (TOF), ion trap (IT), ion cyclotron resonance (ICR), orbitrap and magnetic sector instruments. There are numerous combinations of mass analysers in so called hybrid instruments. The first three are the most commonly used analysers in biological mass spectrometry.

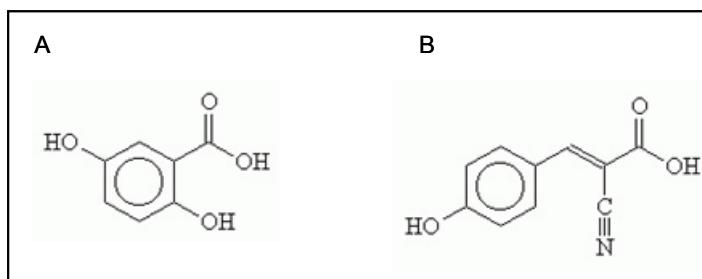
There are several ways to detect ions. Routinely these are recorded when an ion hits a detector plate such as Multi Channel Plates, or MCP. As ions hit the plate a cascade of electrons is released, amplifying the single ion detection. This flow is called image current and can be detected and amplified. When a scan is conducted in the mass analyser, the charge induced in the detector during the course of the scan will produce a mass spectrum, a record of the  $m/z$  values at which ions are present and their intensities.

### 1.4.2 Ionisation methods

Biological mass spectrometry has been and is being developed at a rapid pace since the development of the soft ionisation techniques MALDI and ESI.

#### 1.4.2.1 Matrix Assisted Laser Desorption Ionisation (MALDI)

MALDI was first introduced by Karas & Hillenkamp and Tanaka in 1988 as a ‘soft’ ionisation method with which relatively large macromolecules could be ionised and analysed in the gaseous phase [Karas and Hillenkamp, 1988; Hoffmann, 2002]. In this ionisation method the sample is mixed with an excess of matrix molecules and allowed to crystallise and then a laser is used to excite and ionize analytes from the solid to the gas phase. The matrices used in MALDI are typically acidic compounds (e.g. carboxylic acids) with an absorption in the region of the laser wavelength. The most commonly used matrices for protein/peptide analysis are 2,5-dihydroxybenzoic acid (DHB) and  $\alpha$ -cyano-4-hydroxycinnamic acid ( $\alpha$ -CCA) (Figure 1.12).



**Figure 1.12 Examples of commonly used MALDI matrices.** Two commonly used matrices used for protein/peptide analysis are A) 2,5-dihydroxybenzoic acid (DHB) and B)  $\alpha$ -cyano-4-hydroxycinnamic acid ( $\alpha$ -CCA). DHB forms a crystal rim and ‘hot spots’ of crystallised peptides, and is relatively salt tolerant,  $\alpha$ -CCA forms semi-homogenous spots which makes it more amenable for automated spectral acquisition.

#### 1.4.2.1.1 Principles of the MALDI process

##### (i) The Formation of a 'Solid Sample'

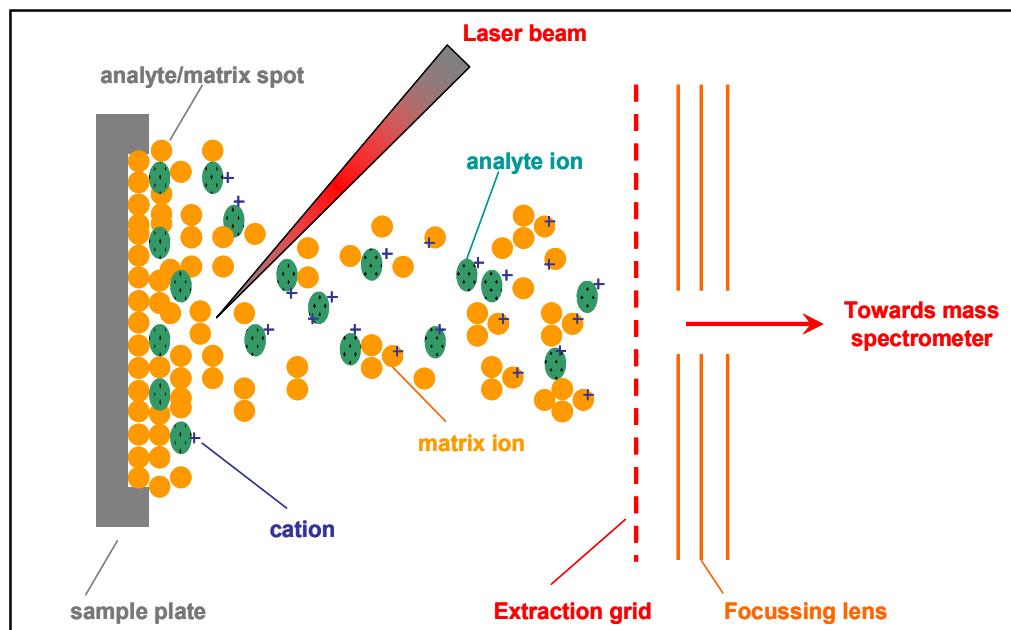
The analyte sample is mixed with a suitable matrix compound at a 1-10 times molar excess and allowed to co-crystallise with the evaporation of the solvent. The number of matrix molecules exceeds those of the analyte, separating its molecules and thereby preventing the formation of sample clusters, which inhibit the appearance of molecular ions. The incorporation of the sample molecules into the lattice structure of the matrix is a pre-condition of the functioning of the laser desorption/ionisation process. The matrix serves to minimise sample damage from the laser pulse by absorbing most of the incident energy and increases the efficiency of energy transfer from the laser to the analyte. As such, the sensitivity is increased.

##### (ii) Matrix Excitation

This step involves ablation of portions of the solid solution by pulses of laser energy for a short duration. Some of the laser energy incident on the co-crystallised sample is absorbed by the matrix, causing rapid vibrational excitation, bringing about localised disintegration of the solid solution forming clusters made up of a single analyte molecule surrounded by neutral and excited matrix molecules. The matrix molecules evaporate away from these clusters to leave the excited analyte molecule.

##### (iii) Analyte Ionisation

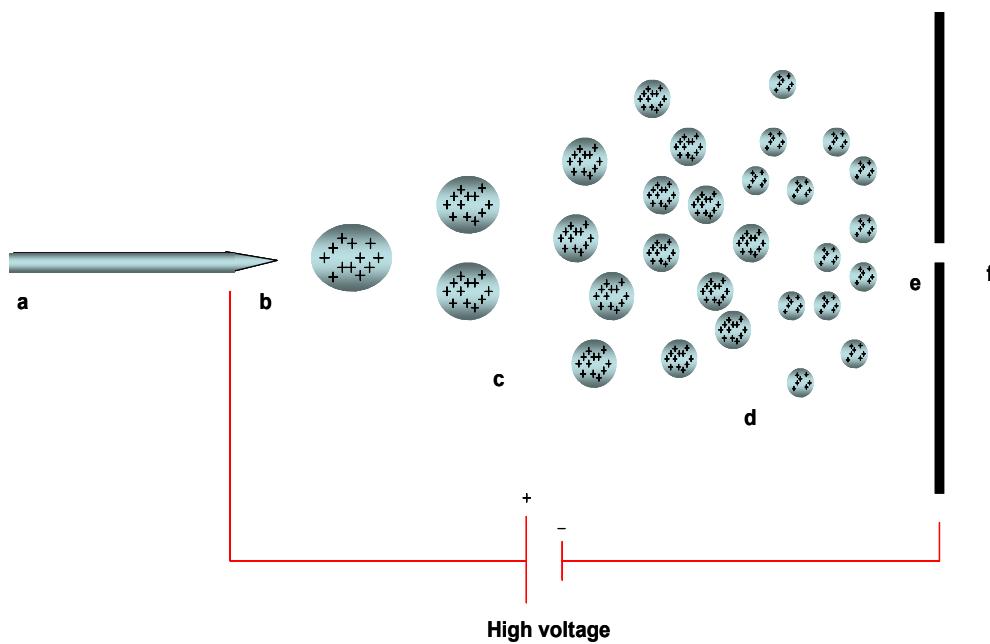
The analyte molecules become ionised by simple protonation by the photo-excited matrix, leading to the formation of the typical  $[M+X]^+$  type species (where X= H, Li, Na, K, etc.). Some multiply charged species, dimers and trimers can also be formed. Negative ions are formed from reactions involving deprotonation of the analyte by the matrix to form  $[M-H]^-$  and from interactions with photoelectrons to form the  $[M]^-$  radical molecular ions [Dreisewerd, 2003]. These ionisation reactions occur in the first tens of nanoseconds after irradiation, and within the initial desorbing matrix/analyte plume. These ions are then accelerate through an electrical field toward a mass analyser. It is important to note that these principles are hypothetical since some aspects of the MALDI process are not yet fully understood (Figure 1.13).



**Figure 1.13 The MALDI process.** Analyte molecules are co-crystallised with an excess of matrix molecules. A hypothesis to account for ion formation by MALDI is that irradiation of these crystals with a laser beam desorbs matrix-analyte ion clusters, which undergo gas phase reactions. As a result such clusters dissociate to leave free analyte ions and matrix ions. These ions are then accelerated through an electrical field toward a mass analyser.

### 1.4.2.2 Electrospray Ionisation

In contrast to MALDI, ESI ionises analytes from a liquid phase. The analyte is dissolved in an organic solvent mixture, typically methanol or acetonitrile, containing a small concentration of acid (e.g. formic acid 0.1-1%). The introduction of the sample into the mass spectrometer can be carried out by a number of methods. In the simplest case, sample is directly infused through a syringe and a narrow transfer capillary. Another example is the so-called nano-spray sample delivery method. In this system, a small amount of sample is placed into a needle, which has a very small tapered opening on one side. Sample is forced out because of capillary forces and high voltage is applied to the needle. The most commonly used method is the coupling of the electrospray directly with reverse phase chromatography. In this setup the capillary end of the chromatographic system is connected to the needle to which the voltage is applied. Typical flow rates of 200 to 500 nL min<sup>-1</sup> (nanospray) are used for the chromatography. A fine spray of charged droplets emerges from the capillary and is directed into the vacuum chamber of the mass spectrometer through a small orifice. An electrostatic field is formed between the capillary and the walls of the mass spectrometer, and as the droplets travel they evaporate resulting in the formation of gas-phase ions. The magnitude of the charge-repulsion effect becomes more significant, and at a certain charge/solvent composition (termed the Rayleigh limit), Coulomb explosion of the analyte-solvent clusters occurs. The clusters become smaller and more highly charged within the skimmer region until single molecular ions are formed either by further explosion of clusters or by desorption of molecular ions from the clusters. The charged ions are accelerated through the analyser towards the detector. These ions can then be analysed according to their mass-to-charge ratio (Figure 1.14) [Mann and Wilm, 1995].



**Figure 1.14 Schematic representation of electrospray ionisation.** This figure shows the schematic representation of the ESI process. Sample is delivered through a capillary (a) and a tapered needle (b). Through a high voltage, droplets are extracted (c). Due to the evaporation of solvent, the charge repulsion reaches a critical value (d The Rayleigh limit), when droplets explode (Coulomb explosion), creating multiply charged ions. These enter the mass spectrometer (e) under the applied electrical field (f).

## 1.4.2 Mass analysers

### 1.4.2.1 Time-of-Flight (TOF)

Due to the pulsed nature of MALDI ionisation, it is most commonly used in combination with a time-of-flight (TOF) analyser. The TOF mass spectrometer was introduced commercially more than 40 years ago, yet only recently its high mass range and high sensitivity multichannel recording capabilities have been realised, making this type of spectrometer an attractive instrument in biological research. The TOF mass spectrometer is the simplest type of mass analyser and has a very high sensitivity over a virtually unlimited mass range (Figure 1.15). The sample ions are generated in the source zone (s), and are expelled in bundles that are produced by the laser desorption on the source-focusing lenses. A potential, ( $V_s$  - the source extraction) is applied across the source to extract ions which accelerate from the source into the field-free 'drift' zone of the instrument (d).

TOF is a measure of the duration of time required for ionised proteins and peptides to travel through the MS chamber to the detector plate. As Figure 1.15 illustrates, the fundamental principle that permits MS to separate analytes is the fact that small ions fly faster than larger ones. The ions'  $m/z$  ratios may be calculated from the time that each one requires to reach the detector plate. The flight time is proportional to the square root of the mass to charge ratio. Knowing the acceleration voltage and the length of the drift region the  $m/z$  ratio can be determined by measuring the flight time. The range of typical MALDI flight times is between a few  $\mu\text{s}$  and some  $100\mu\text{s}$ . The drift regions are typically 1-4m long. Differences in TOF and thus  $m/z$  ratios allow the distinction and, in many cases, the identification of different proteins and peptides. Calibration of the instrument is performed with known reference masses.

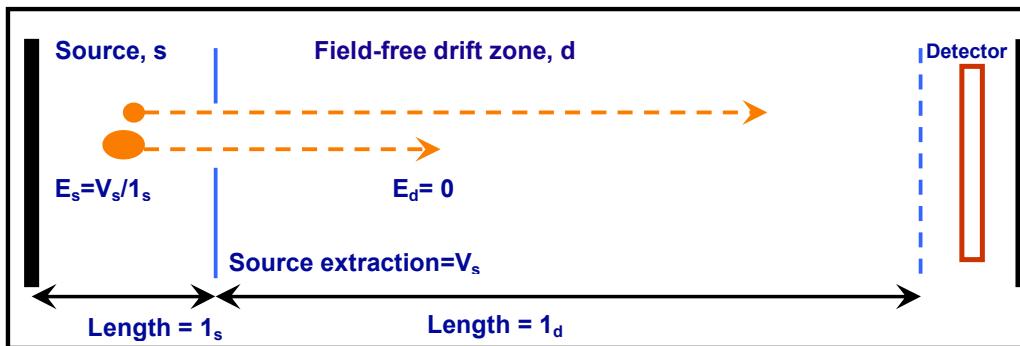


Figure 1.15 Schematic diagram of the process of time-of-flight mass spectrometry

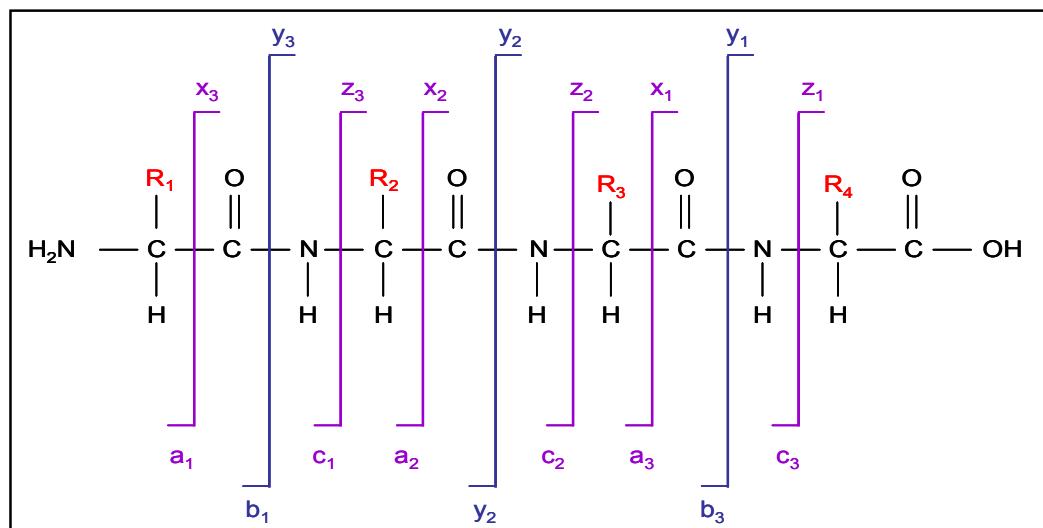
Once the ions produced in the ion source have been separated by the mass analyser they are commonly detected using an electron multiplier detection device. The signal is sent to a computer, which records incoming signals and displays them graphically in a chromatograph or mass spectrum. Thus, the final product of this kind of analysis is a list of  $m/z$  ratios that represent a peptide mass map, also called a peptide mass fingerprint [Mann et al., 1993; Pappin et al., 1993].

#### 1.4.2.2 Quadrupole analysers

ESI sources are typically coupled with ion traps and quadrupole analysers or hybrid instruments combining different analysers in tandem such as Q-TOF, triple Q, IT-Orbitrap and IT-FT-ICR. Protein identification of samples presented in this thesis were analysed with a Q-TOF instrument. The quadrupole analysers consist of four parallel metal rods. Each opposing rod pair is connected together and a radio frequency (RF) voltage is applied between each pair. A current voltage is then directly superimposed on the RF voltage. Ions travel down the quadrupole in between the rods. Only ions of a certain  $m/z$  are able to reach the detector for a given ratio of voltages, while other ions have unstable trajectories and will collide with the rods. This allows selection of particular ion, or scanning by varying the voltages.

A triple quadrupole mass spectrometer has a linear series of three quadrupoles. The first (Q1) and the third (Q3) quadrupoles act as mass filters, while the middle (Q2)

quadrupole is employed as a collision cell. The collision cell is an RF only quadrupole and uses Ar or He gas to induce collisional dissociation of selected parent ions from Q1. Subsequent fragments (daughter or product ions) are passed through to Q3 or a TOF where they may be filtered or scanned fully, generating a collision-induced dissociation (CID) spectrum. Peptide fragmentation caused by collision mainly occurs at the lowest energy amide bonds of peptides. When the charge is retained by the amino terminal fragment, a, b, and c type ions are formed, while x, y and z type ions are formed when the charge is retained by the carboxy-terminal fragments (Figure 1.16). The mass difference between sequential b- and y- ions thus corresponds to the mass of the amino acids in the sequence. The nomenclature was proposed by Roepstorff et al. in 1984 (Figure 1.16; Roepstorff and Fohlman, 1984).



**Figure 1.16 Schematic representation of peptide fragment ions nomenclature.** The overview of the possible fragmentation on the peptide backbone and the nomenclature of the resulting fragment ions are shown. Different amino acids are distinguished by the side group displayed in red (R). The nomenclature was proposed by Roepstorff et al. in 1984 [Roepstorff and Fohlman, 1984]. When the charge is retained on the C-terminal side of the product ions, fragments are named x, y and z, while when the charge is retained on the N-terminal side a, b and c type ions are formed. The resulting ions are dependent on many factors, such as the type of fragmentation method used, analyser principle and primary sequence dependency. Also fragmentation of the side chains is possible. These ions are indicated as v and w ions (not shown in this figure).

## 1.5 Aims and scope

The primary aim of this study was to set up a separation and analysis scheme to rigorously investigate the serum proteome using mass spectrometry as a central technique. As discussed, the serum proteome contains an archive of histological information. Ovarian cancer is a lethal gynaecological malignancy that has an urgent need for new biomarkers. The serum of ovarian cancer patients has been investigated for several decades, yet, only a handful of putative markers have been identified. In this work several strategies have been employed to address the complexity of the human serum proteome and to identify putative biomarkers of ovarian cancer. Chapter three is concerned with the analysis of serum samples pre-dating diagnosis of ovarian cancer using a previously established magnetic bead-based and MALDI-TOF MS technology platform focussing on the serum peptidome. The hypothesis here is that tumour-specific exopeptidase activities generate surrogate markers during the blood clotting process.

Chapter four describes the establishment and optimisation of this technology platform in the host laboratory at UCL. The main focus of this chapter is the reproducibility of the technology platform. Chapter five describes the analysis of serum samples from the UKOPS collection to discover statistically significant MS peaks which could discriminate case versus control samples. As a complementary approach Chapter six shows the analysis of these samples using MARS and ProteoMiner protein enrichment strategies coupled with 2D-DIGE based separation and identification of differentially expressed protein features followed by MALDI-TOF PMF and LC-MS/MS protein identification.

## Chapter 2: Materials and Methods

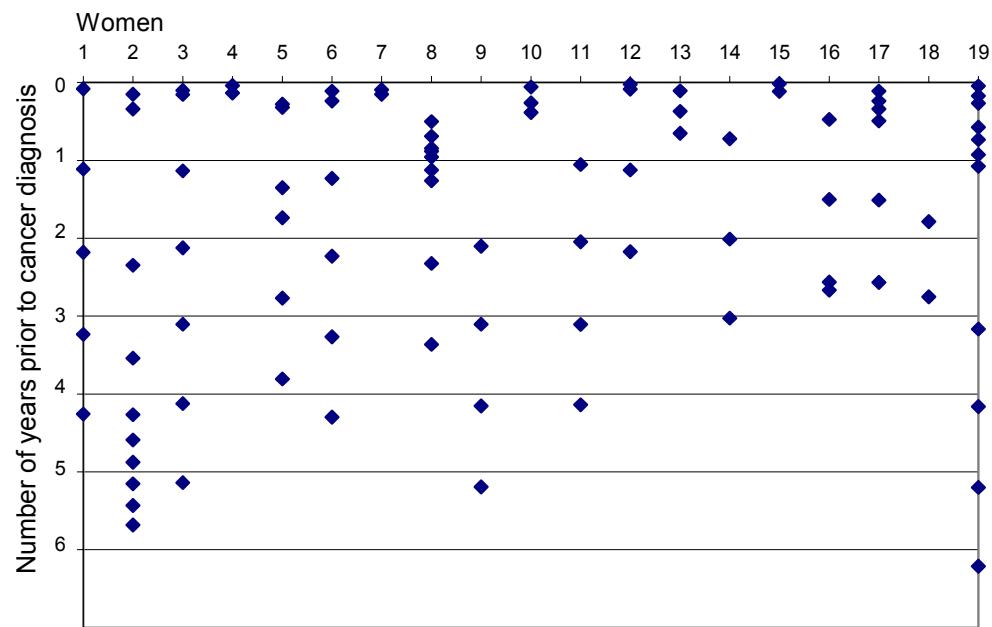
### 2.1 Serum samples and sample collections

In this study serial serum samples collected from women later diagnosed with ovarian cancer and matched healthy controls from a UKCTOCS (United Kingdom Collaborative Trial for Ovarian Cancer Screening) pilot study were also used for proteomic analysis using the platform developed in the laboratory of Professor Paul Tempst at the Memorial Sloan Kettering Cancer Centre (MSKCC) in New York USA (Chapter 3) [Villanueva et al., 2004]. Volunteers were selected using criteria which ensured volunteers had no previous history of ovarian cancer upon recruitment and in total 22,000 women were recruited.

Serum samples were taken every year from 1996/1997 up to and including 2001. All cases and controls satisfied the following criteria: (a) age  $\geq$  50 years, and (b)  $>$  12 months amenorrhoea following a natural or surgical menopause or  $>$  12 months of hormone replacement therapy commenced for menopausal symptoms. The exclusion criteria were: (a) a history of bilateral oophorectomy, (b) active malignancy (women with a past history of non-ovarian cancer malignancy were eligible if they had no documented persistent or recurrent disease), (c) increased risk of ovarian cancer due to familial predisposition – exclusion criteria were entry criteria for the UK Familial Ovarian Cancer Screening Study and (d) a previous history of ovarian cancer. Information on reproductive history, family history of cancer and hormone replacement therapy use was obtained from all women prior to the start of screening. These volunteers underwent annual screening for 2-6 years.

From this sample collection, a subset consisting of 92 samples from 19 women, which pre-dated a diagnosis of ovarian or fallopian tube cancer from  $<$  1 to 6 years was analysed at the MSKCC (Figure 2.1). The matched controls for this set of samples came from 183 healthy volunteers (from the general population) with no previous history of cancer and no incidence of cancer as far as known since recruitment onto the pilot study. The general procedure for selecting controls was based on using sera that reached the laboratory, and were processed on the same day

and placed in the same sample freezer rack as the case sample. If it was not possible to find a match using this method then preceding samples were chosen. Matching was also done based on age (within 5 yrs) and HRT use. Each case sample had two matched controls except for one sample which only had one.



**Figure 2.1 Scatter plot illustrating the timescale of serial serum samples collected from women predating a diagnosis of ovarian cancer.** A total of 92 serial samples from 19 volunteers were collected and analysed using a MALDI-TOF MS-based proteomic profiling platform. '0' on the x-axis represents time of diagnosis.

Serum samples from the UK Collaborative Trial of Ovarian Cancer Screening (UKCTOCS) study were used for the protocol comparison study (Chapter 4). The UKCTOCS trial involves just over 200,000 apparently healthy postmenopausal women aged 50-74 years of age. All participants provide a serum sample at registration and 50,000 participants provide additional samples annually for 6 years. All participants are followed up using data from the Office of National Statistics which provides information on cancer diagnoses and cause of death in this cohort. In addition, all the participants are sent health questionnaires 3 and 7 years after recruitment to the study.

Serum samples from the United Kingdom Ovarian Cancer Population Study (UKOPS) collection were also used (Chapters 5 & 6). UKOPS is a multi-centre study set up by the Institute for Women's Health at University College London (UCL) that aims to predict which women in the population are at greatest risk of getting ovarian cancer. The study aims to recruit 1,000 women from the UK who have been diagnosed with ovarian cancer. This includes women undergoing surgery for possible ovarian cancer or benign tumours or who have had a previous diagnosis, and 2000 healthy women who act as controls for the study.

Finally, commercial serum (Human Sera S7023-1 Sigma-Aldrich) was used for the platform optimisation and as a quality control (QC) in all profiling experiments.

### 2.1.1 Sample collection and handling procedures

All UKOPS serum samples were collected according to a previously established protocol outlined by Villanueva et al. who used an optimised magnetic bead peptide extraction method coupled with MALDI-TOF MS to profile low mass serum peptides and proteins from healthy and diseased serum samples [Villanueva et al., 2004]. Venous blood was collected into BD Vacutainer SST tubes, (Becton Dickinson # 367988). The tube was gently inverted 5 times to mix clot activator with blood. The blood was then allowed to clot for 1 hour at room temp (RT) in a vertical position. The SST tubes were placed on wet ice in a vertical position prior to centrifugation at 2,000 x g for 10 min at RT. The serum (upper phase) was then aliquoted into Falcon tubes and frozen at -80 °C. Samples were then shipped on dry ice to the collection laboratory where they were thawed, aliquoted (500 µL) into bar-coded straws, heat sealed and stored at -80 °C.

All UKCTOCS samples used in this study were collected in Greiner gel tubes. These samples had been allowed to clot, centrifuged at room temperature (RT) then divided into aliquots in straws that were heat sealed and stored at -80°C. The time from venipuncture to centrifugation was 30 hours for each sample (protocol 1; Green; GN). Additionally, for the handling protocol comparison study, samples from the same 25 UKCTOCS volunteers were collected in Becton Dickinson red-top tubes, allowed to clot at RT for 60 minutes. These samples were then placed on wet ice for 2 hours before centrifugation. Following this samples were transferred to straws and stored at -80°C (protocol 2; Yellow; YE). A third protocol used a 5 minute clotting time at RT, followed by incubation on wet ice for 3 hours before centrifugation. This set of samples was also transferred to straws for storage at -80°C (protocol 3; Gray; GY). Three variants of protocol 3 were also prepared where samples were stored in cryovials at -80° instead of straws (protocol 4; Cryovial; CR); were placed on wet ice for 6 hours instead of 3 hours (protocol 5; Orange; OR); were incubated for 3 hours at RT instead of on wet ice (protocol 6; White; WH). These protocols were chosen to assess the effects of different transfer times, temperatures, clotting times and storage tubes on the serum proteome in the context of clinically feasible collection protocols.

From 1995-2001 the pre-UKCTOCS samples (Pilot study) were collected in Becton Dickinson red-top tubes. All samples were transported to the central laboratory by courier at ambient temperature. All samples had recorded transit times of less than 48 hours. Upon reaching the central laboratory, samples were immediately centrifuged and aliquoted into storage tubes with plastic push-on caps, which were stored at -20°C. In 2004 all samples were moved to a -80°C freezer. For the analysis performed at the MSKCC, a 100 µL aliquot of each of these samples was shipped on dry ice. Upon arrival at the MSKCC samples were thawed and further aliquoted (50 µL) and stored at -80°C. Samples were thawed before processing on the MSKCC automated platform and analysed by MALDI-TOF MS.

## 2.2 Automated magnetic bead-based serum peptide extraction

### 2.2.1 Preparation of calibrant mixture for automated runs

For instrument and spectral calibration, a calibrant mixture was spotted beside sample spots on the MALDI targets. The calibrant mixture was prepared fresh before each run. A standard peptide mixture was purchased from Bruker and resuspended in 125 µL of 0.1% TFA as per the manufacturer's instructions. 20 µL of this mixture was then diluted 1:3 with 50% (v/v) acetonitrile (ACN). Synthetic peptide 782 was prepared at a concentration of 2 µg/µL, then diluted 1:25 with 0.1% TFA followed by a 1:10 dilution with 50% (v/v) ACN. 20 µL of both the diluted standard peptide mixture and the synthetic peptide 782 were combined and diluted a further 1:5 in 50% (v/v) ACN and labelled 'peptide mix' (Table 2.1). Protein mixture 1 was also purchased from Bruker and resuspended as per the manufacturer's instructions. 10 µL of the resuspended protein mixture was diluted 1:1 in 50% (v/v) ACN and labelled 'protein mix' (Table 2.1). To prepare a master mix for 96 calibrant spots, 102 µL of peptide mix was mixed with 17 µL of protein mix and 17 µL of 50% (v/v) ACN was added for a final volume of 136 µL. All the preparations were kept on ice until they were placed in a cooled rack in the robot for mixing with pre-made  $\alpha$ -cyano-4-hydroxycinnamic acid ( $\alpha$ -CCA) MALDI matrix and automated spotting. The final amounts on target were 30 fmol of each peptide and 500 fmol of each protein.

Calibrant	m/z
Peptide mix	
Peptide 782	782.04
Angiotensin II	1,047.20
Angiotensin I	1,297.51
Substance P	1,348.66
Bombesin	1,620.88
ACTH fragment 1-17	2,094.46
ACTH fragment 18-39	2,466.73
Protein mix	
Insulin	5,734.56
Ubiquitin	8,565.89
Cytochrome C	12,361.09
Myoglobin	8,476.77

**Table 2.1 Calibrants used for MALDI-TOF spectral calibration.** The final amounts on target were 30 fmol for each peptide and 500 fmol for each protein. All m/z values are calculated for singly charged ions except myoglobin which was doubly charged.

### 2.2.2 Automated liquid handling protocol for bead-based serum peptide extraction

A Tecan Genesis Freedom liquid handling workstation with 1 mL syringes was used for all steps of automated serum peptide bead-based extraction and MALDI target spotting. The robot was set up during the morning of the day of the runs by cleaning the liquid handler, degassing the water used for the runs, ensuring the waste container had enough room to receive discarded liquids and ensuring that the fixed robot tips were clean and accurately aligned. The system was also flushed twice with degassed water to ensure there were no air bubbles in the system.

Serum sample plates were removed from the -80°C freezer and allowed to thaw at room temperature for approximately 10 min before each run. Samples were assigned randomised positions in the 96-well plates. C18 Dynabeads at 2 µg/µL stock were prepared by washing 320 µL of Dynabead slurry twice in 200 µL of deionised water and then resuspending in 320 µL of deionised water. This was done to remove ethanol from the stock solution.

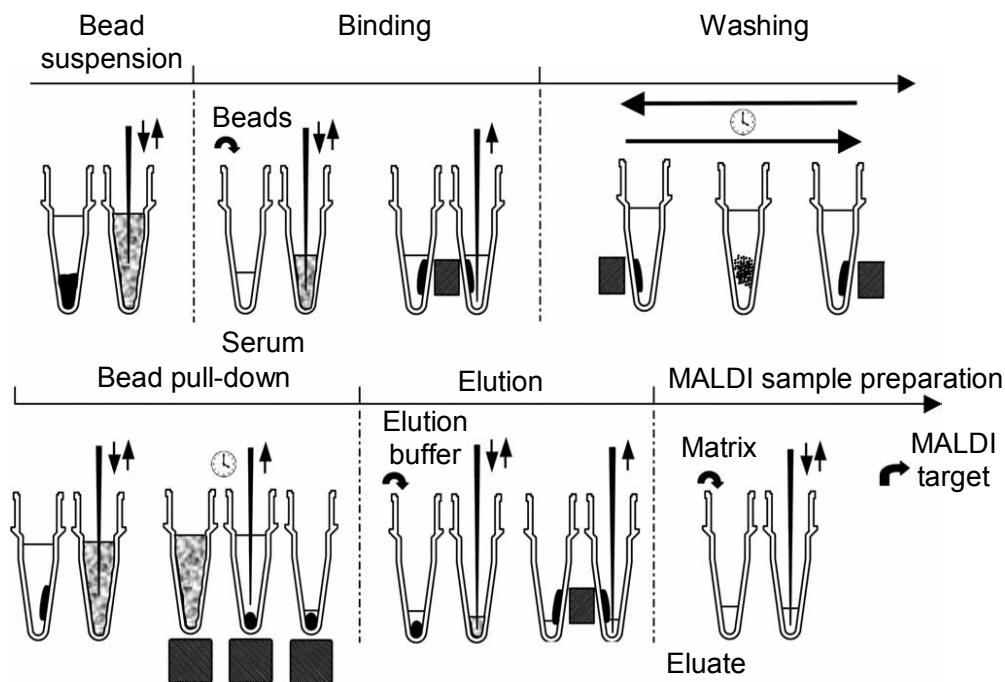
The Dynabeads were gently mixed by aspiration and dispersal for 5 min until completely re-suspended and 40  $\mu$ L was added to each tube of a strip of eight 0.2 mL thin-wall tubes and placed in a holder on the robot deck. Fresh 0.1% TFA was added to the TFA trough on the robot before each run. Next, a 96-well skirted microtiter plate was prepared with 75  $\mu$ L of 50% (v/v) acetonitrile in each well of the first column and 95  $\mu$ L of pre-prepared  $\alpha$ -CCA matrix solution in each well of the second column. The third column contained 65  $\mu$ L of calibrant mix in row A and 70  $\mu$ L of matrix solution in row B. The wells of the plate were tightly then sealed with self-adhesive foil using a rubber roller. The plate was then attached to a cooler rack with a piece of Parafilm wrapped around the microtiter plate and the inner part of the cooler rack to ensure that the plate would remain in place when the robot tips pierced the foil. Adhesive tape was used to secure the cooling rack to the robot deck. The cooler rack had been chilled at -20 °C for several hours before use. A cleaned MALDI target plate was placed in its position on the robot deck.

The magnetic bead-based reversed-phase extraction protocol adopted for this project was previously outlined by Villanueva et al. [Villanueva et al., 2004]. However, some modifications of the published protocol were made before it was adopted at the host laboratory. These were mostly used to minimise bead loss and carry-over during the processing steps. These modifications are highlighted below.

First the magnetic beads in the thin-wall tubes were re-suspended by pipetting up and down 10 times. A measured volume of bead suspension (12.5  $\mu$ L) was transferred to the well of a 96-well microtiter plate (Starlab 1402-9700) containing an aliquot of serum (50  $\mu$ L). Magnetic beads and serum were then mixed by aspirating and dispensing 10 times, incubated for 2 minute to allow sufficient binding of serum polypeptides to the beads. Next, the beads were pulled to the side of each well using magnetic force (Jancox Metal Products Inc. REL033-01) and the supernatant was removed and discarded. Then 200  $\mu$ L of washing solution (0.1 % trifluoroacetic acid, TFA) was added, the beads were pulled five times from left to right and back on the side magnets and then were allowed to settle on one side of the tube wall for 30 seconds. The washing solution (200  $\mu$ L) was removed. This washing step was repeated once more, however during the second wash only 120  $\mu$ L of washing

solution was initially removed. At the conclusion of the washing step, beads were further re-suspended in the remaining 80  $\mu$ L of washing solution and then pulled to the tip of the wells by magnets positioned beneath the plate. A further 60  $\mu$ L of supernatant was removed, the sample plate was then moved to the side magnet and the remaining 20  $\mu$ L of washing solution was removed. In the original protocol the removal of the remaining washing solution was performed while the beads were at the tip of the wells. However, in our laboratory, bead loss was noted at this step and so beads were therefore moved to the side magnet to prevent contact of the fixed tips with the magnetic beads.

For elution, 10  $\mu$ L of elution solvent 50% (v/v) acetonitrile was added to the bead pellet. Beads were mixed with elution solution by moving the plate back and forth on the side magnets 5 times. The beads were then allowed to settle on one side of the tube and a 5  $\mu$ L fraction of the eluate transferred to another well. In the original protocol elution solution was added while beads were at the tip of the wells and mixing was done with the fixed tips. However, bead carry-over and losses were noted. Thus, modifications were made to enable elution and mixing on the side magnet. Finally, 5  $\mu$ L of pre-made  $\alpha$ -CCA matrix solution (Agilent Technologies, UK) was added to the eluate and mixed, and 1  $\mu$ L aliquots were deposited in replicates onto a stainless steel MALDI target in every other column of the 384-spot layout. Spots were allowed to dry at room temperature prior to MS profiling (Figure 2.2)



**Figure 2.2 Schematic illustration of the magnetic bead-based extraction of serum peptides.** Briefly, magnetic bead pellets are re-suspended, a measured volume of bead suspension is transferred to a tube containing an aliquot of serum and the magnetic beads and serum are mixed. Beads are pulled to the side by magnetic force and supernatant is removed and discarded. Washing solution is added, beads are pulled five times from left to right and back, beads are pulled to the side and washing solution removed. At the conclusion of the washing step, beads are further re-suspended, pulled to the tip of the tube by magnets positioned underneath, and the supernatant removed. An elution solvent is mixed with the bead pellet and beads are pulled to the side and a fraction of the eluate transferred to another tube. Matrix solution is added to the eluate and mixed and 1  $\mu$ L is spotted onto a MALDI target.

### 2.2.3 MALDI-TOF MS serum profiling

#### 2.2.3.1 Autoflex MALDI-TOF MS at MSKCC

Serum polypeptide profiles were generated in two mass ranges; low mass range (LMR) 700-4000Da m/z segment and high mass range (HMR) 4–15 kDa m/z segment using the ‘AutoXecute’ function of the software on an Autoflex MALDI-TOF/TOF mass spectrometer (Bruker Daltonics, Bremen, Germany). For spectral acquisition a sum of 400 laser shots, delivered in four sets of 100 shots (at 50 Hz) to each of four different locations on the surface of the matrix spot were acquired in linear mode geometry under 20 kV (18.6 kV during delayed extraction) of ion acceleration and -1.3 kV multiplier potentials, and with suppression of mass ions set to m/z <400. Delayed extraction was maintained for 80 ns ( $\leq$  4 kDa) or 50 ns for ( $\geq$  4 kDa) to give appropriate time-lag focusing after each laser shot.

#### 2.2.3.2 Ultraflex MALDI-TOF MS at UCL

MALDI-TOF MS at UCL was performed using an Ultraflex MALDI-TOF/TOF instrument (Bruker Daltonics, Bremen, Germany). In the LMR a sum of 400 laser shots, delivered in eight sets of 50 shots (at 10 Hz) to each of eight different locations on the surface of the matrix spot were acquired in linear mode geometry under 20 kV (18.6 kV during delayed extraction) of ion acceleration and -1.3 kV multiplier potential, and with suppression of mass ions set to m/z <400. Delayed extraction was maintained for 80 ns to give appropriate time-lag focusing after each laser shot.

For acquisition of the HMR 4–15 kDa m/z segment a sum of 500 laser shots were acquired in linear mode with suppression of mass ions set to m/z <3,000. Delayed extraction was maintained for 50 ns to give appropriate time-lag focusing after each laser shot. The initial 100 shots for the HMR acquisition were delivered at the same location as the first 50 shots used for the LMR since the AutoXecute function requires a home position for each individual MALDI spot. Therefore, an extra 100 shots were required for the HMR owing to the ablation of sample at the home position.

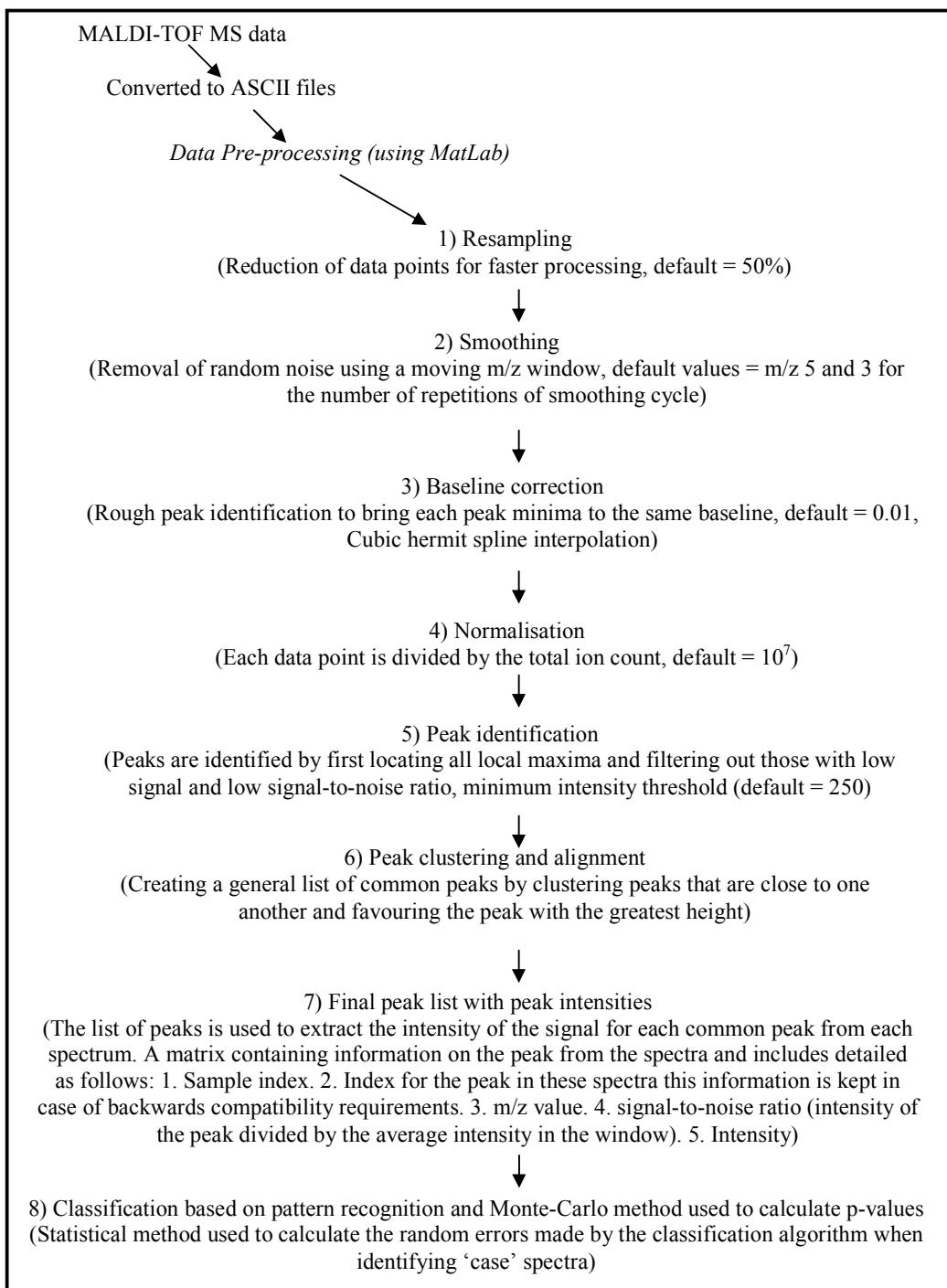
## 2.2.4 Data processing and analysis

The MALDI-TOF MS data presented in this study were analysed with two different systems.

### 2.2.4.1 Data processing and analysis 1

Data collected at the MSKCC for the UKCTOCS pilot study (Chapter 3) was analysed in collaboration with the Computer Learning Centre at Royal Holloway, University of London, UK. The workflow used for spectral processing is shown in Figure 2.3 (MatLab script for each function can be found in Appendix 1). Spectra were externally calibrated using 13 calibrant peaks from the calibrant spots associated with each sample (Table 2.1). Smoothing was done by averaging the intensities within a moving window and baseline subtraction involved estimation of the baseline from the mass spectrum. Spectra were normalised by dividing each intensity value by the total ion count. The obtained values were then multiplied with a constant  $C$  ( $C = 2*10^5$ ). Peak definition/detection involved finding local peak maxima in the mass spectra with a signal-to-noise ratio exceeding an optimised threshold (set to 4 in this study). The noise level was defined as the average of the intensities at the  $m/z$  ratio within a moving window with a fixed size (e.g. 500 Da). Local maxima were located by finding the  $m/z$  ratios with the highest intensities among their neighbours. The peaks identified were quantified as the intensity at the local maximum. Peaks were then internally aligned across all spectra. At the peak alignment step, the peaks of multiple mass spectra within the mass error rate (100 ppm) were grouped together as a “peak group”. Since not all peaks occur in all spectra, a given number of peak points acted as unique anchors for alignment and every other sample was aligned with this ‘superset’. To this end, the superset was split into clusters which were defined in two steps. Firstly, all the intervals between neighbouring peak positions in the superset exceeding a mass resolution of 1500 ppm, were found. These intervals split the  $m/z$  into clusters of order 1. This was then checked to see that each sample had no more than 1 peak in a cluster. When more than one peak was found, the cluster was divided into smaller clusters to ensure only 1 peak per cluster. Thus, all peaks were aligned to certain clusters. Once peaks had been aligned spectra were then labelled

‘case’ or ‘control’. Two pattern recognition algorithms (the nearest neighbour algorithm and the support vector machine) were used to classify the samples in their respective groups. Pattern recognition algorithms construct decision rules on the basis of the training set of spectra used. Due to the limited number of ‘case’ samples the ‘training’ and ‘test’ spectra were the same. The Monte-Carlo method was used to calculate the p-values for the errors made by the classification algorithm [Gammerman et al., 2008].



**Figure 2.3 Workflow used to process MS spectra.** The MatLab scripts for each of these steps can be found in Appendix 1.

#### 2.2.4.2 Data processing and analysis 2

All data collected at UCL was processed and analysed using ClinProTools™ software (V2.0 & 2.2, Bruker Daltonics, Germany). Spectra were first subjected to a 0.80 level convex hull baseline subtraction. Following this the detection of peaks was based on the analysis of a smoothed first derivative where the smoothing was determined by the “resolution” parameter. Spectral settings were optimised using ‘400 and 200’ for the resolution parameter for the LMR and HMR respectively. 1 cycle of smoothing was done using the Savitsky Golay algorithm with an m/z width of 1 for the LMR and 5 for the HMR. Once the peaks were detected, peak areas were calculated by integrating the intensities over the region of the peak (between the start and end positions) using the zero level integration function. Peak areas were then normalised to make the total signal equal in all spectra. These peak areas were given as arbitrary units (arb.u.). Spectral recalibration was done with a maximum peak shift of 0.3% and a 15% match of automatically selected internal calibrant peaks. Peak selection was done using a signal-to-noise ratio of 3 for the LMR and 5 for the HMR regions. When different classes of data e.g. groups of spectra generated on different days were loaded into the software, as part of the spectral pre-processing step p-values are automatically generated for all the identified peaks. It is important to note that ClinProTools requires at least 2 spectra in each class. In addition, a 2D peak distribution view is generated to show the distribution of the average peak area of two selected peaks which may be the top discriminatory peaks between two classes of samples (user defined). The peak statistics calculated by ClinProTools were used to calculate the co-efficient of variance.

For classification of clinical samples, each condition was loaded as a separate class and the Support Vector Machine (SVM) algorithm available in the ClinProTools software was used. The optimised model used 1-25 peaks selected automatically by ClinProTools to include 3 k-nearest neighbours in both mass ranges.

## 2.3 Sample preparation for 1D and 2D SDS-PAGE analysis

### 2.3.1 Unfractionated pooled serum

Prior to 2D-DIGE analysis, unfractionated serum samples were pooled according to volume into healthy, benign or malignant groups. Pooled samples were then diluted 1:100 for an accurate measure of protein concentration using the Pierce BCA protein assay, using BSA to generate a standard curve. Equal amounts of protein were labelled with each of the three Cy dyes for 2D-DIGE analysis (see section 2.4).

### 2.3.2 Protocol for HPLC immunoaffinity depletion using the Multiple Affinity Removal System (MARS).

As a complementary approach, the Multiple Affinity Removal System was used to facilitate the differential analysis of the pooled serum samples by allowing the removal of the 7 most abundant proteins in serum. The Multiple Affinity Removal System (MARS) is comprised of an affinity HPLC column (size: 4.6 x 50 mm, Agilent part number 5185-5984) packed with immobilised affinity-purified polyclonal antibodies for removal of albumin, transferrin, IgG, IgA, haptoglobin, antitrypsin and fibrinogen with high specificity and optimised mobile phases. All chromatographic steps were performed at 20°C on an Agilent 1100 HPLC system.

From each pool, 30 µL of serum was diluted five times with MARS Buffer A containing protease inhibitors (COMPLETE™, Roche) and centrifuged at 16,000 x g at room temperature for 5 minutes to remove particulates. Automated sample injection was set up for 30 µL of diluted serum sample per injection in Buffer A at a flow rate of 0.25 mL/min for 9 min. Flow-through fractions, ~0.75 mL per injection, containing the lower abundant protein species were collected from each injection manually at 2-4 min into 0.5 mL Eppendorf tubes and stored at -20°C until further analysis. The bound fractions were eluted with 100% Buffer B at a flow rate of 1.0 mL/min for 3.5 min. The column was regenerated by equilibrating with Buffer A for 10 min.

### 2.3.3 Protein desalting and concentration

In order to resolve proteins from depleted serum samples on 2D gels, flow-through fractions from five injections were pooled into a 5 mL Zeba™ desalting spin column (Pierce, Rockford, IL) and desalting. Desalting samples were concentrated to 0.5 mL using a spin concentrator with a 5 kDa Molecular Weight Cut-Off (MWCO) membrane; samples were spun at 4000 x g for approximately 1 hour at 10 °C. Concentrated retentates were transferred into fresh Eppendorf tubes and speed vacuumed to dryness. Samples were resuspended in 2D lysis buffer (8 M urea, 2 M thiourea, 4% CHAPS, 0.5% NP40 and 10 mM Tris pH 8.3). Protein content was estimated using the Pierce BCA protein assay using BSA to generate a standard curve.

### 2.3.4 ProteoMiner Protein Enrichment Kit

Pooled samples were applied to spin columns from the ProteoMiner Protein Enrichment Kit (BioRad Catalogue # 163-3000). The ProteoMiner Protein Enrichment Kit is comprised of several spin columns packed with a large, highly diverse bead-based library of combinatorial peptide ligands. It is considered to be a novel sample preparation tool used for the compression of the dynamic range of the protein concentration in complex biological samples. Best results are obtained with protein concentrations greater than 50 mg/mL. When complex biological samples (e.g. human serum) are applied to the beads, the high abundance proteins saturate their high affinity ligands and the excess protein is washed away. In contrast, the medium and low abundance proteins are concentrated on their specific affinity ligands. This reduces the dynamic range of protein concentrations, while maintaining representatives of all proteins within the original sample.

First the spin columns (20% beads, 20% v/v aqueous EtOH, 0.5% v/v acetonitrile) were prepared by centrifugation at 1,000 x g for 2 min to remove the storage solution. The collected material was discarded. The columns were then washed by adding 1 mL deionised water and rotating them end-to-end over a 5 min period. Again the columns were centrifuged at 1,000 g for 2 min to remove the water and the collected

material was discarded. The wash steps were repeated twice using 1 mL wash buffer (PBS; 150 mM NaCl, 10 mM NaH<sub>2</sub>PO<sub>4</sub>, pH 7.4). At the final wash step columns were centrifuged again for an additional 1 min at 1,000g to remove any remaining buffer.

Pooled serum samples were centrifuged at 10,000 x g for 10 min to remove particulates. 1 ml of serum (>50mg/mL), normalised for protein concentration was applied to the spin columns and incubated with the beads by rotation for 2 hr at room temperature. Columns were centrifuged at 1,000 x g for 2 min and the collected material was retained for analysis. The columns were centrifuged again at 1,000g to remove residual material. Next, 1 ml of wash buffer (PBS) was added to each column and the columns were rotated over a 5 min period. The columns were centrifuged at 1,000 x g for 2 min and the collected material was discarded. Again the columns were centrifuged at 1,000 x g for an additional 1 min to remove any remaining material. This wash step was repeated twice and then a final wash step using deionised H<sub>2</sub>O was carried out.

Bound proteins were eluted with 100 µL of 2D lysis buffer (8 M urea, 2 M thiourea, 4% CHAPS, 0.5% NP40 and 10 mM Tris pH 8.3) by gentle vortexing over a 15 min period at ambient temperature and the eluate collected by centrifugation at 1,000 x g for 2 min to elute bound proteins. The elution step was repeated twice to ensure all bound material was collected. Protein concentration of the eluates was estimated using the Pierce BCA protein assay using BSA to generate a standard curve (632.4 µg recovered from healthy pool, 687.4 µg from benign and 786.8 µg from malignant pool). The eluted samples were stored at -20°C prior to downstream 2D-DIGE analysis.

## 2.4 Two-Dimensional Difference Gel Electrophoresis (2D-DIGE)

Two-dimensional electrophoresis is a powerful and widely used method for the analysis of complex protein mixtures extracted from biological samples. This technique sorts proteins according to two independent properties in two discrete steps: the first dimension step, isoelectric focusing (IEF), separates proteins according

to their isoelectric points (pI) and the second-dimension step, SDS-polyacrylamide gel electrophoresis (SDS-PAGE), separates proteins according to their molecular weights ( $M_r$  relative molecular weight). A few thousand different proteins can thus be separated, and information such as the protein pI, the apparent molecular weight, and the amount of each protein provided. Fluorescence two-dimensional difference gel electrophoresis (2D-DIGE) is a more recently developed 2D gel-based proteomics technique that provides a sensitive, rapid and quantitative analysis of differential protein expression between two or more biological samples (see below).

#### **2.4.1 Protein labelling with NHS-cyanine dyes (DIGE-labelling)**

The NHS-cyanine dye Cy2 was purchased from GE Healthcare, whilst NHS-Cy3 and NHS-Cy5 were synthesised “in-house” by Dr P. Gaffney [Chan et al., 2005]. Protein labelling and 2D-DIGE were performed according to Gharbi et al. [Gharbi et al., 2002]. For this study, protein pools and fractions were labelled in triplicate with NHS-Cy3 or NHS-Cy5 at 4 pmol dye/μg protein on ice in the dark for 30 min. Equal amounts of protein from each clinical condition were also pooled together and labelled with NHS-Cy2 to create an internal standard which was run on all the gels against the Cy3- and Cy5-labelled samples to aid in spot matching and quantitation. Labelling reactions were quenched with a 20-fold molar excess of free L-lysine to dye and left on ice for 10 min. Equal amounts of proteins labelled with Cy3 and Cy5 were mixed appropriately and the same amount of Cy2-labelled pool was added to each mixture.

Samples were reduced by adding 1.3 M dithiothreitol (DTT) to a final concentration of 65 mM. Ampholine/Pharmalyte carriers (1:1 mix, pH 3-10), were added to a final concentration of 2% and bromophenol blue was added to each sample. The final volume of each sample was adjusted to 450 μL with 2D-DIGE lysis buffer plus DTT. For isoelectric focusing (IEF), 24 cm, non-linear pH 3-10 IPG strips (GE Healthcare) were rehydrated with Cy-dye labelled samples in a re-swelling tray overnight in the dark at RT, according to the manufacturer’s guidelines. The separation of the Cy-dye labelled proteins in the first dimension by IEF was carried out on a Multiphor II apparatus (GE Healthcare) for a total of 80 kWh at 18°C.

For protein separation in the second dimension, 1.5 mm 12% SDS-PAGE gels were cast between 24 cm low-fluorescence glass plates. The inner surface of one plate of each set was coated with Bind Silane solution (PlusOne, GE HealthCare) to bond the gels. This allowed easier handling of gels during scanning and protein post-staining, storage and spot excision. Fluorescent reference markers were placed at the edges of these bonded plates to facilitate the generation of coordinates for each protein feature in the final pick lists. The inner surface of the other plate was treated with Repel Silane (PlusOne, GE Healthcare) to ensure easy separation of plates after running. After IEF, IPG strips were equilibrated in equilibration buffer (6 M urea, 30 % (v/v) glycerol, 50 mM Tris-HCL pH 6.8 and 2% (w/v) SDS) in two steps for 15 minutes each with gentle rocking. In the first step, the equilibration buffer was supplemented with 65 mM DTT to reduce disulphide bonds, while in the second step 240 mM iodoacetamide (IAM) was added to the equilibration buffer to alkylate reduced thiol groups. IPG strips were then rinsed with Tris-Glycine-SDS electrophoresis buffer (Severn Biotech) and transferred onto the second dimension gels. Strips were overlaid with 0.5% (w/v) low-melting point agarose in Tris-Glycine-SDS electrophoresis buffer with bromphenol blue. Gels were run in an Ettan 12 apparatus (GE Healthcare) at 2 W per gel at 8°C until the dye front had run off, thereby avoiding the fluorescence signal from bromophenol blue and free dye. All steps were carried out in a dedicated clean room.

#### **2.4.2 Detection of Cy-Dye labelled proteins**

Gel images were obtained by scanning the gels between plates on a Typhoon™ 9400 multiwavelength fluorescence scanner using ImageQuant software (both from GE Healthcare). Excitation and emission wavelengths for each dye used in this study are shown in Table 2.2. The photomultiplier tube voltage of the Typhoon scanner was adjusted for each channel (Cy2, Cy3, and Cy5) in preliminary low-resolution scans (1000  $\mu$ m) to give maximum pixel values within 10% for each channel, but below the saturation level. These setting were then used for high-resolution (100  $\mu$ m) scanning. Images were generated as .gel/TIFF files and exported to image analysis software for further analysis.

Dye	Excitation (nm)	Emission (nm)
Cy2	480	530
Cy3	540	590
Cy5	620	680
CCB	620	/

**Table 2.2 Excitation and emission wavelengths used to detect each of the Cy-dyes and Colloidal Coomassie Blue (CCB) post-staining.**

#### 2.4.3 Image analysis

Gel images were analysed using DeCyder™ image analysis software V5.0 (GE Healthcare). Firstly, images were analysed using the Differential In-Gel Analysis (DIA) module. DeCyder processes the three images derived for the three Cy dyes (Cy2, Cy3 and Cy5) representing profiles of each of the three samples run on a single gel. DIA performs automatic normalisation, spot detection, filtering and background subtraction and also quantifies protein spot abundance or volume on each image and expresses these values as ratios, indicating changes in expression levels by direct comparison of the corresponding spots on each gel. This ratio can be used to directly evaluate changes between two labelled protein samples run on a single gel and between the test samples and the same spot in the internal standard to give a standard spot volume that allows accurate inter-gel protein spot comparisons. Features resulting from non-protein sources (e.g. scratches on glass plates and dust particles) were filtered out.

Subsequently, the Biological Variance Analysis (BVA) module of DeCyder was used for matching protein spots from different conditions across gels by matching to a user defined master gel image, which identified common protein spots across the sets of gels. User intervention was required at this stage to set landmarks on gels for accurate cross-gel matching. Standardised spot volumes were then averaged across replicate samples for each experimental condition and data plotted graphically within BVA. Statistical analysis was performed and spots displaying a  $\geq 1.5$  average-fold increase or  $\leq 1.5$  average-fold decrease in abundance between clinical conditions with  $P$  values  $<0.05$  or  $<0.01$  from a Student t-test were selected for spot picking and MS-based identification.

#### 2.4.4 Protein post-staining and spot excision

Bonded 2D gels were post-electrophoretically stained with colloidal Coomassie Blue G-250 (CCB) to visualise proteins for accurate spot picking. Gels were stained according to a modified protocol by Neuhoff et al. 1988 [Neuhoff et al., 1988]. Briefly, bonded gels were fixed in 35% (v/v) ethanol with 2% (v/v) phosphoric acid for more than three hours on a shaking platform and then washed three times for 30 min each in ddH<sub>2</sub>O. Gels were then incubated in 34% (v/v) methanol, 17% ammonium sulphate and 3% (v/v) phosphoric acid for one hour prior to the addition of 0.5 g/L Coomassie Blue G-250 (Merck Biosciences) and left to stain for two to three days. De-staining was not required. Post-stained gels were scanned on the Typhoon™ 9400 scanner using the red laser with no emission filter (Table 2.2). Post-stained images were imported into the BVA module of DeCyder and matched with the processed Cy-Dye images. Using the reference markers fixed onto the glass plates during gel casting, a pick list of coordinates (.txt file) for protein features that were differentially expressed was created for automated spot picking. An Ettan automated spot picker (GE Healthcare) was used with a 2 mm picking head, which excised protein features from gels submerged under 1-2 mm of ddH<sub>2</sub>O. Spots were collected in 96-well plates, drained and stored at -20°C prior to MS analysis.

#### 2.4.5 Protein in-gel digestion

For protein sequence analysis by mass spectrometry, protein spots were subjected to trypsin digestion. Gel pieces were washed three times with 50% (v/v) acetonitrile, dried in a SpeedVac for 10 min, reduced with 10 mM DTT in 5 mM ammonium bicarbonate pH 8.0 (AmBic) for 45 min at 50°C and then alkylated with 50 mM iodoacetamide (IAM) in 5 mM AmBic for one hour in the dark at RT. Gel pieces were then washed three times in 50% (v/v) acetonitrile and vacuum-dried prior to re-swelling with 50 ng of modified trypsin (Promega) in 5 mM AmBic pH 8.0. The gel pieces were then overlaid with 10 µL of 5 mM AmBic and digested for 16 hours at 37°C. Supernatants were collected and trypsin digests were further extracted by washing the gel pieces twice with 5 % (v/v) trifluoroacetic acid in 50 % acetonitrile.

Peptide extracts from each gel piece were pooled, vacuum-dried and resuspended in 5  $\mu$ L of 0.1 % formic acid and stored at -20°C prior to MS analysis.

#### 2.4.6 Protein identification

Protein identification was carried out using Matrix-Assisted Laser Desorption/Ionisation Time-of-Flight (MALDI-TOF) MS by peptide mass fingerprinting. For this, 0.75  $\mu$ L of the trypsin digest was mixed with 0.5  $\mu$ L of matrix solution (saturated aqueous 2,5-dihydroxybenzoic acid, DHB), and applied to a sample target plate and air dried. MALDI-TOF mass spectra were acquired using an externally calibrated UltraFlex mass spectrometer (Bruker Daltonics). Firstly, the mass spectrometer was calibrated using a standard mixture of peptides (calibration mixture 2 from the Sequazyme<sup>TM</sup> kit, Applied Biosystems). Then a sum of 200 laser shots, delivered in sets of 30 shots (at 6.7 Hz) to several locations on the surface of the matrix spot were acquired in the reflector, positive ion geometry under 25 kV for ion source 1, 21.2 kV for ion source 2, 73 kV on the lens, 26.1 kV on the first reflector and 14.9 kV on the second reflector. The reflector detector was set at 5.75 V, delayed extraction of ion acceleration was maintained for 150 ns to give appropriate time-lag focusing after each laser shot and -1.3 kV multiplier potential, and with suppression of mass ions set to  $m/z < 400$ . Internal calibration of each mass spectrum was performed using reference trypsin autolysis peaks 842.51  $m/z$  and 2211.10  $m/z$ . Prominent peaks in the mass range  $m/z$  700-5000 were then used to generate a peptide mass fingerprint, which was searched against updated NCBI and IPI-Human databases using the Mascot search engine, version 2.0.02 (Matrix Sciences Ltd.). For the search criteria, carbamidomethylation of cysteines was selected as a fixed modification, while oxidation on methionine, N-acetylation and pyro-glutamate were selected as variable modifications. A positive identification was accepted when a minimum of 6 peptide masses matched a particular protein (mass error of  $\pm$  50 or 100 ppm, allowing 1 missed cleavage), sequence coverage was  $>25\%$ , MOWSE scores were higher than a threshold value where  $p=0.05$  and the predicted protein mass agreed with the gel-based mass. When a protein 'hit' fulfilled the specified thresholds for identification, unmatched peptides were systematically re-submitted to the

database in a search for possible multiple proteins per gel piece and potential sites of post-translational modifications (e.g. phosphorylation or glycosylation).

In addition, some identifications were made using nano-LC-electrospray ionization collision-induced dissociation tandem MS (LC-MS/MS). This was preformed on an ACQUITY Ultra performance LC system (Waters) with a PepMap C18 100- $\mu$ m inner diameter column (LC Packings) at a flow rate of 400 nL/min, coupled to a Quadrupole Time-Of-Flight (QTOF Premier) mass spectrometer (Waters/Micromass, Manchester, UK). Spectra were processed using MassLynx software (Waters) and submitted to Mascot database search routines including +2 and +3 peptide charges, and a mass tolerance of  $\pm$  100 ppm. Positive identifications were accepted when at least two peptide sequences matched an entry with MOWSE scores above the p=0.05 threshold value.

## **Chapter 3: MALDI-TOF MS analysis of serum samples pre-dating diagnosis of ovarian cancer**

### **3.1 Introduction**

One of the first reports on the use of magnetic beads for serum peptide and protein extraction coupled with MALDI-TOF MS profiling was published by Villanueva et al. [Villanueva et al., 2004]. The group described an automated technology platform for the simultaneous measurement of serum peptides that was simple, scalable and generated reproducible patterns. Peptides and proteins were captured and concentrated using reversed-phase (RP) batch processing on C8-coated magnetic beads in an automated format on a liquid handling robot followed by a MALDI-TOF mass spectrometric analysis. The optimised protocol was based on a detailed investigation of serum handling conditions, RP ligands, eluant selection, small-volume robotics design and spectral acquisition across a study set. The improved sensitivity and resolution allowed detection of approximately 400 polypeptides (0.7-15 kDa range) from a single droplet (50 µL) of serum and almost 2,000 unique peptides in larger sample set [Villanueva et al., 2004]. The group also described a pilot study which indicated that sera from brain tumour patients could be distinguished from healthy controls based on a pattern of 274 peptide masses. This in turn allowed the generation of a learning algorithm that correctly predicted 96.4% of the samples as either healthy or diseased [Villanueva et al., 2004].

In summary, the system that they described and further optimised satisfied all criteria of MALDI-TOF compatibility, high resolution, reproducibility and throughput, and the limited application provided a proof-of-concept that sera from cancer patients with solid tumours contain peptides detectable by MALDI-TOF MS that reflect the activity of the cancer. They further identified these peptide peaks by tandem MS sequencing and database interrogation. In their study they found signature peptides that fell into several tight clusters or ‘ladders’ of serum protein-derived peptides such as C3F and FPA generated by a 2-step process

involving endoproteases such as kallikreins, thrombin and factor I as well as unknown exopeptidase activities that produce cancer type-specific differences which were superimposed on the proteolytic events of the *ex vivo* coagulation and complement degradation pathways. Thus, they went on to hypothesize that tumour-specific exopeptidase activities produce ‘surrogate’ markers from abundant polypeptides generated during the clotting stage, facilitating correct classification of diseased samples [Villanueva et al., 2004; Villanueva et al., 2005]. Through collaboration, this platform was used at the MSKCC to analyse a set of samples from a pilot study designed to explore the possibility of using MS-based pattern recognition to detect onset of ovarian cancer at an early stage. To this end, during a visit to the Memorial Sloan Kettering Cancer Centre, (MSKCC, New York, USA) in 2004/5, training was provided and reproducibility of the platform assessed, prior to analysis of the pilot study samples.

The first aim of the study presented in this chapter was to assess the reproducibility of the automated bead-based serum peptide extraction protocol and MS-based profiling platform developed at the MSKCC. The second aim was to use this automated platform for the analysis of serum samples that pre-dated diagnosis of ovarian cancer and to determine whether the MALDI-TOF MS profiles obtained could be used to predict ovarian cancer and to compare this with the performance of serum cancer antigen CA-125.

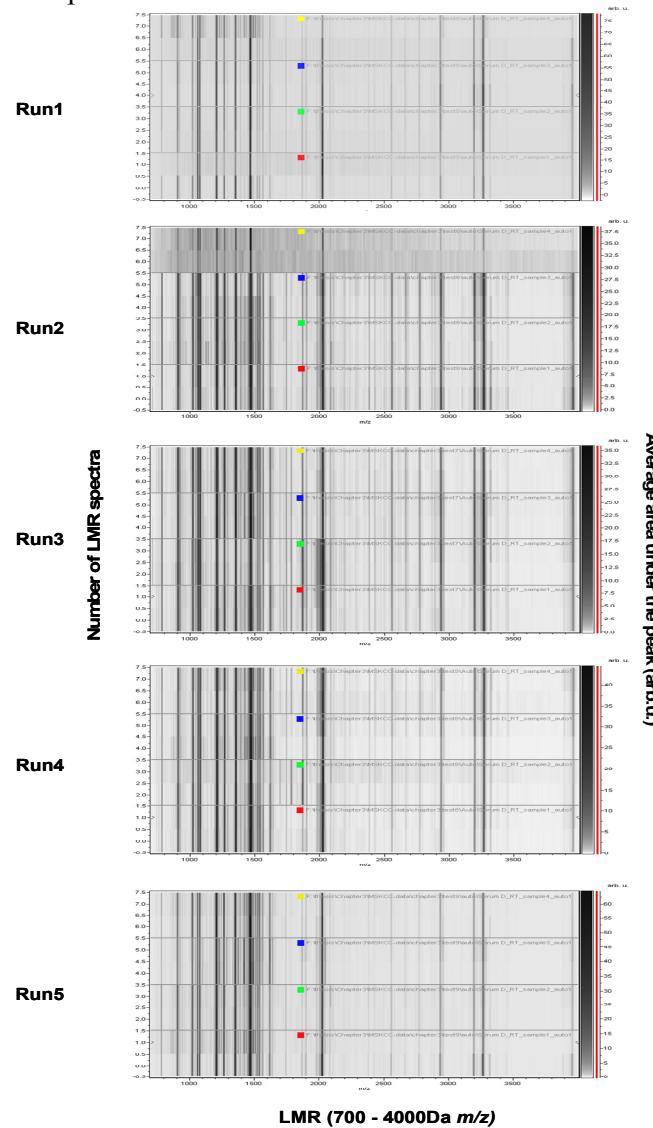
### 3.2 Reproducibility of the automated platform at MSKCC

As mentioned previously, critics have argued that the published results of serum profiling studies looking for cancer biomarkers do not demonstrate biomarker reproducibility. Reproducibility is a measure of the robustness of any technology and is vital for providing support for new and emerging platforms. Hence, the reproducibility of the platform developed by Villanueva et al. [Villanueva et al., 2004] was evaluated using commercial serum from Sigma (Cat. No. S-7023 Lot. 034K8937) as a quality control at the MSKCC. Four replicates of 10  $\mu$ L of serum were each mixed with 5  $\mu$ L of C8-coated magnetic beads (Chemicell) for peptide extraction following the protocol outlined in Chapter 2 (Materials and Methods section 2.2) and peptide profiles in the 0.7 to 15 kDa range were generated by MALDI-TOF-MS. The coefficient of variance for all peaks detected in the low mass range (LMR; 700-4000 Da) (average standard deviation divided by the average peak area) was calculated between the 4 samples as a measure of intra-assay reproducibility. The preparation and analysis was then repeated once a day over 5 days to yield inter-assay reproducibility values. All data processing was performed using ClinProTools software (V2.0). The intra-assay reproducibility for all detected peaks varied across the runs from  $12 \pm 1.2\%$  to  $33.9 \pm 6.9\%$ , although this was  $< 20.11\%$  when run 1 was excluded. Taking the average peak areas for all 5 runs (i.e. 20 samples processed together) the overall inter-assay CV value was  $32.8 \pm 6.4\%$  (Table 3.1).

Run Number	Ave No. of peaks	Ave peak area (arb. u.)	peak area StdDev	peak area CV (%)
1	78	28.81	6.9	33.9
2	70	30.06	4.0	18.3
3	117	22.01	1.2	12.0
4	92	26.73	2.7	17.9
5	116	20.71	2.5	20.1
Overall inter-assay	92	25.42	6.4	32.8

**Table 3.1 Intra/inter-assay reproducibility of MSKCC platform.** The average standard deviation and coefficient of variance (Av. SD / Av. peak area) were calculated for all detected peaks using ClinProTools software (V2.0). Intra-assay reproducibility was calculated by running 4 samples per run, while inter-assay reproducibility was calculated by assessing the variation between 5 runs.

Spectral heat maps created in ClinProTools software (V2.0) showed some obvious peak area differences in the intra-assay comparisons (Figure 3.1). These differences, which could be the result of inconsistencies in the complex MALDI ionisation process, are likely to account for the seemingly high CV values. Furthermore, the average number of peaks obtained are comparable to the relative number of peaks previously reported [Villanueva et al., 2004]. The assay CVs are also considered acceptable.



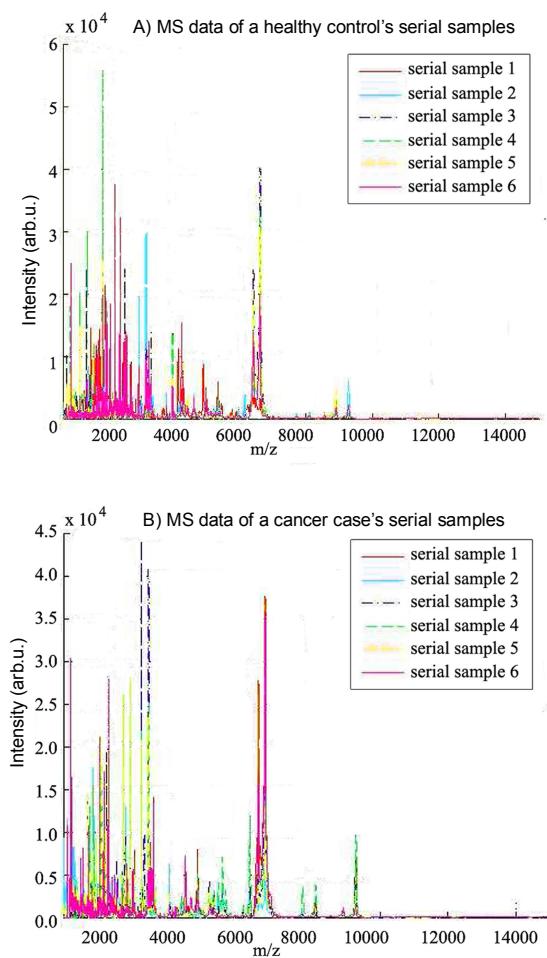
**Figure 3.1 Spectral comparisons across runs.** Four replicates of 10  $\mu$ L of serum each were mixed with 5  $\mu$ L of C8 beads (Chemicell) for peptide extraction following the protocol outlined in Chapter 2 (Materials and Methods section) prior to MALDI-TOF MS analysis. Five replicate runs were then performed on different days. Spectra were processed and displayed as heat maps using ClinProTools software (V2.0).

### 3.3 Analysis of serial samples pre-dating diagnosis of ovarian cancer

Following the evaluation of the reproducibility of the platform, 92 serial serum samples from 19 women which pre-dated a diagnosis of ovarian cancer were analysed. The samples came from a pilot study of ~22,000 women which involved regular serum sample collection for cancer antigen CA-125 assay and following up volunteers for up to 7 years (1995-2001) prior to actually diagnosis. Each of the 19 volunteers who developed ovarian cancer (in one case, non-epithelial) had between 2 and 11 serial samples. Each case sample had 2 matched healthy controls which were taken and handled at approximately the same time as the case sample. In addition samples were matched on the use of hormone replacement therapy. Other information such as date of birth, CA125, the date samples were taken, the date samples were received at the laboratory and tube type used for serum collection was also available. It is hypothesised that during the clotting process tumour-specific proteases generate fragment ‘ladders’ of marker peptides in serum producing subtle changes in the MS profiles. These changes have been used to discriminate diseased sera from the sera of matched healthy controls which had been collected at the same centre at approximately the same time and thus handled and sorted in the same manner [Villanueva et al., 2004; Villanueva et al., 2005]. The main aim of the work presented in this chapter was to demonstrate that the information contained in mass spectra, in combination with the level of CA-125, is useful for early detection of ovarian cancer.

The data presented in this chapter came from 80 samples from 18 volunteers as the non-epithelial ovarian cancer case, and samples which did not have both of the matched control samples were subsequently removed. The 240 samples were processed, extracted and spotted in duplicate for MALDI-TOF analysis. One spectrum was chosen from each pair at the data processing and analysis stage. Example spectra from serial samples of a healthy control and cancer case are shown in Figure 3.2. These show generally that many of the peaks detected were common across the sample sets, but that there was considerable variation in peak areas. A total of 240 spectra were analysed in collaboration with Professor Alex Gammerman’s group at the Computer Learning Research Centre, Royal

Holloway, University of London, who used this data to build class prediction algorithms [Gammerman et al., 2008].

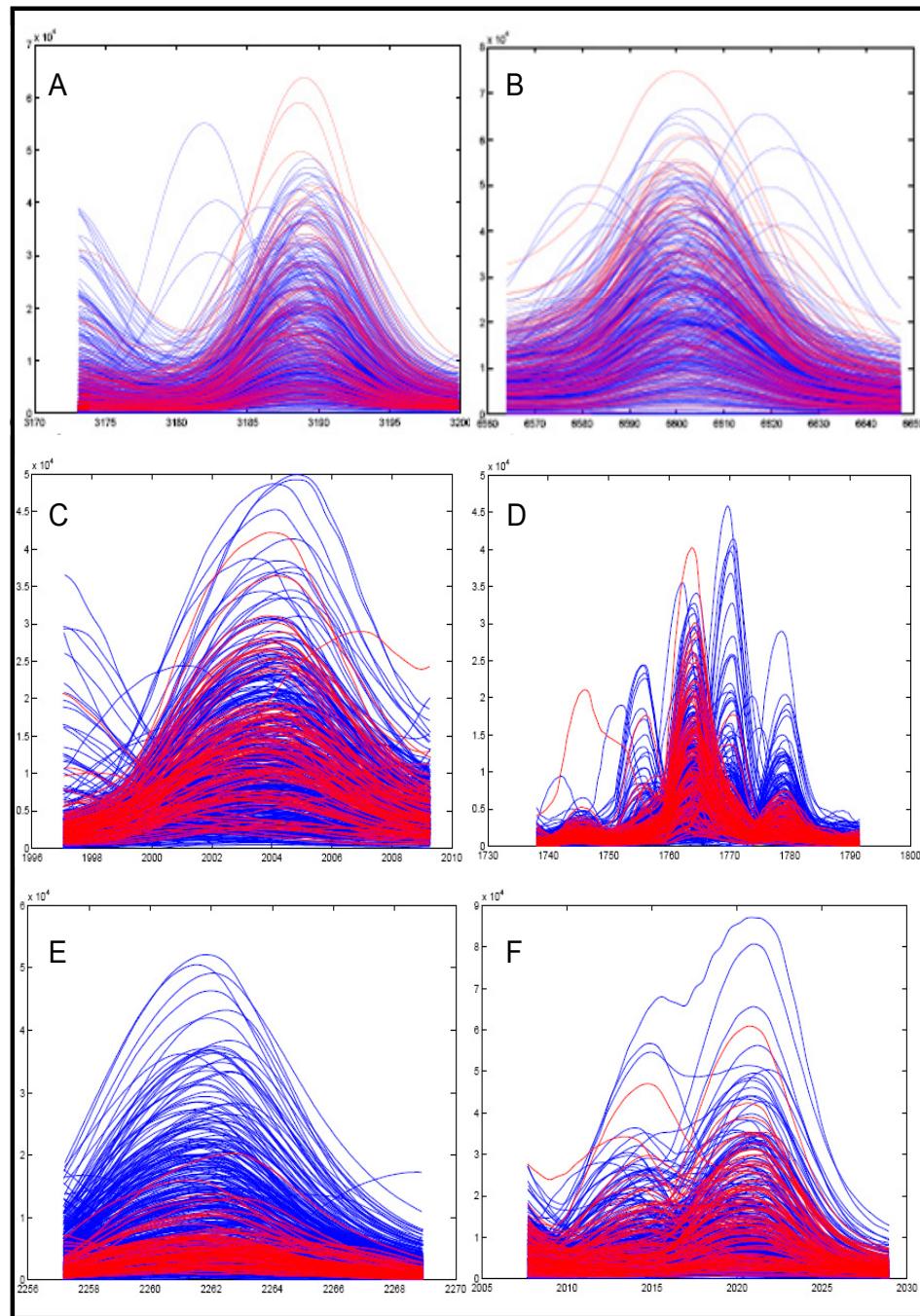


**Figure 3.2 Spectral comparisons across serial samples.** MS profiles of six serial samples from (A) a healthy control and (B) a cancer case are overlaid for comparison. The data from the low and high mass range have been combined.

After spectral pre-processing, (described in Chapter 2 section 2.2.4), 7216 ‘non-aligned peaks’ were identified in the 265 spectra, (including the non-epithelial cancer case plus controls). After peak alignment these peaks were clustered into 402 peak groups. The peaks were ordered according to their frequency (i.e. the percentage of samples having the same peak). Overall, 20 peaks were found to exceed 40% frequency (Table 3.2 and Figure 3.3). The peak intensities of the 20 most frequent peaks in each sample and the corresponding CA-125 measurement were then used to create a vector consisting of 21 numbers for a classification algorithm.

Peak number	mean $m/z$	$m/z$ range	Number of samples having the peak	% of total
1	3188.9	3185.3-3191.0	246	92.8
2	6646.1	6636.5-6652.8	245	92.5
3	3330.5	3325.2-3333.4	198	74.7
4	2004.1	2001.2-2005.3	190	71.7
5	1764.6	1762.0-1766.6	184	69.4
6	818.5	817.4-818.9	165	62.3
7	9307	9294.7-9319.7	154	58.1
8	2982.3	2978.8-2985.5	146	55.1
9	2020.9	2019.7-2021.9	144	54.3
10	4292.5	4288.0-4300.8	140	52.8
11	3280	32.76.2-3282.1	139	52.5
12	2548.2	2543.5-2550.2	137	51.7
13	2562.8	2561.4-2564.2	123	46.4
14	8942.2	8930.8-8955.3	118	44.5
15	3296.9	3294.3-3299.1	115	43.4
16	1888.8	1887.7-1889.7	114	43
17	899.9	898.6-901.0	113	42.6
18	3172.1	3169.1-3176.4	109	41.1
19	3229.8	3226.7-3234.2	109	41.1
20	5010.4	5004.0-5017.0	109	41.1
39	2016.8	2013.6-2019.6	56	21.1

**Table 3.2 Top 20 peaks and peak 39.** The top 20 peaks are those present in more than 40% of the samples. Peak number 39 occurred more rarely but was found to be useful for case versus control discrimination.



**Figure 3.3 Spectral views of peaks.** After spectral pre-processing (described in Chapter 2 section 2.2.4) 20 peaks were found to be common in over 40% of the samples. Representative peak profiles for peaks (A) 3188.9 m/z, (B) 6646.1 m/z, (C) 2004.1 m/z, (D) 1764.6 m/z, (E) 2562.8 m/z and (F) 2016.8 m/z, are shown here in blue for healthy and red for cancer case.

For classification, for each  $t$  (time) = 1-18, the null hypothesis was that the assignment of the label “case” within each triplet in  $St$  (start time) was random. For example, the correct identification of the ‘case’ labelled samples, the 240 samples were divided into 80 triplets, each consisting of a case sample and the two matched control samples. The 80 triplets were further divided into 18 triplet groups corresponding to the 18 cases (with the size of the group varying between 2 and 10 samples). Each triplet was assigned a non-negative value  $t$ , the time to diagnosis (months) for the case measurement in each triplet. For each  $t = 0, 1, 2, \dots$   $St$  (start time) was assigned to be the set of triplets taken  $t$  months before the diagnosis. As such the largest  $St$  (for  $t = 0, 1$ ) contained 18 triplets, whereas the smallest  $St$  contained 14 triplets. The classification algorithm used a rather limited set of rules for the identification of the cancer ‘case’ labelled sample within each triplet. Each classification rule is described by three numbers,  $(p; w_1; w_2)$ , which are a peak number  $p$  (1 – 20) and weights  $w_1$  (0; 1) and  $w_2$  (-1; 1). For each triplet, the classification rule was used to predict the sample with the largest  $(w_1 \log C + w_2 \log P)$ , where  $C$  was the CA-125 level and  $P$  is the area of peak  $p$ , labelled as “case”. The logarithms were taken to remove the arbitrary units of measurement of CA-125 and the peak area.

The baseline rule in the classification algorithm used CA-125 measurements alone to classify the triplet samples. The output for the algorithms reported on the number of errors (E1), made on identifying the triplets in each  $St$ . Then another dimension was added using the top 20 peaks (E2) and finally the top 100 peaks (E3). The number of errors in E1 increased as the time to diagnosis increased, demonstrating that CA-125 measurements alone are insufficient for predicting ovarian cancer and for early diagnosis (Table 3.3). Using the top 20 peaks (E2) the number of errors also increased with time from diagnosis, but not to the same degree as E1, suggesting that early diagnosis information was present in the spectra.

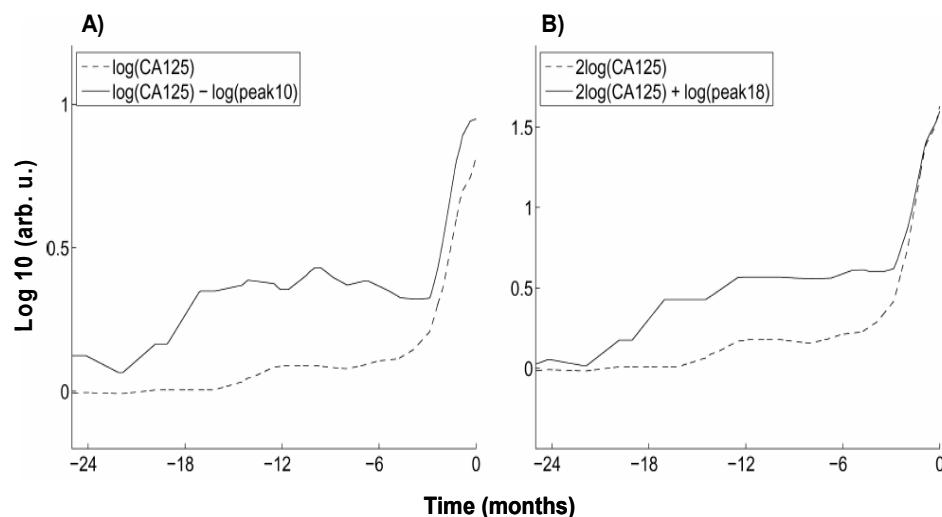
Results showed that the classification algorithm made the smallest numbers of errors when the top 100 peaks (E3) were used from each of the triplets sets ( $St$ ) (Table 3.3). For example, in Table 3.3 the entry 2 corresponding to  $t = 6$  means

that out of 15 cases with samples taken at least 6 months before diagnosis the best classification algorithm made 2 errors on the most recent of those samples. This is a very small number of errors. The Monte-Carlo method was used to calculate valid p-values and involved randomly reassigning “case” labels and counting the number of errors which were as good as or better than the number of errors obtained for the true labels (Q). The p-value was then estimated as the ratio of Q/N where N = 10<sup>6</sup>. It should be noted that these results are heavily biased since the training set St included the test samples. However, the p-value of 0.012% for 7 months prior to diagnosis is highly significant. Furthermore, peak number 10 (4292.5 m/z) was the most frequent feature used in the classification algorithm.

<i>t</i>	St	E 1	p-value 1	E 2	p 2	w 2	p-value 2	E 3	p 3	w 3	p-value 3
0	18	2	0.000001	1	-9	1	0.000001	1	-9	1	0.00006
1	18	2	0.000001	2	3	1	0.00002	1	-14	2	0.00001
2	15	4	0.0018	3	8	1	0.0094	2	18	2	0.0052
3	15	5	0.0086	3	8	1	0.0095	2	18	2	0.0056
4	15	6	0.031	3	8	1	0.0097	2	18	2	0.0056
5	15	6	0.031	3	-14	1	0.0017	2	-14	1	0.0047
6	15	7	0.088	2	-10	1	0.011	2	-10	0.5	0.0037
7	15	7	0.088	3	-10	1	0.011	2	-10	0.5	0.0037
8	14	8	0.31	3	-10	1	0.025	2	-39	1	0.021
9	14	7	0.15	3	-10	1	0.025	2	18	2	0.012
10	14	7	0.15	3	-10	1	0.025	2	18	2	0.012
11	14	7	0.15	3	-14	1	0.032	2	18	2	0.012
12	14	7	0.15	4	-10	1	0.13	2	18	2	0.012
13	14	8	0.31	3	-10	1	0.024	3	-10	1	0.063
14	14	9	0.52	4	-10	0	0.12	4	-10	0	0.29
15	14	9	0.52	5	-10	0	0.39	4	-60	0	0.51
18	14	10	0.74	4	-10	0	0.12	3	-60	0	0.15

**Table 3.3 Classification results.** The columns are *t*, the time to diagnosis in months; |St|, the number of cases with measurements taken  $\geq t$  months before diagnosis; E1, the number of errors when classifying the triplets in St with CA-125 alone; p-value 1, the corresponding p-value; E2, the minimal number of errors when classifying with CA-125 plus one of the peaks 1-20; p2, the peak number with the best discriminative power, (the minus sign indicates an assigned weight of -1, otherwise +1); w2, is the value of weight assigned to CA-125 (0 or 1); p-value 2, the corresponding p-value; E3, the minimal number of errors when classifying with CA-125 and one of the peaks 1-100 (weight -1 or 1); p3 and w3, the peak number and the value of the weights for CA125, respectively, attaining E3 errors; p-value 3, the corresponding p-values.

These results suggest that using a combined classification approach (CA-125 plus MS peaks) ovarian cancer can be detected up to 12 months prior to diagnosis at a significance level of  $<0.05$ . Furthermore, when CA-125 and the 20 most frequent peaks were used in equal weight (E2), peak 10 (4292.5 m/z) was found to be the most discriminating feature. Peak 18 (3171.1 m/z) was also a significant discriminator when the 100 most frequent peaks were used. Interestingly, the changes in the area of peak 10 were complementary to changes in CA-125 levels in samples prior to the time of diagnosis (Figure 3.4).



**Figure 3.4 Dynamics of peak 10 combined with CA-125.** Results suggest that using a combined classification approach (CA-125 plus MS peaks) ovarian cancer can be detected up to 12 months prior to diagnosis at a significance level of  $< 0.05$ . Here the dynamics of A) peaks 10 in combination with CA-125 (solid line) and CA-125 alone (dashed line). B) Peaks 18 in combination with CA-125 (solid line) and CA-125 alone (dashed line) are shown on a logarithmic scale. Each plot essentially shows the deviation of the value taken by the corresponding classification rule on the cases from the values taken on the controls. The horizontal axis shows the time to diagnosis in months.

### 3.4 Discussion

It is universally agreed that any technology platform for biomarker discovery needs to demonstrate high reproducibility and robustness. Analytical reproducibility is a significant challenge in protein profiling. A number of MALDI-TOF MS protein-profiling strategies have been developed for improved analytical performance. In particular, MALDI-TOF-MS protein profiling has been combined with advanced biostatistics to identify proteomic biomarker patterns for human diseases and improved reproducibility of the spectral output has been critical for avoiding false discoveries using this approach.

The use of mass spectrometry (MS) for the direct analysis of proteins and peptides from human serum for disease biomarker discovery was first reported in 2002 [Petricoin et al., 2002; Petricoin et al., 2002]. However, critics argued that the published results of serum profiling for diagnosis of ovarian cancer did not demonstrate reproducibility in independent subjects [Baggerly et al., 2004; Baggerly et al., 2005]. The apparent discrimination reported could be explained through the over-fitting of the data that occurs when multivariable models are used to fit a large number of possible predictors (such as mass spectrometry peaks) or by differences in sample handling of diseased and control samples to discriminate among a group of subjects with or without cancer [Petricoin and Liotta, 2004; Petricoin, III et al., 2002; Ransohoff, 2005].

Previously reported intra experiment CVs of peak intensities vary greatly between individual peaks, and reported mean CVs of the peak area varies across studies from 4% to 26% [de Noo et al., 2005; West-Norager et al., 2007]. However, often, only the most abundant and stable peaks are considered. In biomarker research utilizing MALDI-TOF MS profiling, the aim is to identify peaks that show consistent differences in intensities (or peak areas) between case and control samples, and thus the reproducibility of peak areas is of highest importance.

The data presented in this chapter was obtained through collaboration with a group at the MSKCC, who have previously established an automated magnetic

beads-based strategy for serum peptide and protein extraction coupled MALDI-TOF MS-based profiling platform [Villanueva et al., 2004; Villanueva, 2006]. The work presented here assessed the reproducibility of the existing platform and found intra-assay reproducibility for the peaks to be below 20% (except run 1). However, significant inter-experiment variation was found (~33%) which is comparable to the CVs reported by others and thus considered acceptable. Run-to-run variation is a well-known problem with these types of high-throughput profiling strategies. Inter-assay variation is often high because of differences in the numbers of peaks obtained and possibly due to other confounding factors such as temperature and humidity variation from day-to-day affecting matrix-analyte co-crystallisation prior to MS analysis. Results presented in this chapter demonstrate how the analysis of the same sample over several runs under identical conditions can yield different peak numbers.

The matrix (co)crystallization and desorption/ionization steps in MALDI-TOF MS have been derived empirically, and the thermodynamic and physicochemical processes of phase transition and ionisation are poorly understood [Cohen and Chait, 1996]. Matrix molecules crystallize in different shapes and dimensions, proteins tend to accumulate at the droplet periphery, and the composition of the matrix solution and the rate of crystal growth influence the spectral output. These phenomena produce shot-to-shot variations, and are related to sampling different parts of the target surface and progressive sample ablation with repeated laser shots [Cohen and Chait, 1996]. Studies have also demonstrated ion suppression effects in MALDI-TOF MS. Ion suppression occurs when an ion suppresses the peak signal of other ions in the sample, and peptides with greater hydrophobicity show the greatest suppression effects. Peak area is thus associated with the concentration of the individual protein, to its primary structure, and to the complexity of the sample [Cohen and Chait, 1996]. In summary, peak area in MALDI-TOF MS profiling has significant analytical variation and is poorly understood.

Following the initial assessment of platform reproducibility an analysis of serum samples that pre-dated diagnosis of ovarian cancer was performed. The results

presented here demonstrate that the predictive power of CA-125 alone was limited for early diagnosis. However, using a combined classification approach (CA-125 plus MS peaks) ovarian cancer can be detected up to 12 months prior to diagnosis at a significance level of  $<0.05$ . Of the 20 most frequently occurring peaks, statistical analysis showed that the information provided by peak 10 (4292.5 m/z) was complementary to the information provided by serum CA-125 measurements and the majority of OC cases show either a tendency of serum CA-125 growth or a tendency of peak 10 to decrease, or both. Furthermore, peak 18 (3171.1 m/z) was also a significant discriminator when the 100 most frequent peaks were used. The identification of these two peaks would facilitate immune-based assay development for detailed validation of these findings.

It is important to note that these conclusions are based on exploratory results (namely, the p-values obtained) and further work is needed to validate these findings. It can be speculated that these peaks maybe a fragments of host immune/acute phase proteins e.g. inter- $\alpha$ -trypsin inhibitor heavy chain (ITIH4) or Complement C3F, which are abundant serum proteins. These proteins have been shown to form peptide 'ladders' through tumour specific exopeptidase activity during the clotting process. Although, none of the peak masses matched those reported by Villanueva et al. it is important to note that the study involved an analysis of ovarian cancer samples, whereas previously, breast, bladder and prostate cancer samples were analysed [Villanueva et al., 2004; Villanueva, 2006]. In addition, the sample collection which was not standardized, handling and data analysis procedures were also different to those used by the group at MSKCC.

Finally, the technology platform was adapted in the host lab at UCL for the analysis of other cohorts of serum samples (following chapters).

## **Chapter 4: Optimisation of an automated magnetic bead-based extraction protocol for mass spectral profiling of human serum**

### **4.1 Introduction**

High-throughput sample preparation and protein profiling with MALDI-TOF MS analysis is a relatively new tool for diagnosis of human diseases. Indeed several groups have reported the use of peak pattern discrimination for the correct classification of ovarian cancer [Petricoin et al., 2002], prostate cancer [Adam et al., 2002; Qu et al., 2002], breast cancer [Li et al., 2002] breast, prostate and bladder cancer [Villanueva et al., 2006], although, at present none of these are in clinical use. It is universally agreed that any new technology platform for biomarker discovery needs to demonstrate high reproducibility and robustness [Srinivas et al., 2002]. However, a major obstacle to reliably determining quantitative changes in protein expression is to overcome errors imposed by technical and biological variation [Molloy et al., 2003].

A general mass spectrometry-compatible bead-based protocol for the extraction of serum peptides and proteins requires the optimisation of numerous experimental conditions. Factors to be considered include bead type used for peptide extraction, bead-to-serum ratio, pH, loading, washing, and elution conditions. Furthermore, the effects of pre-analytical variation from sample handling and storage need to be considered. Indeed the humidity, temperature, storage, and time for preparation of sera have all been shown to induce spectral changes [Timms et al., 2007; Villanueva et al., 2005; West-Norager et al., 2007].

The aims of the studies presented in this chapter were to adapt and establish a previously reported bead-based peptide and protein extraction and MALDI-TOF MS serum profiling platform in the host laboratory at UCL. The original protocol was optimised and adapted for MALDI-TOF MS analysis of human serum. The instrument used in the earlier studies was a Bruker Daltonics Autoflex TOF-TOF. However, in the host lab at UCL the available instrument was a Bruker Daltonics

Ultraflex TOF-TOF, thus mass spectral acquisition parameters were also optimised to establish a robust protocol at UCL. With respect to data processing and analysis ClinProTools software (Bruker) was used to evaluate the effects of modifications on the methods, since the ‘bespoke’ analysis methods developed at MSKCC were unavailable. In addition, the effects of different sample handling conditions on MALDI-TOF MS serum peptide profiles were also explored to determine a clinically feasible handling method for serum samples.

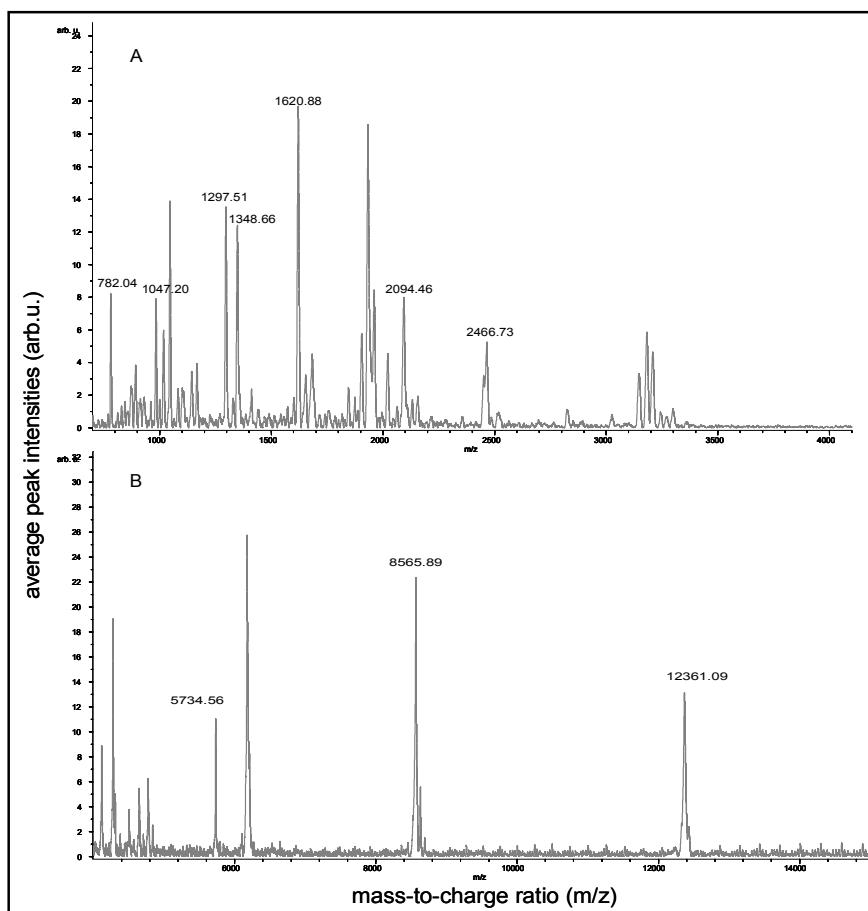
## 4.2 Optimisation of MALDI-TOF MS spectral acquisition parameters

Initial experiments used a cocktail of commercially available peptides and proteins (Table 4.1) in combination with manually prepared commercial serum (Sigma-Aldrich) to establish optimised spectral acquisition methods for the low (700-4000 Da) and high mass ranges (4-15 kDa). Spectral acquisition was split into two mass ranges to minimise errors associated with data processing i.e. baseline subtraction and smoothing. The purpose of baseline subtraction is to remove the broad structures of a spectrum and to create a baseline for the accurate selection of peaks based on signal-to-noise and intensity thresholds. Notably, noise levels increase in the high mass range and requires additional smoothing compared to the low mass range. Thus, it is advantageous to acquire and process spectral data in two separate mass ranges.

Calibrant	m/z
Peptide mix	
Peptide 782	782.04
Angiotensin II	1,047.20
Angiotensin I	1,297.51
Substance P	1,348.66
Bombesin	1,620.88
ACTH fragment 1-17	2,094.46
ACTH fragment 18-39	2,466.73
Protein mix	
Insulin	5,734.56
Ubiquitin	8,565.89
Cytochrome C	12,361.09
Myoglobin	8,476.77

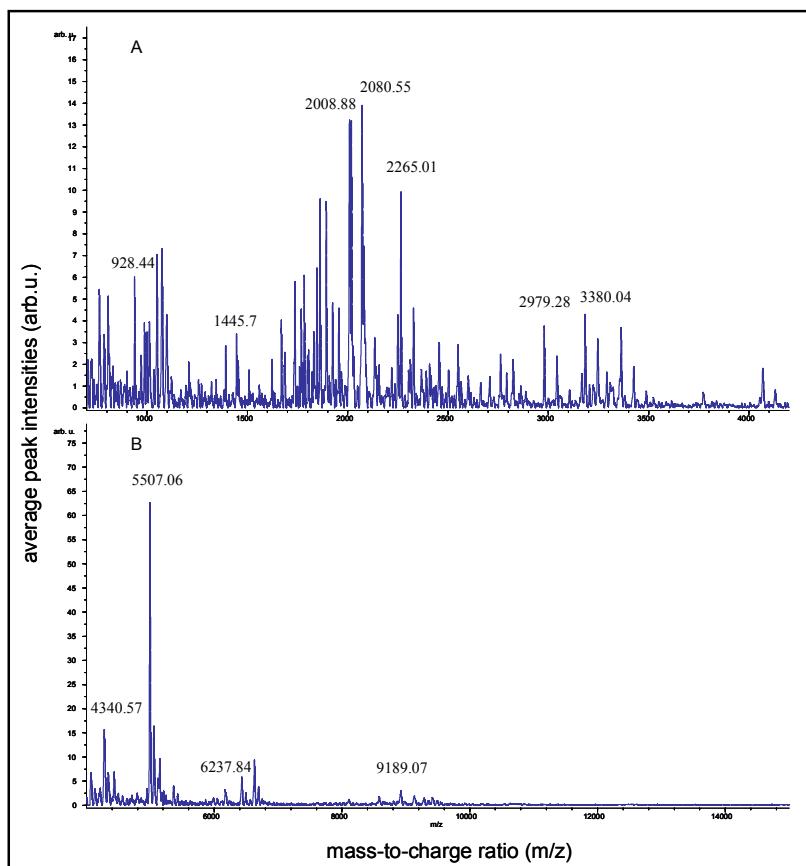
**Table 4.1 Calibrants used for MALDI-TOF MS spectral acquisition optimisation and calibration.** Calibrant mixture was freshly prepared on the day of each experiment according to the method outlined in Chapter 2. Briefly, peptide and proteins were diluted and mixed to a final concentration of 30 femtomoles per peptide and 500 fmol per protein. All m/z values are calculated for single-charged ions except for myoglobin which generated a doubly-charged ion.

For MALDI-TOF MS profiling of human serum a number of MS spectral acquisition parameters were tested and optimised. These included the voltages applied to the lens and ion source, laser energy being delivered to sample spots and the raster file associated with the laser firing pattern. This was necessary to facilitate optimised and accurate automated detection of the peptides and proteins in the sample eluates using the instruments 'AutoXecute' function. The mass-to-charge ratios of the reference calibrant peptides and proteins were used to make the necessary adjustments to the MS acquisition protocol to ensure the observed masses matched expected masses within a mass error of  $\pm 10$  ppm (Figure 4.1).



**Figure 4.1 Mass spectral chromatographs illustrating acquired peaks from the calibrant mixture.** A) Low mass range (700-4000Da) showing peptide calibrants and B) High mass range (4-15kDa) showing protein calibrants. Calibrants were freshly prepared according to the protocol described in Chapter 2 (Materials and Methods section) and spotted 1:1 (0.5  $\mu$ L calibrant mix plus 0.5  $\mu$ L  $\alpha$ -CCA matrix) before MALDI-TOF MS analysis. MS parameters were adjusted to ensure accurate measurement of the peptide and protein m/z ratios with high intensity and low noise.

In parallel, to ensure efficient detection of serum peptides and proteins these adjustments were tested on serum eluates prepared using a manual bead extraction procedure. For this part of the study, C8 porous magnetic beads (Chemicell) used in the original study were used and were obtained from the MSKCC. This reagent is now no longer commercially available. MS spectra of two replicate samples were analysed in ClinProTools software to determine peak numbers. At this stage, an average of 143 and 109 serum peaks were detected in the LMR and HMR respectively (Figure 4.2). Overall average CVs were 18.7 % in the LMR and 19.4 % in the HMR. After the optimisation of the MS spectral acquisition parameters, the bead-based extraction protocol was optimised on a liquid handling robot for high-throughput sample analysis (Chapter 2 section 2.2.2).



**Figure 4.2 Mass spectral chromatographs of commercial serum.** Spectral profiles generated during MS spectral acquisition optimisation are shown. Serum samples were manually processed as described in Chapter 2 and spotted 1:1 (0.5  $\mu$ L sample eluate plus 0.5  $\mu$ L  $\alpha$ -CCA matrix) before MALDI-TOF MS analysis. Data was analysed in ClinProTools software A) Low mass range (700-4000 Da) and B) High mass range (4-15 kDa).

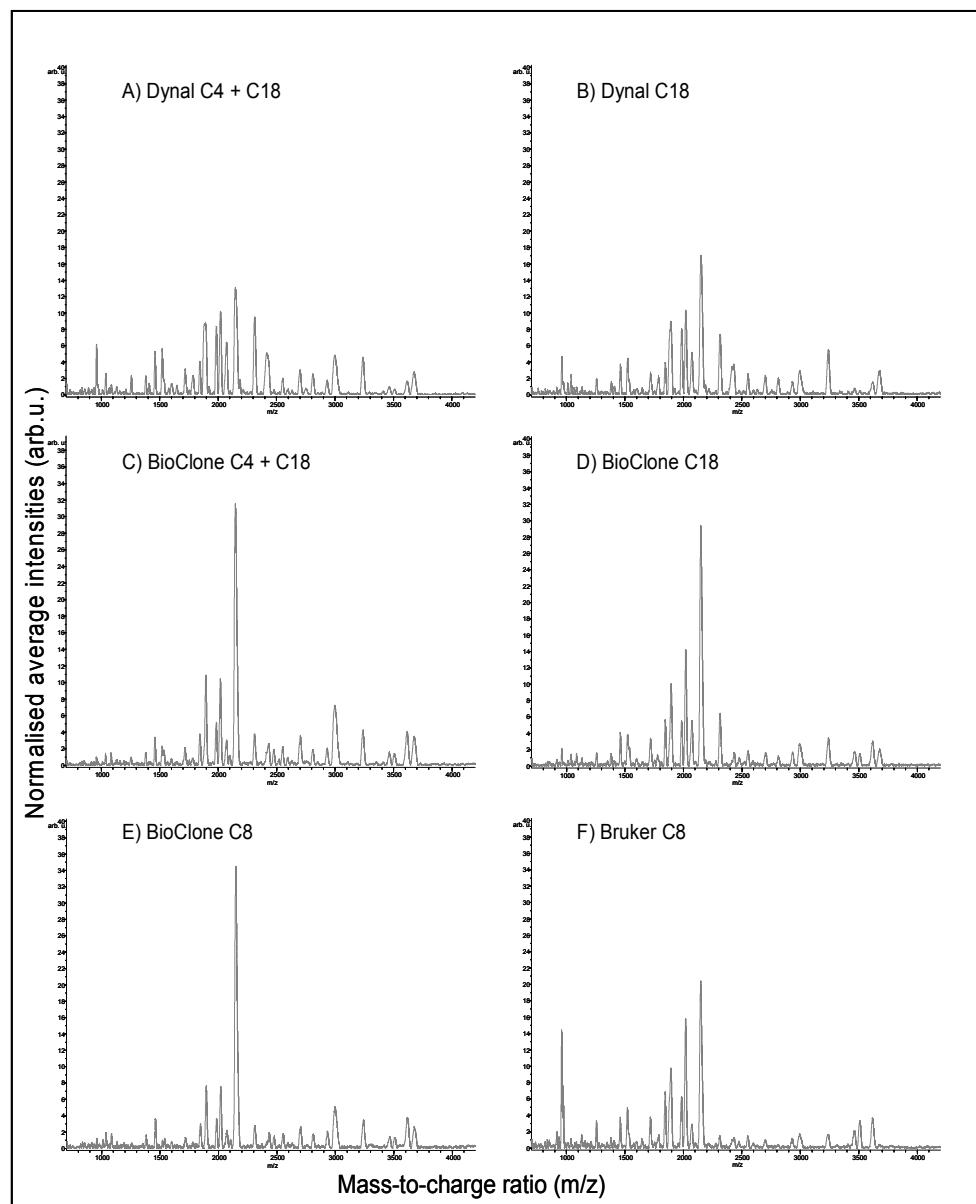
### 4.3 Optimisation of magnetic bead-based extraction protocol at host institute.

One of the methods recently adopted for the extraction of peptides and proteins from human serum is reversed-phase (RP) capture on magnetic beads derivatised with a variety of binding chemistries. By using magnetic beads coated with these chemistries it is possible to automate the capture of peptides and proteins using liquid handling robotics thereby providing high throughput and reproducibility in sample processing. Indeed, the capture of peptides and proteins using RP batch processing in a magnetic bead-based format was previously automated at the MSKCC on a liquid handling robot allowing simultaneous processing of 100s of serum samples at a time [Villanueva et al., 2004; Villanueva et al., 2006]. The RP reagents utilised in the original study (C8-coated magnetic beads) were no longer commercially available therefore the performance of beads from alternative sources was investigated for the establishment of an automated serum profiling platform at UCL.

The nature of the stationary phase is a vital factor in any chromatographic separation, since it determines the retention of specific ligands. For example, weak cation exchange beads carry negative surface charges which reversibly adsorb oppositely charged proteins and large peptides. Bound samples can be sequentially removed using a step-wise elution with increasing concentrations of salts, decreasing the pH or a combination of both. Reverse phase (RP) beads are usually coated with carbon chains for peptide and protein binding through hydrophobic interactions. Sequential removal is then achieved by increasing the concentrations of organic solvents such as acetonitrile. The length and deposition of carbon chains onto the bead surfaces affect the selectivity for peptide binding. Larger polypeptides are preferentially captured on less hydrophobic surfaces (C1-3), while smaller peptides are captured on more hydrophobic surfaces (C8-18). These chemistries have been applied to magnetic beads to facilitate batch-wise binding and elutions.

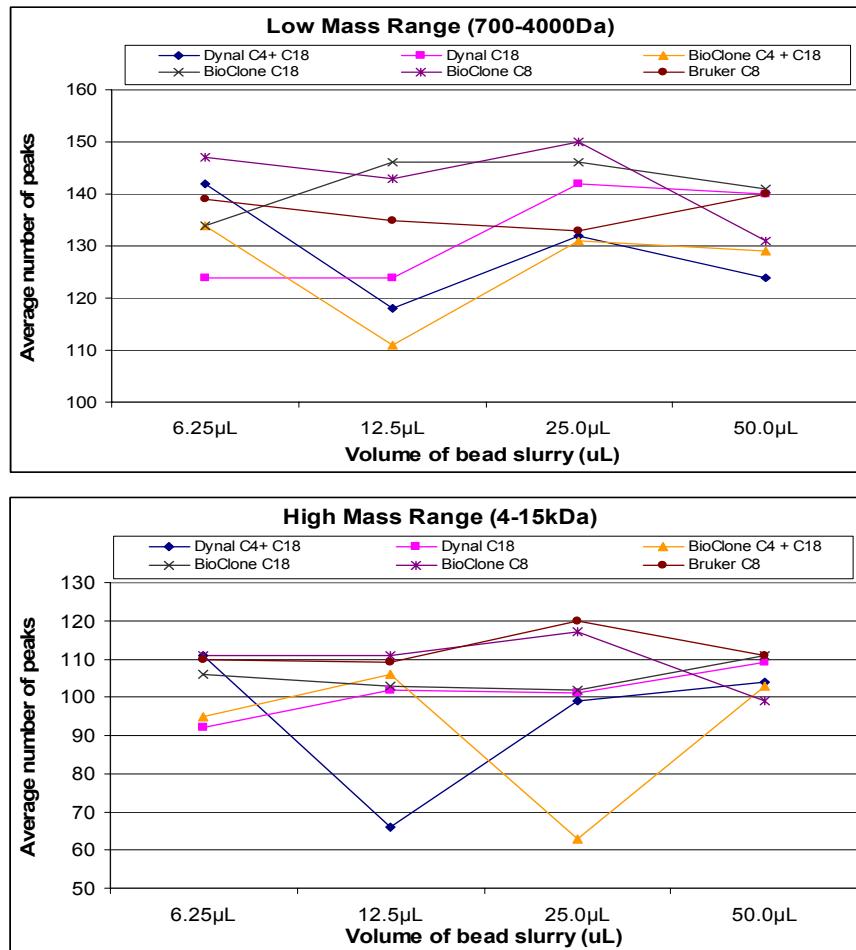
### 4.3.1 Optimisation of bead type and bead-to-serum ratio

Initial experiments were performed to compare the number of peptide species captured by different commercially available magnetic beads. This was done to determine the most appropriate stationary phase and ‘bead-type’ for serum peptide and protein extraction. Three main types of RP magnetic beads are commercially available from a number of manufactures including BioClone, Bruker Daltonics and Invitrogen (Dynal beads). The polypeptide affinity of C4, C8 and C18 RP beads, as well as a combination of C4 and C18 beads from BioClone, Bruker Daltonics and Invitrogen (Dynal) were compared. In addition, differing bead slurry-to-serum volume ratios (1:1, 1:2, 1:4 and 1:8) were tested after equalisation of bead concentration (to 2 $\mu$ g/ $\mu$ L) to determine the optimal ratio for capturing and recovery of peptides and proteins. Since batch preparation methods were the most effective way to carry out cross-comparisons of multiple conditions concurrently, sample conditions were standardised by using 50  $\mu$ L of Sigma serum for all comparisons. Each condition was run in triplicate on the robot and spotted in duplicate onto a MALDI target and the 6 spectra per condition were acquired using the MS parameters optimised in the previous section. The MALDI-TOF MS spectra were processed using ClinProTools software (V2.0) as described in Chapter 2 section 2.2.4, and the average spectra and peak statistics were compared. Overall, a similar number of peaks were detected in each bead type in both the LMR and HMR (Figures 4.3 and 4.4). However, C8 beads alone performed marginally better (more consistently) then C18 beads alone in the high mass range-as expected.



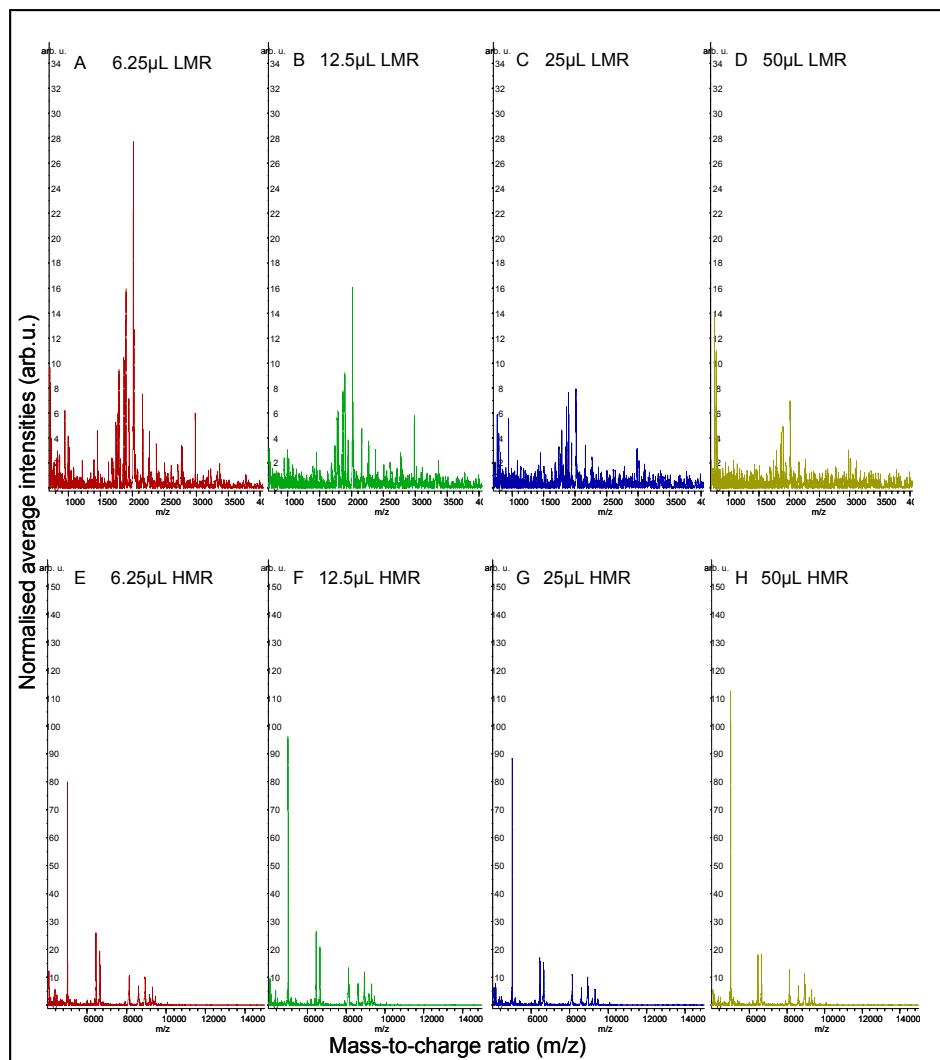
**Figure 4.3 MALDI-TOF spectra illustrating the average LMR (700-4000Da) serum peptide profiles used in the comparison of magnetic beads.** Average spectra are shown for Sigma serum (n=6) extracted with equal amounts of (A) Dynal C4 and C18 RP bead slurry. (B) Dynal C18 beads. (C) Equal amounts of BioClone C4 and C18 RP bead slurry; (D) BioClone C18 beads; (E) BioClone C8 beads; (F) Bruker C8 beads. 12.5  $\mu$ L of bead slurry was used for extraction of Sigma serum essentially as described in Chapter 2 section 2.2.2, eluate was mixed 1:1 with  $\alpha$ -HCCA, and 1  $\mu$ L was spotted in duplicate for MALDI-TOF MS analysis. Samples were run in triplicate and the average spectra generated by ClinProTools (V2.0) are presented here.

Generally for all bead types, a 25  $\mu\text{L}$  bead slurry volume was found to capture the highest number of peptide peaks above an S/N ratio of 3 in the LMR and 5 in the HMR (Figure 4.4), although there were some fluctuations. This was perhaps surprising since one may expect more peptides to be detected at higher bead-to-serum ratios. This hints at ion suppression effects.



**Figure 4.4 MALDI-TOF comparison of the extraction of serum polypeptides using different coated magnetic beads.** A volume of 50  $\mu\text{L}$  of neat serum was mixed with 6.25  $\mu\text{L}$ , 12.5  $\mu\text{L}$ , 25  $\mu\text{L}$  and 50  $\mu\text{L}$  of bead slurry (all equalised to 2  $\mu\text{g}/\mu\text{L}$ ). This mixture was incubated at room temperature for 2 minutes. Beads were then pulled side-to-side 10 times with a magnet and allowed to settle on one side of a PCR tube before supernatant was removed and discarded. Beads were then washed twice with 0.1% TFA. Bound peptides were eluted with 5  $\mu\text{L}$  of 50% ACN. Eluate was mixed 1:1 in MALDI matrix  $\alpha$ -HCCA and 1  $\mu\text{L}$  was deposited on a normal stainless steel MALDI target for MS analysis. The number of peaks obtained for bead conditions were calculated for (A) LMR and (B) HMR using ClinProTools software (V2.0) and S/N cutoffs of 3 & 5, respectively.

Indeed, analysis of the changes in the spectra showed that increasing the bead amount led to a reduction in the peak area of lower mass range peaks (Figure 4.5). The high mass range peaks were relatively unaffected. Furthermore, there was some fluctuation in the number of peptide peaks detected using 12.5  $\mu$ L versus 25  $\mu$ L in the LMR (Table 4.2). This suggests that concentration of the eluate affects the low mass range signal possibly as a result of poor sample crystallisation and/or ion suppression which maybe due to ‘competitive’ binding of peptide and protein species.



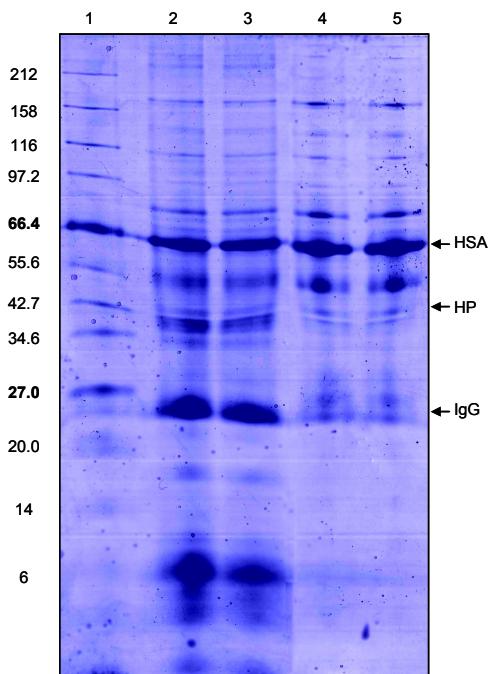
**Figure 4.5 MALDI-TOF spectral comparisons of extraction using different serum-to-bead ratios.** A-D show Low Mass Range (700-4000 Da) peptide profiling while E-H show High Mass Range (4-15 kDa). Results for Dynal C18 beads and representatives spectra of all bead slurry volumes tested are shown here. Data were processed using ClinProTools software (V2.0).

The reproducibility of each bead type was also investigated (Table 4.2). The overall coefficient of variance (CV) for all detected peaks in the LMR ranged varied from 19.4% to 45.4% and 9.9% to 15.8% in the HMR. These CVs were subsequently improved through modifications of the robotic volume aspirations and dispersion speeds which minimised bead loss during the washing steps. Apart from a few outliers reproducibility across the beads and dilutions was found to be similar. On comparison of the quality of spectra, Dynal C18 beads were found to be marginally better overall at capturing serum polypeptides. Dynal C18 beads also proved to be the most cost effective option.

Bead type	Slurry Vol. $\mu$ L	Ave number of LMR peaks	Ave LMR peak area (arb. u.)	CV (%)	Ave number of HMR peaks	Ave LMR peak area (arb. u.)	CV (%)
Dynal C4+ C18	6.25	142	21.30	30.59	111	75.02	12.95
	12.50	118	28.76	20.43	66	98.60	12.50
	25.00	132	24.49	20.14	99	92.31	11.73
	50.00	124	27.17	20.27	104	56.71	12.06
Dynal C18	6.25	124	25.73	23.37	92	85.99	11.52
	12.50	124	26.81	20.53	102	58.55	11.56
	25.00	142	20.15	22.29	101	61.06	10.65
	50.00	140	22.19	19.67	109	73.47	10.53
BioClone C4 + C18	6.25	134	25.37	20.06	95	82.11	9.87
	12.50	111	30.92	19.37	106	70.71	11.63
	25.00	131	17.78	20.98	63	103.39	12.54
	50.00	129	26.13	20.21	103	79.93	11.50
BioClone C18	6.25	134	24.19	23.46	106	78.85	12.01
	12.50	146	13.83	27.45	103	77.19	14.21
	25.00	146	19.88	25.59	103	76.56	11.56
	50.00	141	23.51	21.58	111	48.14	12.48
BioClone C8	6.25	147	22.32	30.15	111	75.95	15.80
	12.50	143	23.80	22.06	111	73.86	13.83
	25.00	150	20.95	20.57	117	58.05	10.37
	50.00	131	25.39	23.76	99	82.53	12.20
Bruker C8	6.25	139	23.26	20.30	110	73.51	11.10
	12.50	135	23.95	29.19	109	75.08	14.73
	25.00	133	23.58	33.55	120	49.90	12.66
	50.00	140	21.45	45.40	111	71.18	14.19

**Table 4.2 Intra-assay reproducibility for each bead type and condition.** Spectra were analysed using ClinProTools software (V2.0). Resulting average peak areas were used to calculate co-efficients of variance. The overall average peak number, average peak area (arb. u.) and CV in the LMR ( $S/N > 3$ ) and HMR ( $S/N > 5$ ) are shown.

Dynal C18 beads are reported to have a binding capacity of 14  $\mu\text{g}$  peptide per mg of beads. The concentration of protein, determined by Bradford assay in Sigma serum was 90 mg/mL and was therefore 3000 fold in excess of the bead binding capacity. It can be speculated that perhaps more non-specific binding occurs with an increase in the volume of the bead slurry. Furthermore, the presence of high abundant protein species may lead to suppression from signal of low abundant polypeptides. Indeed Figure 4.6 shows several high-abundant serum proteins can bind to C18 magnetic beads. Using larger bead volumes may also lead to poorer elution of bound peptides, as the large bead volume makes the removal of the entire elution fraction more difficult. Perhaps repeat elutions could overcome this problem.



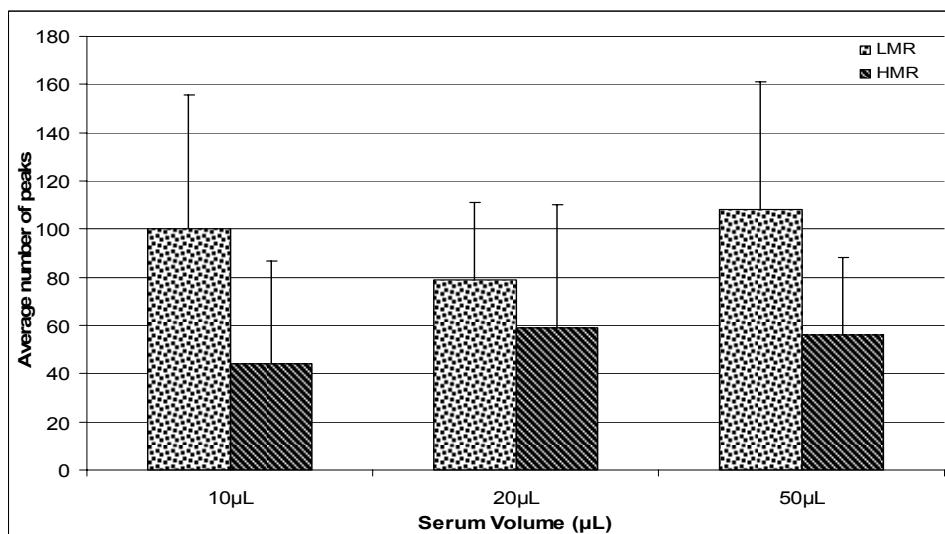
**Figure 4.6 1D-gel view of C18 magnetic bead-extracted serum proteins.** Lane 1 shows molecular weight markers, lane 2 and 3 10 $\mu\text{g}$  of Dynal C18 bead-extracted serum eluate and lanes 4 and 5 show 10 $\mu\text{g}$  of unfractionated serum. It is evident that C18 beads capture larger proteins such as human serum albumin (HSA), haptoglobin (HP) and immunoglobulin G (IgG).

Subsequent to this work, experiments showed that diluting eluates 1:5 with 50% ACN increased the signal and peptide peak numbers. This provided evidence for ion suppression with the dilution reducing the concentration of sample applied to the MALDI target, allowing for more effective detection of sample peptides by mass spectrometry. Furthermore, the MALDI-TOF analysis of eluates showed higher signal-to-noise ratios for peptide species detected from Dynal C18 beads. This increased ion signal may have been partially a result of stronger hydrophobic interactions and better compatibility with elution solvents.

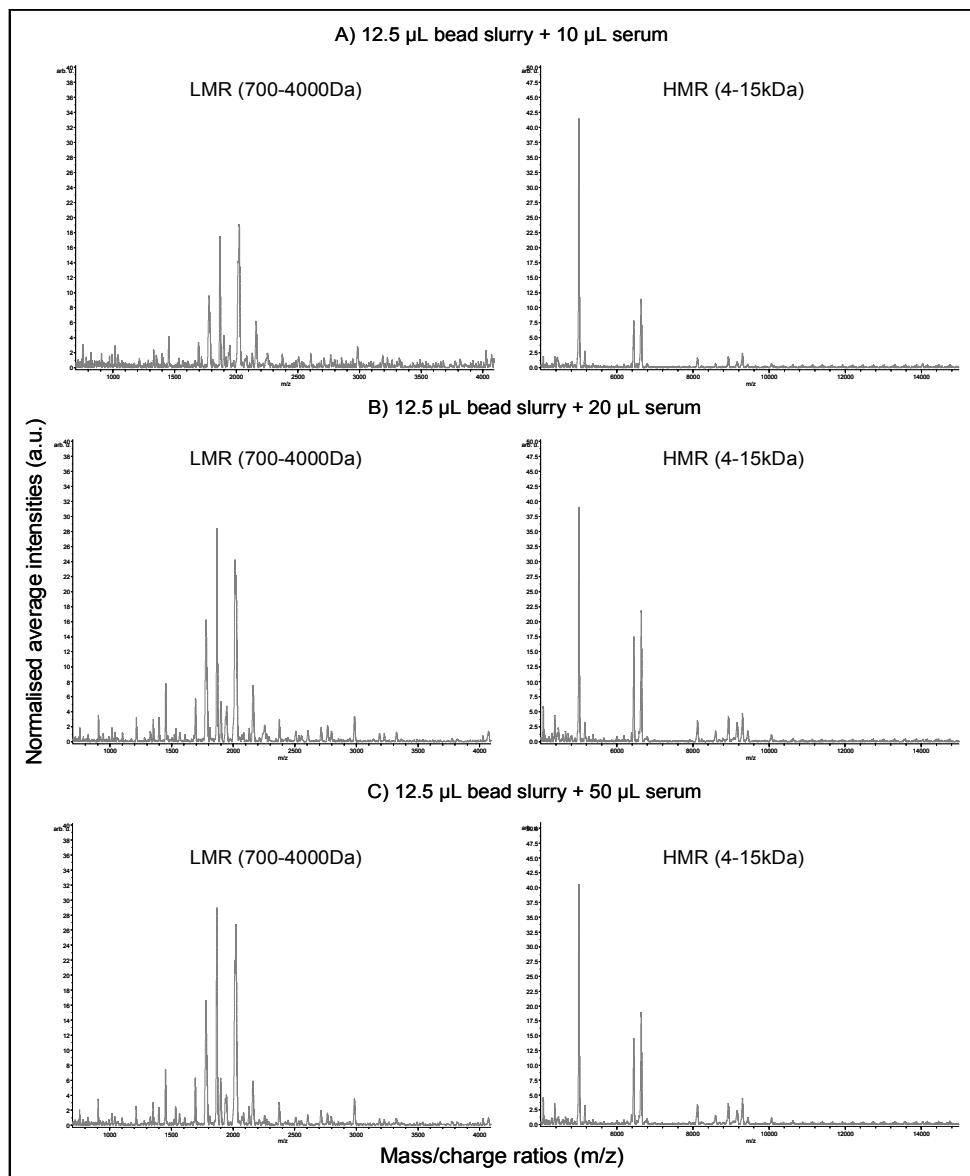
These initial experiments demonstrated that effective peptide capture could be achieved using all bead types, however, because of the quality of spectra and cost per assay, Dynal C18 were selected for further use. Although not optimal, for economical reasons 12.5  $\mu$ L bead slurry volume was selected as being most reproducible during automated pipetting on the liquid handling robot.

### 4.3.2 Further investigation on the effects of altering serum volume

In further experiments to define the optimal serum-to-bead volume ratio, 12.5  $\mu$ L of 50% Dynal C18 bead slurry (2  $\mu$ g/ $\mu$ L) was manually mixed and incubated with 10, 20 and 50  $\mu$ L of commercial serum for 2 minutes (incubation time recommended in manufacturer's instructions). The supernatants were removed and the beads were washed twice. After washing the bound polypeptides were eluted with 5  $\mu$ L 50% ACN and mixed with matrix solution. The eluate/matrix mixture was applied directly to a MALDI target and left to air dry before MALDI-TOF MS analysis using the optimised acquisition parameters described in section 4.1. Results showed that similar numbers of peptides could be captured across the serum volume range, although overall the 50  $\mu$ L volume gave the highest total number of peptides (Figures 4.7 & 4.8).



**Figure 4.7 Optimisation of serum volume.** Serum peptides were extracted as described in the text above. Data was analysed using ClinProTools software (V2.0) to calculate the number of peaks detected in the LMR ( $S/N >3$ ) and HMR ( $S/N >5$ ).



**Figure 4.8 MALDI-TOF spectral comparisons following extraction of peptides and proteins with varying serum volume.** Serum samples were manually processed using 12.5  $\mu\text{L}$  of 50 % Dynal C18 bead slurry (2  $\mu\text{g}/\mu\text{L}$ ) using (A) 10  $\mu\text{L}$ , (B) 20  $\mu\text{L}$  and (C) 50  $\mu\text{L}$  of commercial serum. Five  $\mu\text{L}$  elution solution (50% ACN) was added to each bead pellet, incubated, and the eluate transferred to a fresh tube. Eluate was mixed 1:1 with  $\alpha$ -CCA matrix solution, 1  $\mu\text{L}$  was spotted onto a MALDI plate and allowed to air dry before MALDI-TOF MS analysis. Data was analysed in ClinProTools software (V2.0) and the average spectra are shown here on the same scale.

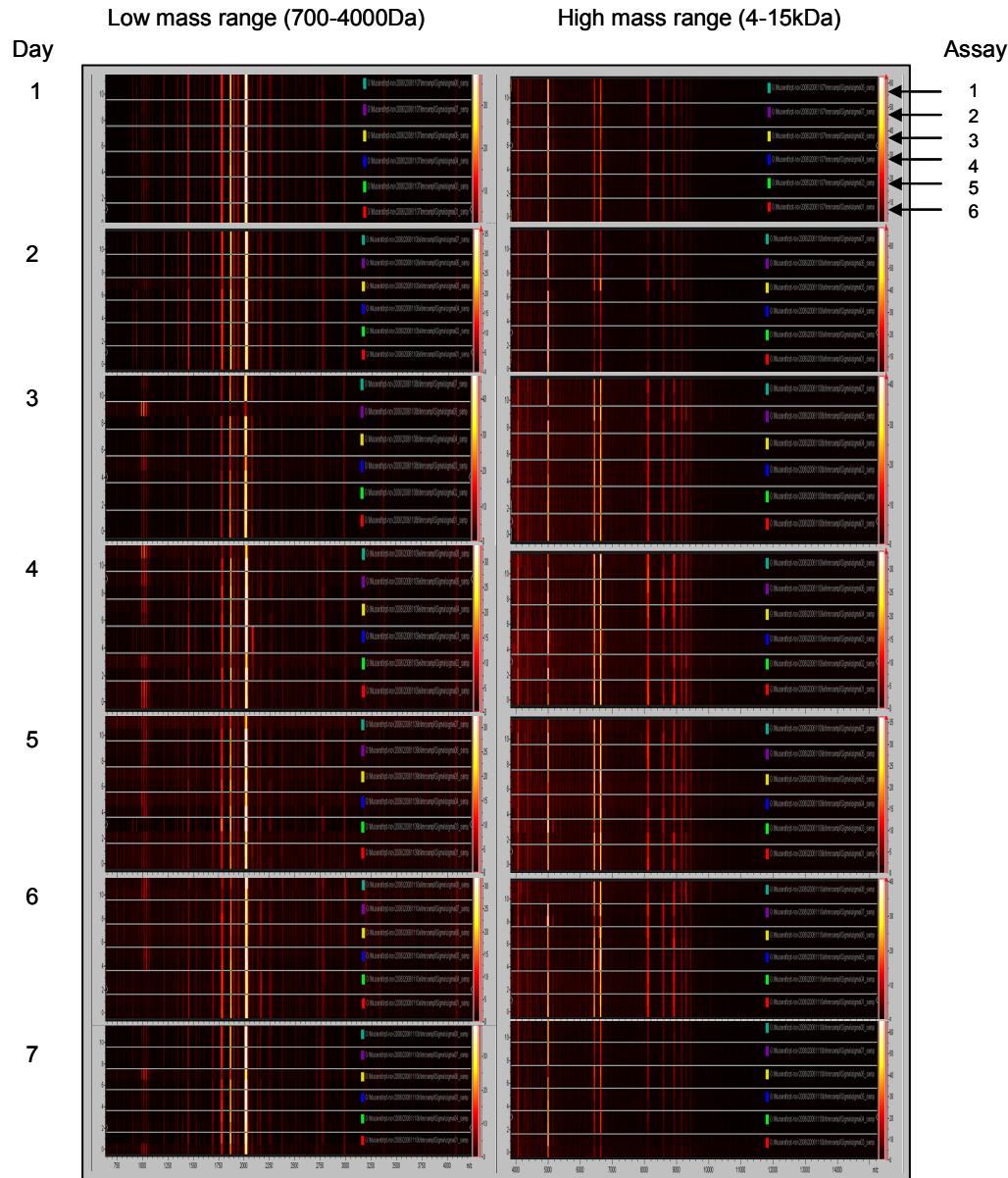
To assess the reproducibility, the average CVs for the peak areas from all matched peaks across 8 spectra within each condition were compared (Table 4.3). A serum volume of 50  $\mu$ L gave an average peak area CV of  $11.1\% \pm 1.5$  for the LMR and  $10.8\% \pm 0.9$  for the HMR. Results suggest that changing serum volume made little difference to the number of peaks detected and the peak CVs.

<b>Intra sample peak variability</b>		
	Ave peak CV (%)	
Serum Volume	LMR	HMR
10 $\mu$ L	11.03 (+/- 1.5)	9.54 (+/- 1.8)
20 $\mu$ L	10.14 (+/- 1.0)	11.24 (+/- 2.4)
50 $\mu$ L	11.1 (+/- 1.5)	10.82 (+/- 0.9)

**Table 4.3 Intra-sample average peak area variability.** Varying volumes of sigma serum samples were processed manually in quadruplicate and spotted in duplicate on a MALDI target before MALDI-TOF MS analysis. Data was analysed in ClinProTools software to calculate the average CVs for all peaks.

#### 4.4 Intra- and inter-assay reproducibility

A major criticism of early MS-based serum profiling was the lack of experimental reproducibility of datasets within and between studies [Baggerly et al., 2004]. Many studies only report reproducibility based on a few of the most intense peaks. Following the platform optimisation studies discussed so far, C18 Dynabeads were selected to undergo a more thorough investigation of the robustness of the automated technology platform. Inter- and intra-assay reproducibility was evaluated using 50  $\mu$ L commercial serum with 12.5  $\mu$ L of C18 Dynabeads (2  $\mu$ g/ $\mu$ L). Six aliquots of standard serum were processed in the same automated run, and the CVs were calculated for all the peak areas between the samples as a measure of the intra-assay reproducibility. The preparation and analysis was then repeated once a day over 7 days to yield inter-assay reproducibility values (Figure 4.9).



**Figure 4.9 Heat map representations of spectra from intra- and inter-assay reproducibility test.** Over the course of 7 days, six aliquots of commercial serum were processed each day on the automated platform. Data was analysed by ClinProTools software (V2.0) to calculate intra-and inter assay reproducibility based on peak area.

The intra-assay reproducibility for all the peaks detected varied significantly across the runs. In the LMR an average number of 69 peaks with an average CV of all peak areas of  $10.3\% \pm 1.6$  were found in Run 1 compared to an average of 133 peaks with an average CV of  $20.9\% \pm 17.3$  in Run 4. In the HMR an average of 34 peaks with an average CV of  $14.3\% \pm 3$  was found in Run 1 compared to an average of 105 peaks with average CV of  $11.4\% \pm 1.6$  in Run 7. Taking the average peak statistics for all 7 runs the overall inter-assay CV values were  $28.4\% \pm 5.4$  and  $17.68\% \pm 3$  for the LMR and HMR respectively (Table 4.4). The CV values are comparable to those previously reported in literature and in chapter 3.

Run Number	Ave number of peaks		Overall Ave CV	
	LMR	HMR	LMR	HMR
1	69	34	$10.3 \pm 1.6$	$14.3 \pm 3$
2	75	89	$12.8 \pm 12.4$	$14.4 \pm 5.4$
3	93	79	$20.9 \pm 17.3$	$12.6 \pm 3.6$
4	133	74	$24.1 \pm 15$	$14.5 \pm 3.4$
5	73	59	$24.4 \pm 11.7$	$15.4 \pm 5.4$
6	79	42	$12.5 \pm 7.5$	$14.6 \pm 3.3$
7	87	105	$16.1 \pm 9.0$	$11.4 \pm 1.6$
Inter-assay	118	123	$28.4 \pm 5.4$	$17.7 \pm 3$

**Table 4.4 Intra/inter-assay reproducibility.** The intra-assay reproducibility was calculated by running 6 samples per run, while inter-assay reproducibility was measured by assessing the variation between 7 runs. Average peak areas for the matched peaks were calculated using ClinProTools software and average co-efficient of variance (SD/peak area) were calculated for the areas of all peaks detected.

#### **4.5 Quantifying variations in serum polypeptide profiles under different sample handling conditions.**

Several factors termed pre-analytical variables have been reported to influence the observed serum proteome by affecting the stability of proteins [Rai et al., 2005]. These include the potential variations introduced during the actual blood collection and handling procedure. For example, variation in sample storage tube type, variable blood clotting times, transport conditions, time to centrifugation, storage conditions and freeze-thaw cycles may all affect the resulting profiles. Evidence also suggests disease specific exo-proteases are active during the clotting process which produce changes in protein degradation that are detectable by mass spectrometry [Villanueva et al., 2006]. Prolonged clotting times and repeated freeze thaw cycles could accelerate these complex break-down processes. As a result, peptides and proteins shed from tumours, typically low in abundance, could be lost in the background variance produced by inconsistencies in sample handling [Timms et al., 2007; Villanueva et al., 2005; West-Nielsen et al., 2005].

The effect of six different processing protocols on MALDI-TOF MS profiles was thus assessed using serum samples from 25 healthy volunteers from the UKCTOCS study. These women gave six blood samples that were processed as indicated in Table 4.5. Changes in the protocol were made to test the effects of storage tube type, varied clotting time, transport conditions, time to centrifugation, storage conditions and freeze thaw cycles. These protocols were chosen to be clinically feasible for the collection and processing of multiple samples, possibly from different centres, and included the standard UKCTOCS protocol (Protocol 1, Green) and that used by the Tempst group at the MSKCC (Protocol 2, Yellow).

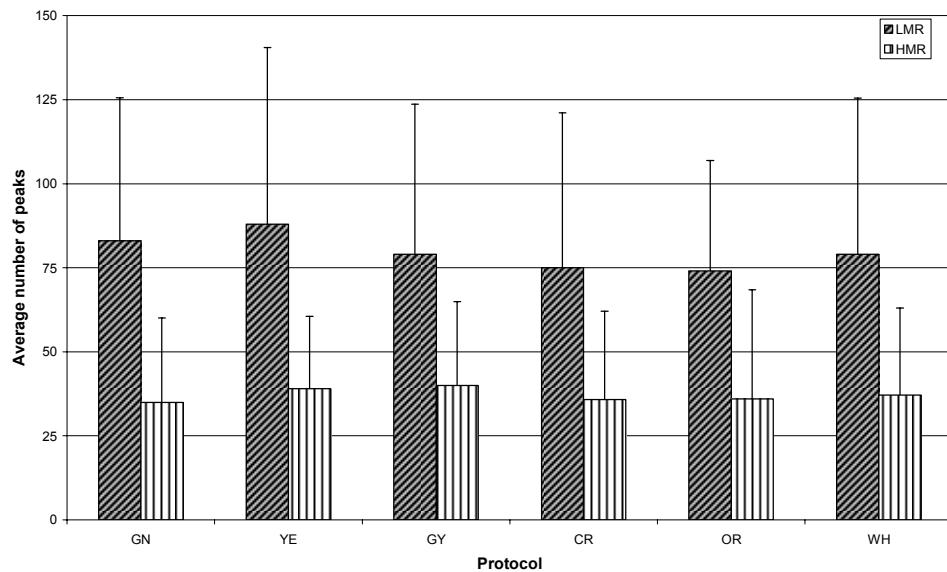
Protocol No.	Colour code	Tube type	Mixing	Clotting	Storage	Time to centrifugation	Aliquoting & Storage at -80°C
1	GN	Greiner gel tubes	Slowly inverted 5x	RT	RT	30 hrs from collection	Straws at RT
2	YE	BD tiger top tubes	Slowly inverted 5x	RT-60'-vertical position	Wet ice- vertical	3 hrs from collection	Straws at RT
3	GY	BD tiger top tubes	Slowly inverted 5x	RT-5'-vertical position	Wet ice- vertical	3 hrs from collection	Straws at RT
4	CR	BD tiger top tubes	Slowly inverted 5x	RT-5'-vertical position	Wet ice- vertical	3 hrs from collection	Cryovials one freeze thaw
5	OR	BD tiger top tubes	Slowly inverted 5x	RT-5'-vertical position	Wet ice- vertical	6 hrs from collection	Straws at RT
6	WH	BD tiger top tubes	Slowly inverted 5x	RT-5'-vertical position	RT	3 hrs from collection	Straws at RT

**Table 4.5 Protocol comparison using 25 healthy volunteer samples.** The shaded boxes indicated where changes were introduced in each protocol.

For variance analysis each volunteer sample was run in triplicate using 50 µL of serum, and 12.5 µL of Dynal C18 beads. The average number of peaks from each triplicate was first compared across the different handling methods using ClinProTools software V2.0, (optimised parameters for peak detection are outlined in Chapter 2 section 2.2.4.2). Briefly, spectra were first subjected to a 0.80 level baseline subtraction. Following this the detection of peaks was based on the analysis of a smoothed first derivative where the smoothing was determined by a given resolution parameter. Once the peaks were detected peaks were aligned and peak areas were calculated by integrating the intensities over the region of the peak. It was found that the number of peaks for each triplicate was protocol dependent (Table 4.6 and Figure 4.10). Protocol 2 (YE) gave the highest average number of peaks in the low mass range, (LMR 700-4000 Da), closely followed by the protocol 1 (GN), while protocol 3 (GY) gave the highest number of peaks in the high mass range (HMR 4-15 kDa).

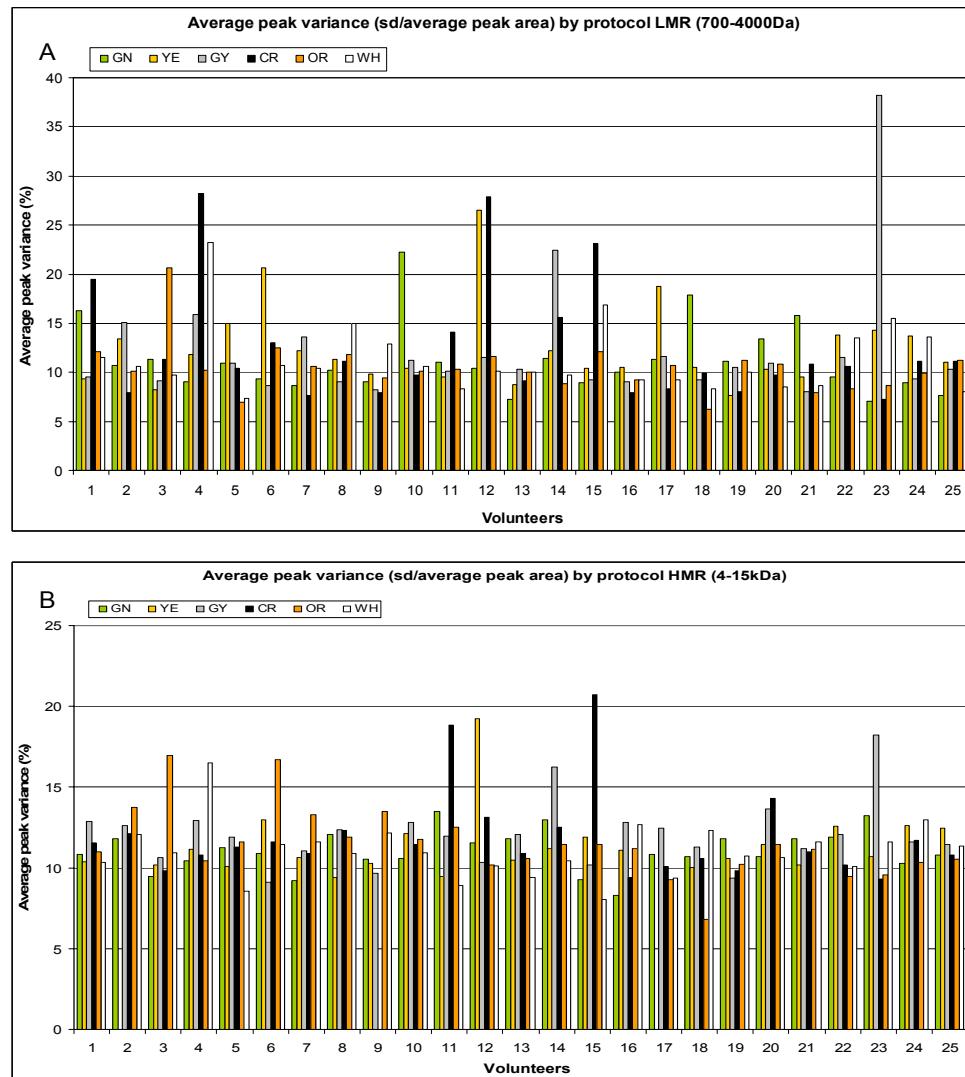
Volunteer Ref	GN-LMR	GN-HMR	YE-LMR	YE-HMR	GY-LMR	GY-HMR	CR-LMR	CR-HMR	OR-LMR	OR-HMR	WH-LMR	WH-HMR
11005404	95	34	41	27	39	44	26	38	71	28	71	30
11006217	146	58	97	NA	96	26	118	35	97	42	61	34
11006440	65	30	40	38	36	40	102	26	74	76	68	41
11006863	70	30	169	33	63	36	59	30	62	55	90	32
11010114	98	28	167	35	88	57	92	54	41	31	57	46
11023647	134	44	61	49	33	19	88	49	31	26	73	56
11026386	64	45	82	30	62	36	23	40	92	30	80	32
11034276	142	35	80	30	47	44	131	38	121	40	38	31
11056019	50	29	50	33	104	27	41	NA	98	29	127	35
11068507	40	21	166	34	107	43	23	26	76	19	71	31
11074916	136	21	83	43	48	27	69	33	56	34	36	39
11084213	101	23	120	33	152	55	69	39	59	21	167	53
11093385	42	31	79	53	122	47	55	28	108	39	54	33
11099224	101	34	42	39	59	50	114	31	64	45	73	36
11099568	56	38	119	44	72	33	113	69	59	37	82	39
11101746	36	33	73	40	83	39	41	25	58	39	36	32
11101936	126	33	33	NA	47	47	60	37	76	36	66	33
11102206	54	37	105	42	76	44	83	37	34	24	53	26
11102296	109	46	164	29	40	37	41	28	96	33	116	35
11102557	66	29	67	37	79	27	42	35	106	26	71	61
11118143	84	47	52	58	68	31	112	33	63	33	52	38
11122713	36	42	148	32	154	39	71	38	47	35	72	39
11122791	95	36	53	44	107	55	62	42	93	41	168	48
11126095	96	28	14	53	61	44	118	35	73	45	135	34
11126328	42	35	101	43	134	45	130	37	106	36	52	16
Overall Average	83	35	88	39	79	40	75	37	74	36	79	37
SD	35	9	46	8	35	10	35	10	24	12	37	10

**Table 4.6 Average number of spectral peaks.** The overall average peak numbers and SD were calculated by aligning the spectra from all 25 volunteers in ClinProTools. Average peak numbers by collection method and volunteer are shown.



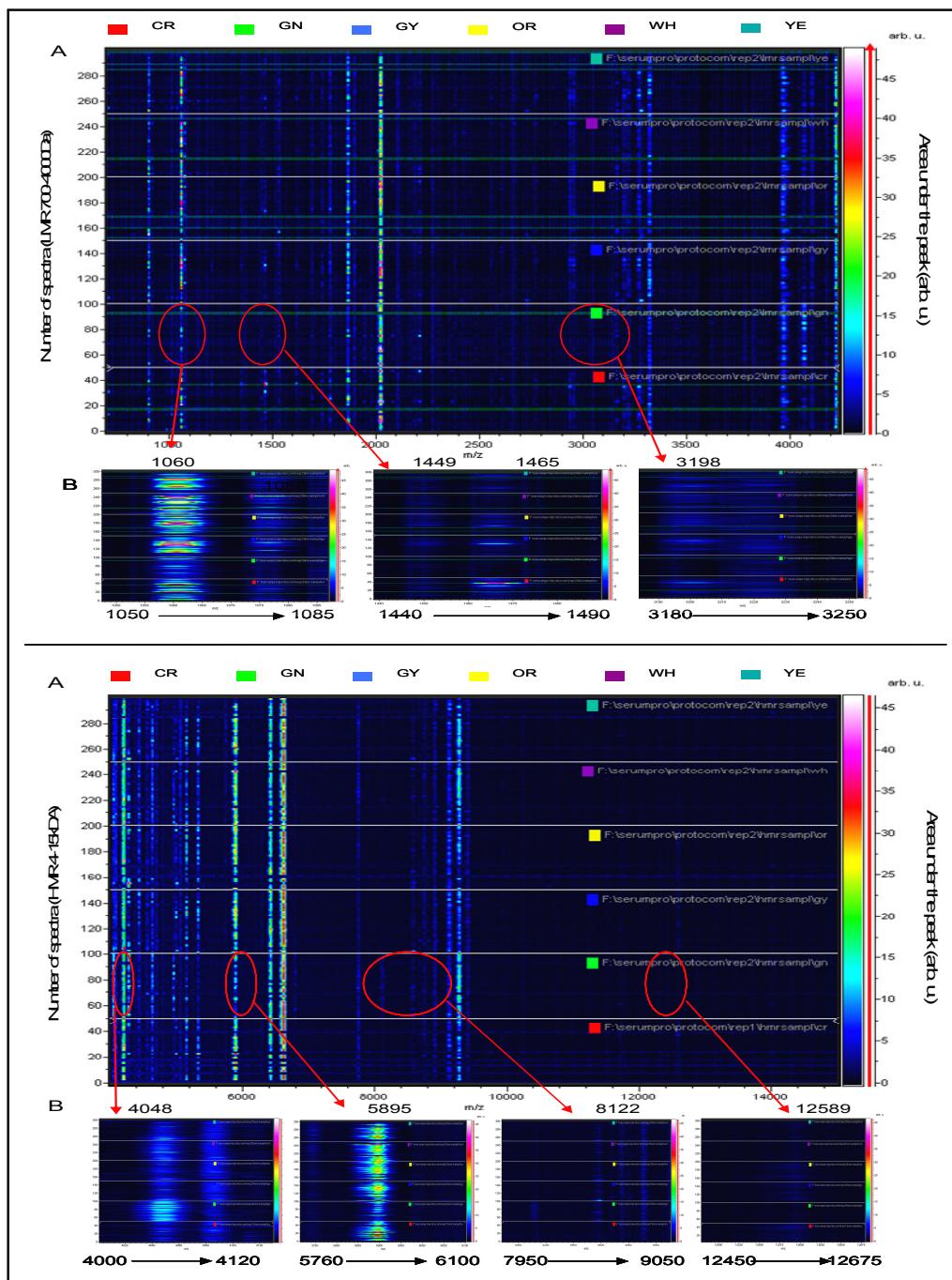
**Figure 4.10 Overall average numbers of peaks across all protocols.** The average numbers of peaks from triplicate samples of 25 volunteers are shown for each protocol in each mass range; LMR (700-4000 Da) and HMR (4-15 kDa). Protocol 2 (YE) showed the highest number of peaks in the LMR, while protocol 3 (GY) gave a slightly higher number of peaks in the HMR.

Despite the high variance in the peak numbers, certain peaks were common to one or more of the protocols. The average variance of all the peaks detected was compared across the protocols. Overall average variance was  $\sim 12\%$  in the LMR and  $\sim 11\%$  in the HMR. No one protocol produced higher variance in all volunteers in either mass range (Figure 4.11).



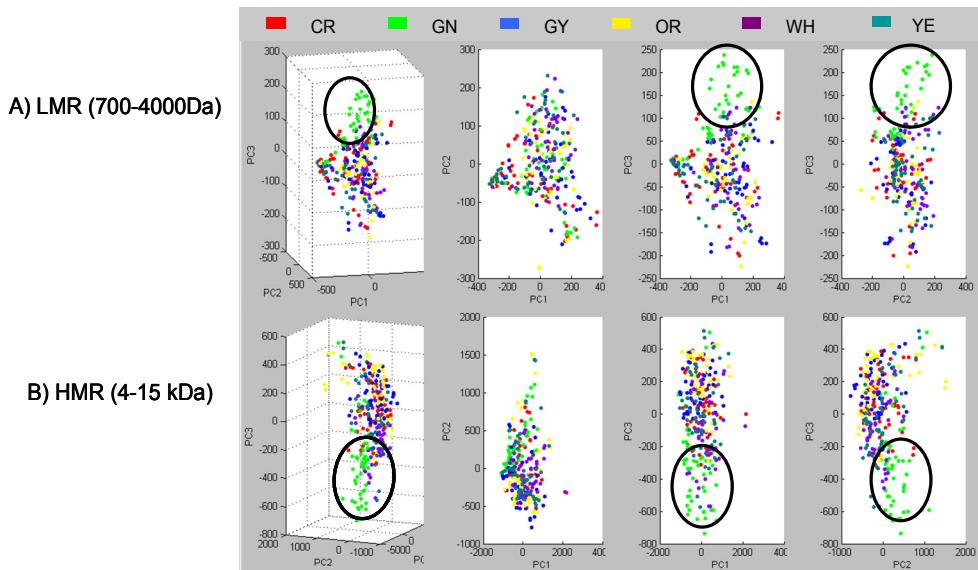
**Figure 4.11 Average peak area variance analyses.** (A) Low mass range (700-4000Da), overall average CV (standard deviation/average peak area) of all peaks from 3 replicates of the same sample by protocol and volunteer, where GN is protocol 1, YE ; 2, GY ; 3, CR ; 4 OR ; 5 & WH ; 6. (B) High mass range (4-15 kDa), average CV of all peaks by protocol and volunteer.

Heat maps were generated in ClinProTools software for peak profile analysis. The average peak areas from each individual, for each protocol were compared. This was done to assess which of the peaks could be directly attributed to differential sample preparation. Discriminatory peaks in several m/z regions from both mass ranges were found to discern protocol 1 (GN) from the other 5 protocols. In the LMR three peaks (1060, 1465 and 3198 m/z) were found to have lower peak areas in protocol 1 compared to the other 5 protocols (Figure 4.12). In the HMR two peaks (5895 and 12589 m/z) consistently had lower peak areas in protocol 1 and two peaks (4048 and 8122 m/z) had higher peak areas (Figure 4.12).



**Figure 4.12 Spectral comparisons across the protocols.** Top panel (A) 300 low mass range (LMR) spectra from experimental replica 2 (25 volunteers had 2 spotting replicates for each of the 6 protocols) and (B) Several LMR m/z areas where clear differences between protocol 1 (GN) and the other 5 protocols are shown. Bottom panel (A) 300 high mass range (HMR) spectra (B) Several HMR m/z areas where clear difference between protocol 1 (GN) and the other 5 protocols are shown.

A principal component analysis (PCA) was performed to determine how samples would group together according to the preparation method. Protocol 1 (GN) was the most distinctive method, with most volunteer samples grouping together and away from samples handled using the other methods (Figure 4.13). This was true for both mass ranges. The most likely explanation for this separation trend is the extended transport/storage time used in this protocol.

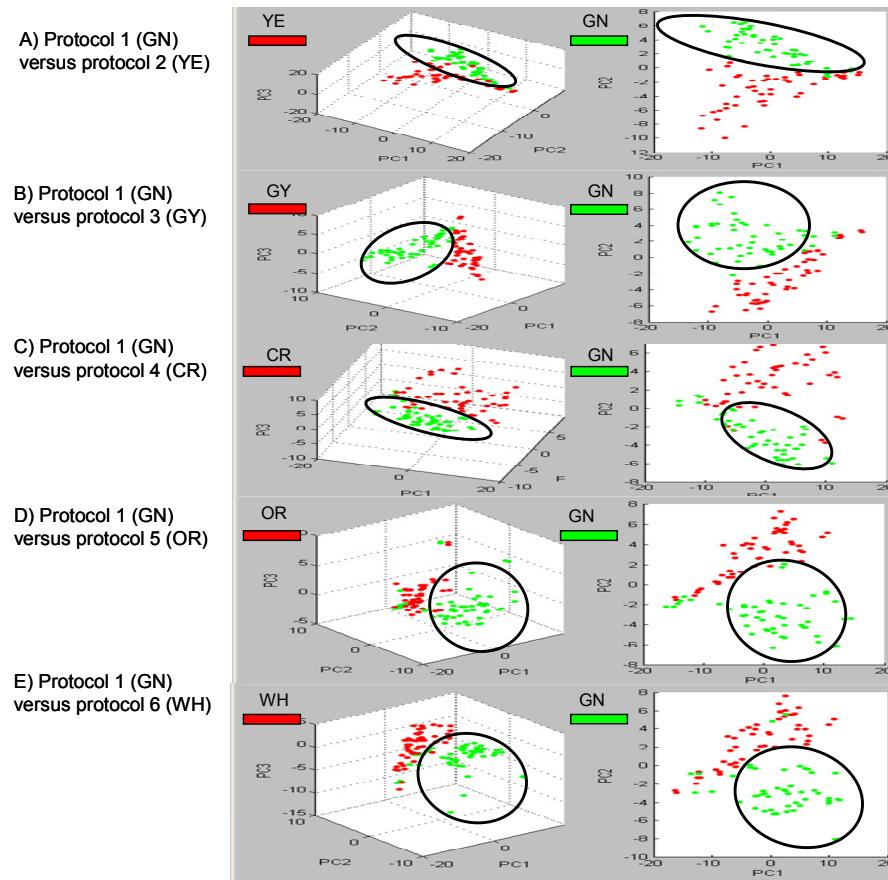


C) Mass ( $m/z$ ) values of each PCA

LMR (700-4000Da)	Mass ( $m/z$ )
PCA 1	3198.48
PCA 2	3822.70
PCA 3	2939.11
HMR (4-15kDa)	Mass ( $m/z$ )
PCA 1	4048.77
PCA 2	8121.65
PCA 3	5895.98

**Figure 4.13 Protocol comparisons by principal component analysis.** A PCA was performed using ClinProTools software (V2.2) to compare samples handled using the different protocols. In the example shown, peaks from replicate number 2 for all samples were used for analysis. The circles denote the clustering of most protocol 1 (GN) samples in (A) the low mass range samples and (B) high mass range and (C) the  $m/z$  values of the mass used for clustering. Please note that the colours in this figure differ from those used for protocol labelling.

A pairwise comparison of protocols by PCA more clearly showed this distinction between protocol 1 (GN), and the others (Figure 4.14).



**Figure 4.14 Pair-wise protocol comparisons by principal component analysis.** A PCA was performed using ClinProTools software (V2.2) to compare samples handled using pairs of protocols. A, B, C and D are the clustering results between pairs of protocols. Protocol 1 (GN) is the most discriminatory protocol.

Overall, 180 peaks (80 on average per protocol) were detected in the LMR (Table 4.6). The peak which discriminated most between the protocols (3198.5 m/z) had an average peak area 3 times lower in protocol 1 (GN) compared to the other protocols. The ANOVA p-value was highly significant ( $p = 6.45E-32$ ). The second most discriminatory peak (3822.7 m/z) showed a 1.5 times greater peak area in comparison to the other protocols ( $p = 3.85E-25$ , Table 4.7).

In the HMR, 91 peaks (35 on average per protocol) were detected in total (Table 4.6). The most discriminatory peak (4048.76 m/z) had an average peak area 2.5 times greater in protocol 1 (GN) compared to the other protocols. The ANOVA p-value was highly significant ( $p = 2.17E-24$ ). This peak was also elevated in protocol 6 (WH). The second most discriminatory peak in the HMR (8122.05 m/z) showed a 2 times greater peak area in comparison to the other protocols ( $p = 3.85E-25$ , Table 4.7).

A) LMR Peak number	Mass <i>m/z</i>	Diff in Ave peak area	ANOVA TEST	CR Ave peak area	GN Ave peak area	GY Ave peak area	OR Ave peak area	WH Ave peak area	YE Ave peak area	CR CV	GN CV	GY CV	OR CV	WH CV	YE CV
1	3198.54	31.2	6.45E-32	40.76	15.43	42.55	46.63	38.9	42.4	70	34	58	29	40	58
2	3822.66	14.89	3.85E-25	22.54	35.49	21.41	22.21	20.61	21.34	31	16	32	27	28	27
3	2939.13	23.81	1.46E-23	37.4	18.83	36.66	42.64	35.97	35.52	61	24	52	34	43	52
4	3033.47	3.26	8.64E-23	5.43	8.45	5.32	5.24	5.19	5.29	31	17	28	24	25	27
5	2580.49	4.51	1.09E-22	10.1	13.75	9.26	9.57	9.24	9.82	28	13	24	24	22	29
6	1793.73	2.54	4.11E-20	3.58	5.55	3.29	3.21	3.01	3.37	28	21	33	31	35	24
7	2956.98	21.57	4.93E-20	32.66	18.55	40.12	36.47	40.07	36.86	46	30	67	46	40	53
8	3274.89	40.84	6.68E-20	78.61	43.12	82.98	83.97	76.49	83.62	55	30	57	29	42	61
9	2770.88	10.93	1.32E-19	22.69	12.97	21.6	23.9	22.26	21.2	43	19	43	41	38	59
10	1030.62	2.79	5.06E-16	3.99	5.79	3.01	3	3.2	3.31	44	30	24	23	41	28
11	1954.19	3.71	1.54E-15	8.87	11.57	7.86	8.26	7.92	9.18	28	15	38	31	33	30
12	1741.47	11.53	1.56E-15	22.7	11.17	21.91	22.38	15.74	18.1	59	28	58	48	37	45
13	1172.34	2.65	1.80E-15	5.08	6.3	4.3	3.64	3.79	4.34	42	24	38	26	38	38
14	1704.79	2.38	1.83E-15	2.86	5.12	2.92	2.9	2.74	3	30	27	35	35	39	30
15	4071.12	114.41	2.94E-15	55.46	157.69	46.71	43.28	78.76	52.81	55	50	39	54	51	46
16	1281.44	1.71	6.71E-15	3.26	4.05	2.47	2.33	2.76	3.15	42	23	43	30	54	61
17	1060.7	89.04	1.35E-14	85.06	49.5	119.13	109.34	138.54	105.1	76	42	73	64	69	65
18	4050.61	6.02	1.48E-14	9.27	14.66	8.64	9.21	9.57	10.09	35	22	39	48	27	45
19	2492	2.78	1.74E-14	5.39	7.36	4.58	4.96	5.04	5.41	29	20	38	28	24	33
20	1076.28	11.47	1.75E-14	11.49	6.37	14.63	14.11	17.84	12.01	68	31	74	60	87	65

B) HMR Peak number	Mass <i>m/z</i>	Diff in Ave peak area	ANOVA TEST	CR Ave peak area	GN Ave peak area	GY Ave peak area	OR Ave peak area	WH Ave peak area	YE Ave peak area	CR CV	GN CV	GY CV	OR CV	WH CV	YE CV
1	4048.76	180.87	2.17E-24	102.76	283.63	108.73	108.94	155.04	117.97	35	30	41	39	38	46
2	8122.05	68.13	1.38E-22	62.5	115.16	47.03	49.95	49.52	54.1	41	30	19	36	29	33
3	5330.18	129.09	6.20E-20	237.3	115.89	212.27	244.98	204.48	181.69	55	24	51	45	45	50
4	12589.6	50.56	1.25E-19	97.77	47.21	75.69	83.1	49.13	57.03	49	25	30	37	22	52
5	5895.89	593.99	6.76E-19	717.23	338.36	797.95	864.4	932.34	713.6	67	59	56	49	45	60
6	9276.3	382.25	5.76E-18	375.96	738.72	362.54	356.46	622.91	522.86	53	33	35	57	38	47
7	7754.93	49.91	8.29E-16	139.01	148.02	98.1	98.94	138.67	122	23	27	23	29	36	26
8	5061.09	57.12	2.81E-15	105.79	84.19	103.73	117.9	136.79	141.31	41	29	36	46	35	25
9	4957.46	88.21	5.08E-14	67.93	146.62	58.4	65.24	125.01	65.23	26	56	27	29	51	42
10	5744.65	36.31	1.59E-11	78.32	72.22	65.67	70.3	84.27	101.98	28	19	27	31	26	25
11	6790.14	32.38	8.79E-11	65.12	88.2	56.02	55.83	61.53	59.66	25	29	21	25	24	20
12	4086.28	34.9	4.14E-10	99.35	75.7	110.6	106.89	105.5	98.55	29	29	26	25	22	25
13	4999	61.4	6.81E-10	65.38	38.56	94.78	99.96	52.38	56.86	64	33	91	82	76	64
14	4637.14	80.8	4.85E-09	152.04	225.11	151.04	144.31	197.93	176.56	41	32	36	46	24	44
15	5244.9	15.31	6.71E-08	52.48	54.16	38.85	41.59	43.25	47.73	45	20	31	50	33	41
16	7221.34	9.87	6.71E-08	44.87	43.82	35	38.12	36.28	42.71	36	18	19	34	23	29
17	5586.37	11.73	4.79E-07	42.31	38.61	30.58	33.46	35.91	39.48	45	18	23	32	25	31
18	7913.92	13.87	7.34E-07	50.15	44.17	36.27	39.39	38.89	44.16	45	16	18	41	23	38
19	12431.06	16.17	1.14E-06	47.18	42.19	33.39	36.81	31.01	35.25	55	21	26	43	39	49
20	7003.11	9.5	2.64E-06	51.54	51.33	42.04	43.74	44.14	48.06	34	16	19	30	23	26

**Table 4.7 Comparisons of average peak areas by protocol.** Peak areas from A) LMR and B) HMR were compared by loading all protocols against each other in ClinProTools software (V2.0). Peaks were sorted by ANOVA test p-values. The most discriminatory peak is listed first (only the top 20 are shown here). To avoid exceeding the software's memory capacity only samples from experimental replicate 2 were used.

A Wilcoxon test was also used to find the most discriminatory peaks between pairs of protocols and an overlap between the m/z values of the most discriminating peaks between protocol 1 (GN) and protocol 2 (YE), protocol 3 (GY) and protocol 4 (CY) (3034 m/z p=0.000001) was found (Table 4.8). Furthermore, a peak at 4071 m/z was also found to discriminate protocols 6 (WH) from 2 (YE p=0.023), 3 (GY p=0.000701), 4 (CR p=0.000701) and 5 (OR p=0.000252). These peaks had a higher average peak area in the samples from protocol 1 (GN) suggesting they are likely to be protein degradation products which become more abundant with prolonged clotting times at room temperature.

Moreover, several peaks in the LMR had lower peak areas in protocol 1 (GN) compared with the other 5 protocols. For example, in table 4.7 peak number 1 3198.58 m/z had an average peak area almost 3 times lower in GN compared with the other protocols. Peaks 2939.13 m/z and 2956.98 m/z also had average peak areas 2 times lower in the GN protocol versus the others. This supports the hypothesis that prolonged clotting times could also lead to protein degradation and loss of signal, and highlights the importance of consistent sample handling.

Protocol	GN	YE	GY	CR	OR	WH
GN		m/z 3034.12 p=0.000001	m/z 3034.23 p=0.000001	m/z 3034.26 p=0.000001	m/z 2273.59 p=0.00713	m/z 3823.1 p=0.000001
YE	m/z 3034.12 p=0.000001		m/z 2023.78 p=0.00785	m/z 3435.71 p=0.0122	m/z 2273.59 p=0.00713	m/z 4071.06 p=0.023
GY	m/z 3034.23 p=0.000001		m/z 2023.78 p=0.00785		m/z 1030.61 p=0.0397	m/z 3322.77 p=0.0069
CR	m/z 3034.26 p=0.000001		m/z 3435.71 p=0.0122	m/z 1030.61 p=0.0397		m/z 1015.6 p=0.00989
OR	m/z 3197.33 p=0.000001		m/z 2273.59 p=0.00713	m/z 3322.77 p=0.0069	m/z 1015.6 p=0.00989	
WH	m/z 3823.1 p=0.000001		m/z 4071.06 p=0.023	m/z 4071.04 p=0.000701	m/z 4071.04 p=0.000701	m/z 4070.99 p=0.000252

**Table 4.8 Protocol comparisons based on Wilcoxon test p-values for the most discriminating peaks.** The Wilcoxon test p-values were calculated for pairs of protocols using average peak area values.

#### 4.6 Discussion

Ideally, for comprehensive serum proteome analysis, universal pre-analytical processing and data handling standards are essential for the discovery of novel protein biomarkers. Furthermore, appropriate biomarker-based tests should be minimally invasive and reproducible. In cancer a simple blood or urine test that detects molecules specific to tumour tissues would be ideal. In addition, the screening technology must be sufficiently sensitive to detect early cancers, but specific enough to classify individuals without cancer as being free of malignancies. The potential use of mass spectrometry (MS) based methods for analysing proteins and peptides from biological fluids for potential biomarker discovery was demonstrated in 2002 [Pearl, 2002; Petricoin et al., 2002]. However, these initial studies were severally criticized on the experimental design and method-induced variability [Baggerly et al., 2004]. Subsequent to this, improvements in many areas of blood-based proteomics studies have been made. As a result, a pool of knowledge about the effect of different variables on MS-based proteome analyses has been generated. Pre-analytical variation from sample handling and storage leading to artefacts and the influences of humidity, temperature, and time for preparation of sera on spectral changes has been evaluated by several groups [Timms et al., 2007; Villanueva et al., 2005; West-Norager et al., 2007].

The aim of the work presented in this chapter was to establish an optimal workflow for the high-throughput analysis of low abundant serum polypeptides. This high-throughput screening platform coupling magnetic bead-based serum polypeptide extraction with mass spectrometry and bioinformatics tools for data analysis would facilitate the discovery of putative ovarian cancer serum markers. This aim was tackled by adapting and modifying a previously established bead-based semi-automated serum peptide extraction protocol and optimising it in the host laboratory at UCL.

Firstly, the automated liquid handling robot was programmed for optimal performance. Various other factors were investigated including the specific beads to be used for peptide extraction, bead-to-serum volume ratio, and intra/inter-assay

reproducibility. Finally different sample collection protocols were examined to aid in determining the most reproducible and clinically feasible method for sample handling.

In order to adapt the automated platform established by Villanueva et al. at the MSKCC the initial experiments involved the use of a cocktail of commercially available peptides and proteins in combination with manually extracted commercial serum to establish optimised spectral acquisition methods in the low mass range (LMR 700–4000 Da) and high mass range (HMR 4–15 kDa). Results from the optimised MS method showed an average of 143 and 109 serum peaks were detected in the LMR and HMR respectively with an overall average CVs were 18.7% and 19.4%.

As previously mentioned, the magnetic beads used in the original study by Villanueva et al. (2004) were no longer commercially available, thus, a comparison of different coated magnetic beads from alternative vendors was performed. Results showed that although spectral profiles of commercially available serum did not differ greatly when peptides and proteins were extracted with different beads, Dynal C18 beads did on average capture more peptide and protein peaks in both mass ranges and were cheaper. Moreover, the efficiency of C18 Dynal beads has been reported and they have been recommended for use by the MSKCC group [Villanueva, 2006].

Investigations into the bead-to-serum volume ratio using Dynal C18 beads demonstrated that a lower volume of bead slurry was optimal for the capture and analysis of serum peptides and low mass proteins. However, to avoid bead loss during the automated peptide extraction process, the next higher bead slurry volume (12.5  $\mu$ L prepared at 2  $\mu$ g/ $\mu$ L) was selected for use in subsequent experiments. It can be hypothesised that high bead slurry volumes lead to the non-specific capture of larger molecular weight serum peptides and proteins leading to crystallisation and ionisation competition during the MALDI process. As a result of the inconsistencies in the initial MALDI process (i.e. discrepancies in ionisation of peptides and proteins caused by temporal and spatial variations), not all ions receive the same charge and thus, do not reach the linear detector at the same time. Therefore, not all peptides and

proteins are detectable to the same degree. Moreover, the resolution of ions is also limited in the linear mode as charged states cannot be determined. This may also explain the high CVs found during reproducibility analysis of each bead type.

Intra-and inter-assay reproducibility experiments were preformed using Dynal C18 beads and commercial serum. They showed that the automated technology platform was robust and reproducible. Average inter-assay CV values for all peaks were 28.4% and 17.7% for the LMR and HMR, respectively. This supports our view that the optimised protocol is applicable to serum screening for putative biomarker discovery. Inconsistencies in automated sample spotting and crystallisation are likely to be accountable for the inherent variability of the assay platform. Intra-assay variances of 14-23% have been reported by others using a similar profiling strategy [de Noo et al., 2005]. one report used 10 major peaks to report CV values of 18% from MALDI-TOF MS measurement, with variance of 14% from sample preparation and 26% variance in inter-day runs [Zhang et al., 2004]. Other studies reported accumulated CVs of 30% in a time/temperature study and 15-36% for normalised intensity of 3 serum peaks in an intra-and inter laboratory reproducibility tests, respectively [West-Norager et al., 2007; Semmes et al., 2005]. It is important to note these studies only report CV values for a few common and relatively higher abundance peaks, without reporting peaks that may show higher variability. Presenting the CVs for all peaks detected in each data set provides a better overview of the robustness of the technology platform.

There are several factors here that can affect the assay reproducibility, including liquid handling errors especially when using organic solvents. Evaporation and crystallisation can be affected by fluctuations in the ambient temperature and relative humidity of the area where the samples are processed and left to air dry before MS analysis. Indeed several groups have reported the influences of humidity on the reproducibility of serum profiles [de Noo et al., 2005; Villanueva et al., 2005; West-Norager et al., 2007]. It is therefore important to establish the assay reproducibility and identify the experimental factors which affect it before trying to distinguish between these and disease-specific peaks in the pursuit of putative biomarkers.

A protocol comparison study using different sample collection and handling methods compatible with the optimised workflow was used for selecting a method for a large scale case-control study which would be practical for both clinical collection and protein profiling. Variance analysis showed that protocol number 2 (YE) gave the lowest overall variance when all peaks were considered and the highest average number of peaks, and therefore this method was selected as the preferred serum collection/handling protocol for the UKOPS serum collection. This method, whilst clinically feasible, does however require rapid processing of samples on ice in the collection centres. Therefore, dedicated staff are required for collection and processing. This method is also recommended by Villanueva et al. (2006) for assessing the effects of tumour specific protease activities in serum during the clotting process. No consistent effects on variance were evident between the various protocols where samples were placed on ice (GY, YE, CR, OR). This suggests that as long as samples are kept on ice, with a transport time less than 6 hours, then there is little effect on serum proteins profiles. Also, it appears that an extra freeze thaw cycle or storage tube has little effect on variance (CR protocol).

Profiles from protocol number 1 (GN) were clearly different from the other protocols. In both mass ranges, several peaks were found to distinguish protocol 1 from the other protocols. PCA also found the greatest separation for protocol 1 over the other methods. Separation was representative for both mass ranges. Thus, although strict control on sample handling protocols has been proposed by many groups to reduce variability, the data shows that sample collection protocols can be more flexible. The critical issue is that all individual samples must be treated in exactly the same manner. This way protease activity can be better controlled and assessed for tumour-specific activity.

The results presented here also show that irrespective of transit/storage at ambient temperature for up to 30 hours, protocol 1 (GN) gave a relatively low overall variance. This finding is important for samples collected in older studies where longer transit times at ambient temperature have been used. Although again, one must ensure that case control samples for comparison have been handled identically. The finding that numerous peaks from both mass ranges had altered peak areas in protocol 1

compared to the other protocols may well be the result of proteolysis products appearing or substrates disappearing over time. Importantly this could make a difference if hypothesised tumour-specific exoprotease substrates have already been degraded [Villanueva et al., 2005]. For this reason, the more stringent protocol 2 (YE) was chosen for further biomarker discovery experiments.

Having adapted and optimised a semi-automated bead-based extraction and MALDI-TOF MS profiling platform and selected a clinically feasible protocol for sample collection and handling, case and healthy control serum samples from the UKOPS collection were analysed to look for potential markers of ovarian cancer and those which can discriminate malignant from benign samples. The results of this are presented in the next chapter.

## Chapter 5: MALDI-TOF MS profiling of UKOPS ovarian cancer, benign cases and healthy control samples.

### 5.1 Introduction

The protocols set out and optimised in chapter 4 demonstrated that the technology platform developed herein for serum profiling is sufficiently reproducible. A natural progression from this point was to apply this platform to well-characterised clinical sample sets. The UKOPS sample set used contains 60 healthy volunteers, 43 and 22 cases of benign and malignant ovarian cancer samples, respectively (Table 5.1).

Group	Number	OC stage	Ave CA125 (U/mL)
H	60		N/A
B	43		50.16
Me	6	I/II	232.06
ML	16	III/IV	1895.3

**Table 5.1 Details for the clinical samples from the UKOPS collection.** Sample details of each cohort including the number of volunteers, ovarian cancer stage (OC stage) and average CA-125 levels are shown.

The collection of these samples was rigorously controlled with adherence to standard operation procedures to limit introduced variation and to maintain, as much as possible, the biological integrity of every sample. Importantly, all samples were identically collected and treated following a previously optimised protocol for MALDI-TOF MS-based profiling [Villanueva et al., 2006]. Briefly, samples were collected in Becton Dickinson tiger-top tubes and allowed to clot at RT for 60 mins. Samples were then stored on wet ice for 2 hours before centrifugation and then were transferred to straws for storage at -80°C until they were analysed. The sample handling was controlled to facilitate identification of tumour-specific exopeptidase-generated peptides which could serve as putative markers for ovarian cancer. Thus, this collection represents a valuable resource ideally suited to high-throughput discovery of cancer biomarkers.

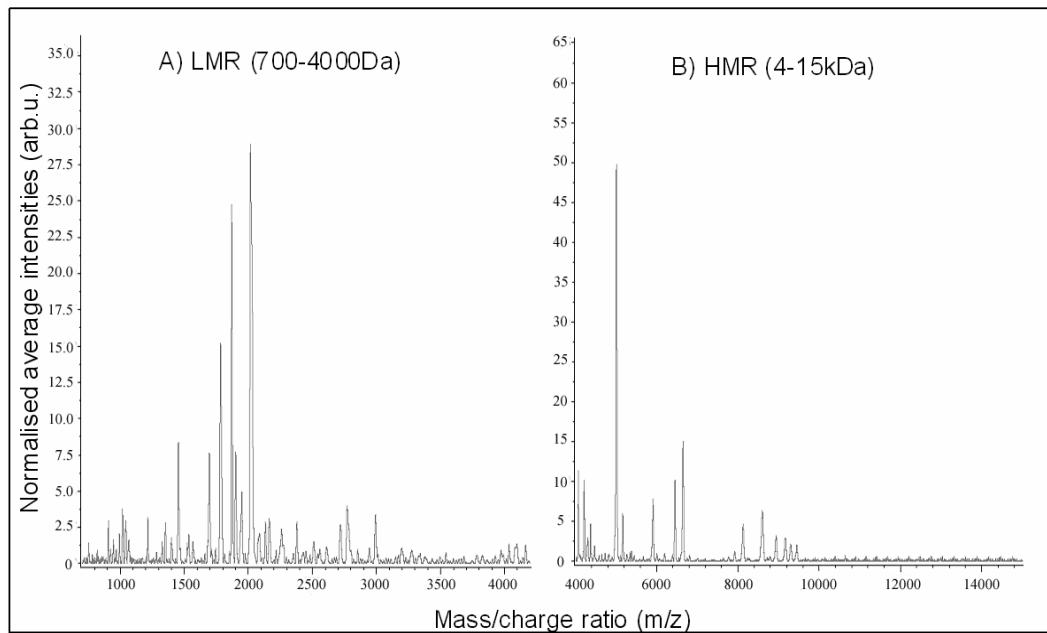
It is important to note that although standard procedures for sample collection and handling now exist, there are still no standards for donors. Biological variation caused by diet i.e. products of digestion from the intake of food before a sample is taken, and cyclic variations due to time of day could lead to variability in serum protein levels. The psychological stress suffered by donors especially those who have been diagnosed with cancer may also contribute to biological variation [Morita et al., 2005; Van et al., 1998]. For example, psychosocial factors have been shown to affect serum interleukin-6 levels among women with advanced ovarian cancer [Costanzo et al., 2005]. Interleukin-6 is the chief stimulator of the production of most acute-phase proteins [Gabay and Kushner, 1999]. Moreover, biological variation in specific cytokine levels could also affect the rate of clotting and hence the degree of protein degradation. Indeed, many of the peptides previously identified as 'surrogate' cancer markers using the techniques described in this thesis, are derived from acute-phase proteins which maybe involved in the complex coagulation and complement pathways [Villanueva et al., 2006].

Commercial serum was used as a quality control sample (QC) to establish baseline parameters for assessing the reproducibility of the technology platform and for optimising the Support Vector Machine (SVM) algorithm used to classify clinical samples. The aims of this chapter were to define experimental variation within the protocol using a previously analysed commercial serum sample (Sigma serum) and to establish a cut-off threshold for technical variance. In addition, to define potential biomarkers of ovarian cancer by analysis of healthy, benign and malignant ovarian cancer cases from the UKOPS collection, which is a tightly controlled case control serum sample collection. The sample processing and data analysis conditions, optimised as described in the previous chapter, were utilised to detect and statistically evaluate differentially expressed peaks generated using MALDI-TOF MS profiling and to determine if these peaks could be used for the discrimination of ovarian cancer samples and for stage classification.

## 5.2 Spectral analysis of QC samples

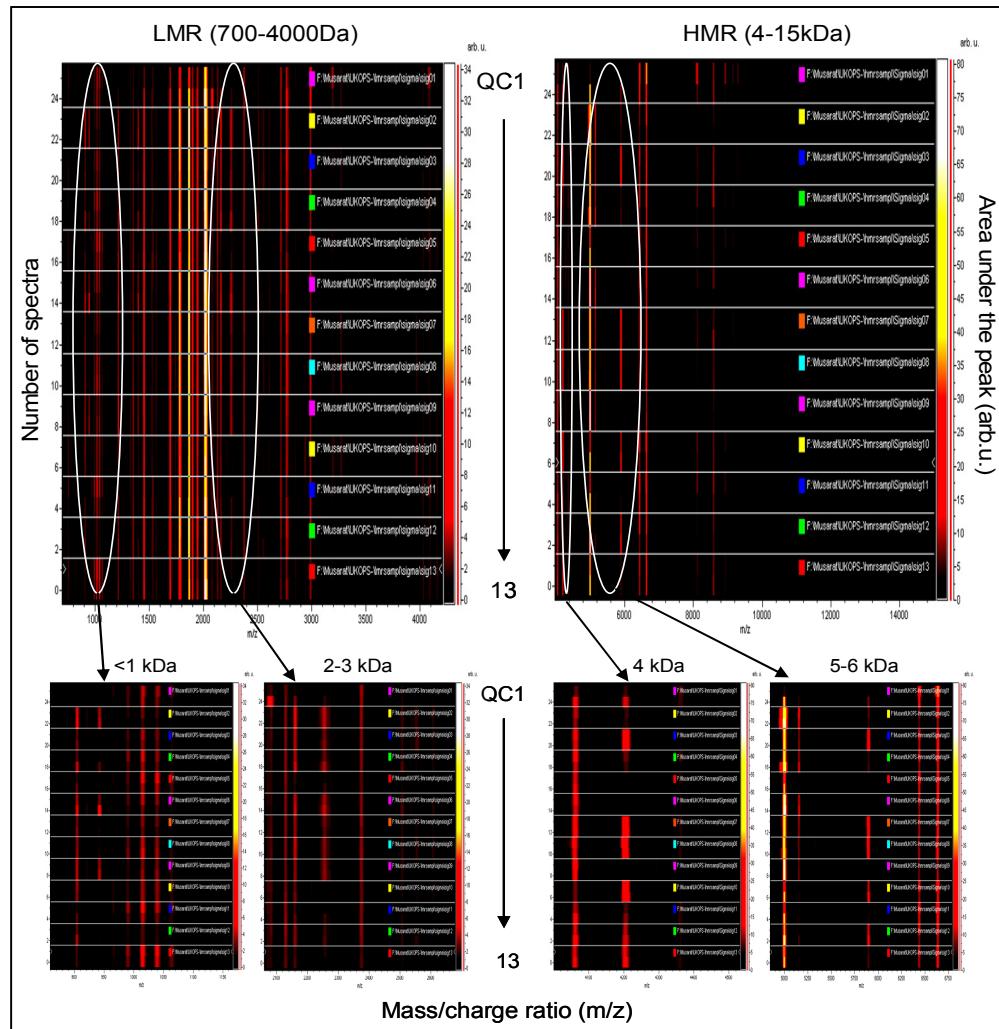
To assess the technical variability caused by automated polypeptide spotting, spot-to-spot inconsistencies in crystallisation and the inherent variability in the MALDI-TOF ionisation process, (discussed in the previous chapter), the intra-assay reproducibility was assessed using Sigma serum samples (QC). The QC samples (n=13) were randomly assigned positions in the assay plates and processed in parallel to the clinical samples.

Following the automated extraction on Dynal C18 magnetic beads, the 13 QC samples were spotted in duplicate onto a MALDI-target plate and a total of 26 MS spectra were acquired in each mass range. Data from all QC samples were analysed in ClinProTools software using the parameters defined in Chapter 2 (section 2.2.4.2) to generate a set of normalised peak areas for each spectrum. The spotted QC replicates were loaded into the analysis software in 13 pairs, the software then generated an average spectrum for each pair. The averaged spectra were aligned and average peak areas for matching peaks were calculated. Thus, for each averaged spectrum the same number of peak areas was obtained. This then allowed the calculation of an overall average spectrum. From this a total of 101 common peaks were detected in the LMR and 59 peaks were detected in the HMR (Figure 5.1).



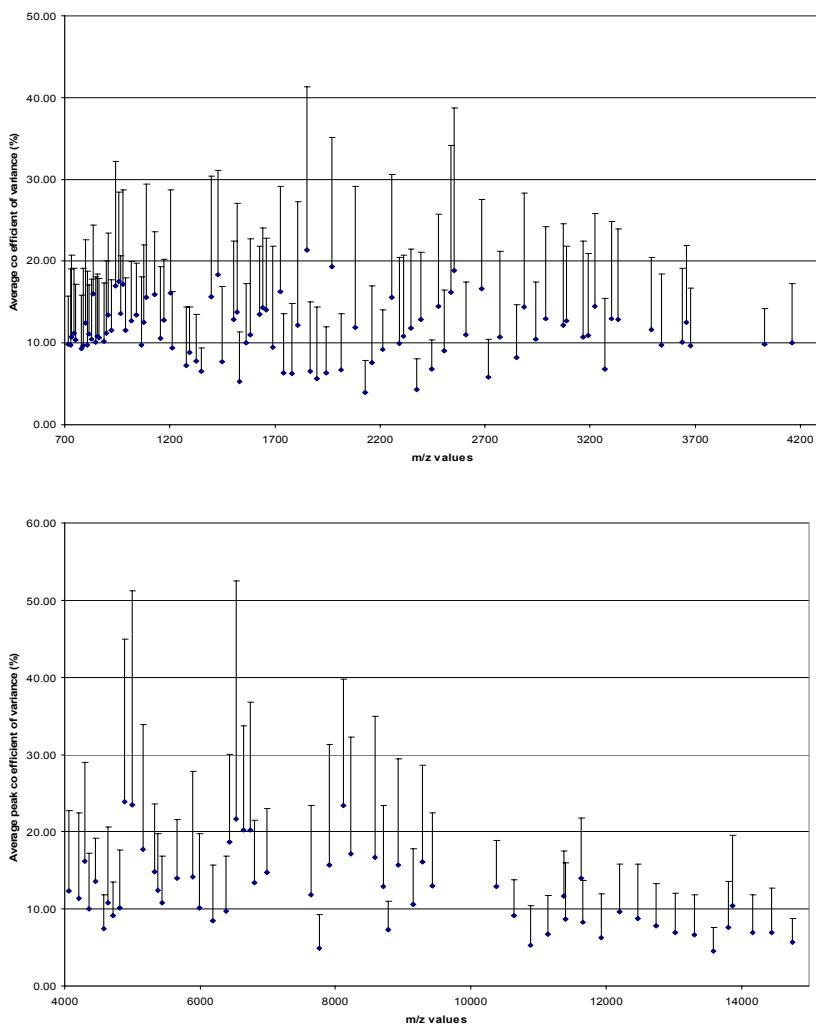
**Figure 5.1 MALDI-TOF profiles of QC serum.** The averaged spectral profiles from 13 Sigma serum samples and 26 individual spectra in the A) LMR and B) HMR are shown.

Heat maps were used to visualise peak profiles from each QC sample pair to quantify possible spot-to-spot variation. The spectral heat maps showed that several regions in the peak profiles did indeed indicate spot-to-spot variation for the same sample preparations, as well as across the 13 QC samples (Figure 5.2).



**Figure 5.2 Heat map representations of spectra from QC serum samples.** Each of the 13 QC samples processed was spotted in duplicate. Spot-to-spot variation is apparent in both mass ranges with several peaks showing discrepancies in peak area between spotting duplicates. The top panel shows the heat map peak profiles from the LMR and HMR and the bottom panel shows expanded sections of several areas where difference were obvious.

The intra-assay reproducibility was assessed by measuring the co-efficient of variance for averaged peak areas across the 13 QC samples (from spotting duplicates). The co-efficient of variance for all peaks ranged from 8.1% in QC sample 10 to 23.9% in QC sample 1 in the LMR and from 8.6% in QC sample 9 to 19.0% in QC sample 10 in the HMR (Figures 5.3). In the LMR, 85% of all peaks were found to have CVs below 15% and in the HMR 75% of all peaks fell below this level of variance. The average co-efficient of variance (CV) of all the peaks ranged from 3.7-21.4% and 4.5-23.9% in the LMR and HMR, respectively. Thus, any changes in peak area in the clinical samples would need to exceed a 1.24 fold change to be considered as true biological differences.



**Figure 5.3 LMR and HMR intra-assay reproducibility.** The CVs of the average peak area of all peaks from the 13 randomly assayed QC serum samples in the LMR (700-4000 Da top panel) and HMR (4-15kDa bottom panel). The error bars indicate the standard deviation of the average CV values.

The QC samples were distributed across two MALDI plates. The inter-plate variation was found to be the similar across the two plates. In the LMR, the overall average peak area of QC samples was  $30 \text{ (arb. u.)} \pm 2.42$  (CV=8.1%) and  $28 \text{ (arb. u.)} \pm 2.42$  (CV=8.6%) on plate 1 and plate 2, respectively. In the HMR, the overall average peak area of was  $122.28 \pm 18.9$  (CV 15.4%) and  $116.17 \pm 16.93$  (CV 14.57%) on plate 1 and plate 2, respectively. Together these results demonstrate that the platform reproducibility was close to 80% with 20% technical variance. As discussed in the previous chapter, several factors can affect the assay reproducibility including fluctuation in the ambient temperature and relative humidity of the area where the samples are processed and left to air dry which can result in changes in the evaporation rate of the organic solvents used. This in turn affects the co-crystallisation and hence the ionisation of peptides during MALDI. Subsequent studies in the host laboratory have shown that diluting the sample eluates 1:5 significantly improves the intra-assay variability. It is fair to say that highly variable peaks are likely to be poor biomarkers.

### 5.3 Spectral analysis of clinical samples

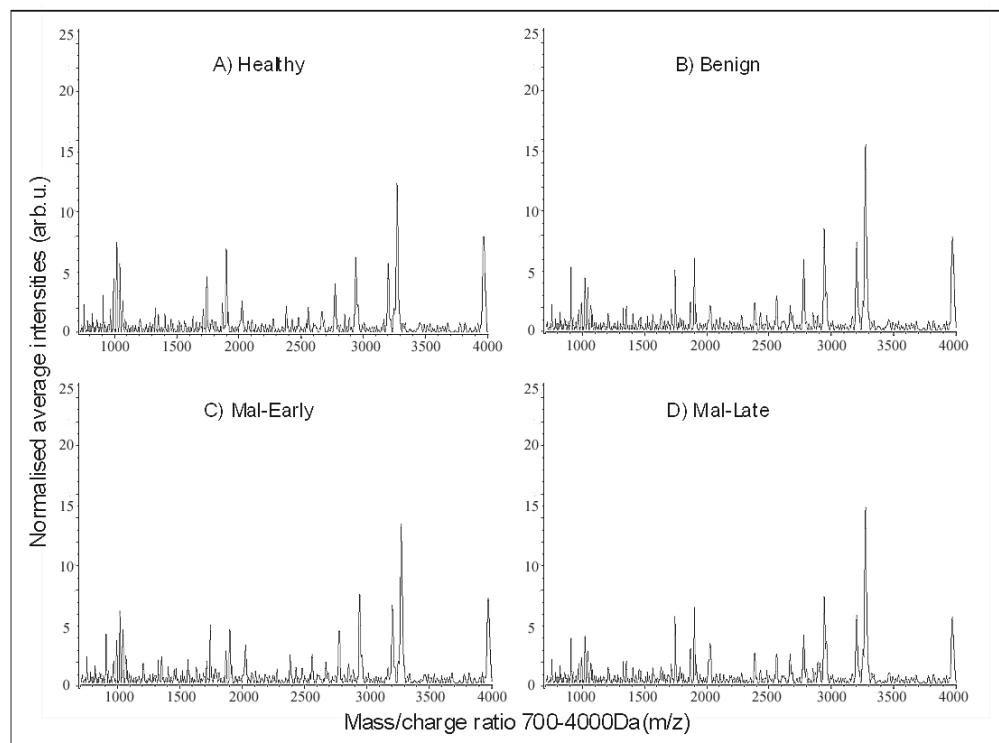
Clinical samples from healthy controls, benign and ovarian cancer cases from the UKOPS collection were processed on the automated bead-based polypeptide extraction protocol followed by MALDI-TOF MS analysis (detailed in Chapter 2). As with the QC samples, each clinical sample was spotted in duplicate on to one of the two MALDI targets and spectra (average of 400 laser shots over 8 locations around the spot) for each spot were acquired in each mass range.

#### 5.3.1 Intra-condition variation

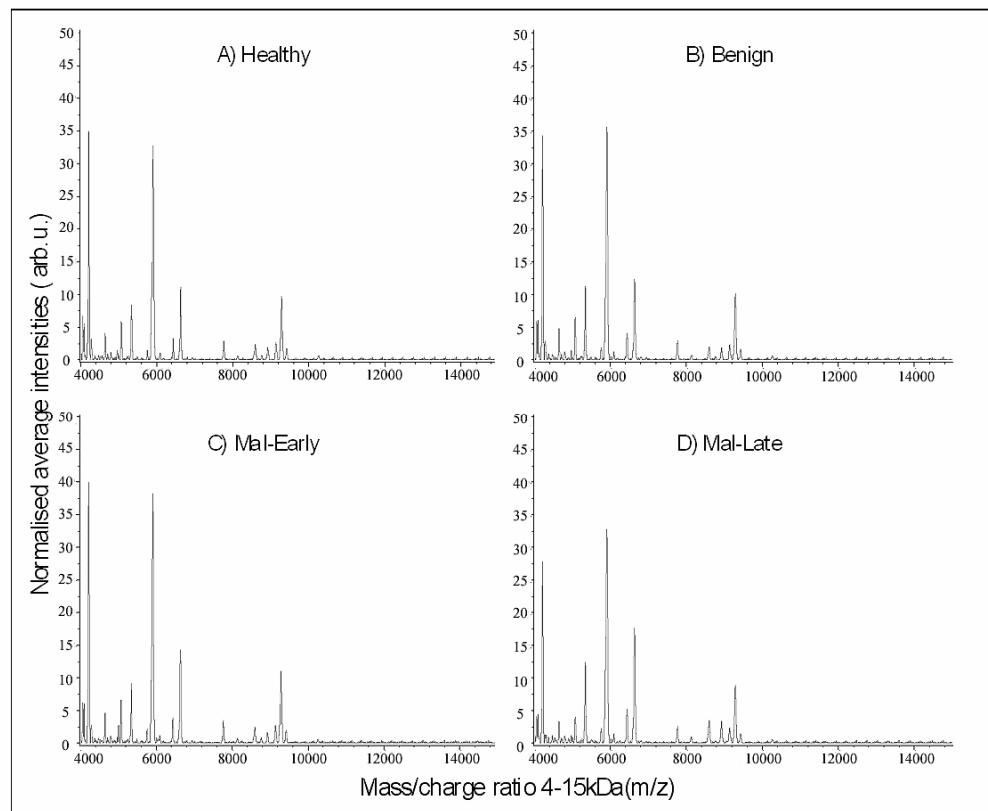
To assess the variation within each clinical group, spectra from the duplicate spots were analysed in ClinProTools. For both mass ranges each pair belonging to the same sample were loaded into the analysis software as a separate condition. These were then averaged and peak statistics were generated. In the LMR, a total of 174 peaks

were detected in the aligned and averaged healthy (H) spectrum ( $n = 60$ ), 166 in the benign (B) spectrum ( $n = 43$ ), 171 in the malignant early stage (Me) spectrum ( $n = 6$ ) and 183 in the malignant late stage (Ml) spectrum ( $n = 16$ ). In the HMR, a total of 99 peaks were detected in the averaged healthy spectrum, 108 in the benign, 98 in the malignant early stage and 73 in the malignant late stage (Figure 5.4A & B). The difference in peak numbers is likely to be the result of better peak recognition in one condition compared with another.

The co-efficient of variance for the average peak area across the samples in the healthy condition ranged from 7.5% to 29.7% in the LMR and 9.0% to 45.1% in the HMR. While in the benign condition, the variance in average peak area ranged from 7.6% to 40.4% and 9.0% to 29.5% in the LMR and HMR, respectively. In the malignant early stage condition, the variance in average peak area ranged from 8.2% to 30.1% and 11.8% to 28.8% in the LMR and HMR, respectively. Finally, in the malignant late stage condition, the variance in average peak area ranged from 8.2% to 18.4% and 9.5% to 20.2% in the LMR and HMR, respectively. The high CVs are likely to be reflective of intra-condition biological variation.



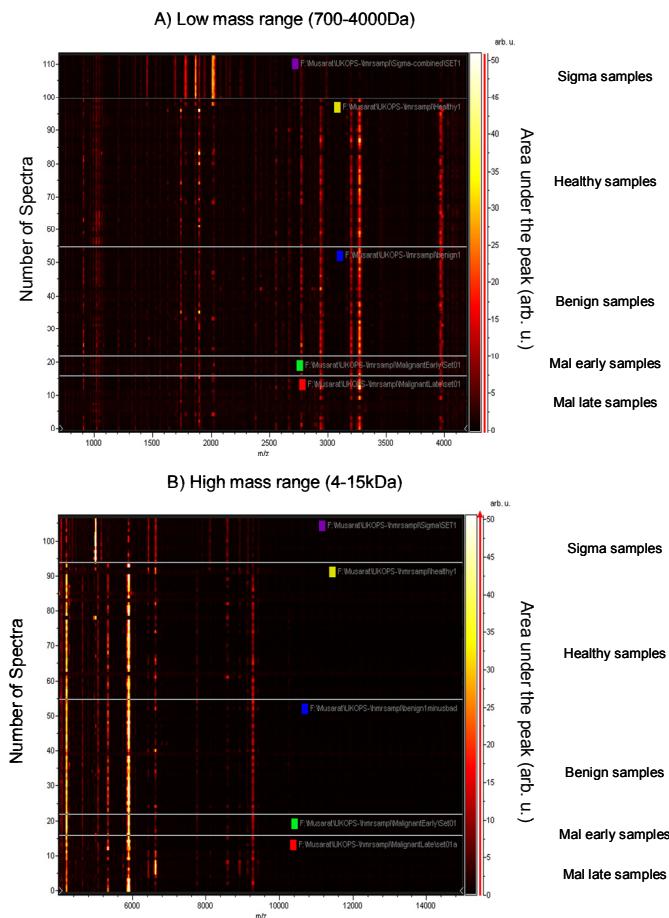
**Figure 5.4A Average LMR spectrum of the clinical samples from the UKOPS collection.**  
Serum peptides were extracted using the automated bead-based extraction protocol, subjected to MALDI-TOF MS profiling and data processed using ClinProTools. The average spectrum for each clinical condition is shown A) Healthy, B) Benign, C) Malignant early stage and D) Malignant late stage. A total of 174 peaks were detected in the average healthy spectra, 166 in the benign, 183 in the malignant early stage and 171 in the malignant late stage.



**Figure 5.4B Average HMR spectrum of the clinical samples from the UKOPS collection.**  
The average spectrum for each clinical condition is shown A) Healthy, B) Benign, C) Malignant early stage and D) Malignant late stage. A total of 99 peaks were detected in the average healthy spectra, 108 in the benign, 73 in the malignant early stage and 98 in the malignant late stage.

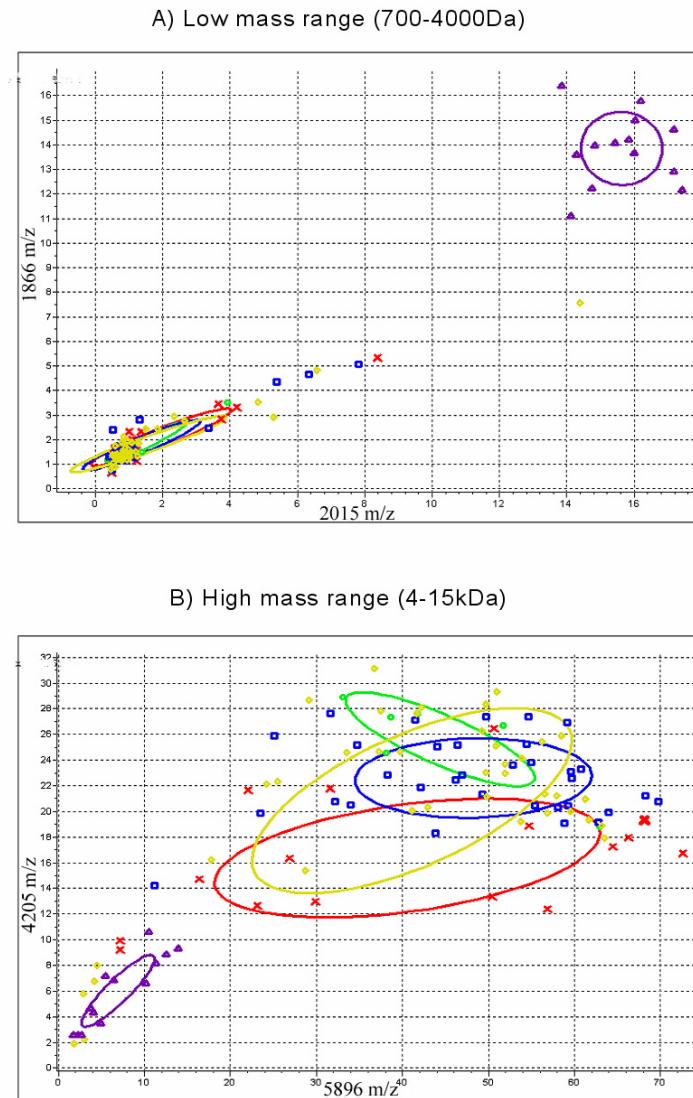
### 5.3.2 Comparison of QC and clinical samples

Heat maps were generated to compare spectral peak profiles from QC samples with UKOPS clinical samples. The peak profiles of QC samples were clearly different from UKOPS clinical samples in both mass ranges. For example, prominent peaks at 1779.7 m/z, 2021.8 m/z and 5060 m/z in the QC samples were less apparent in the clinical samples, whilst prominent peaks at 3250 m/z, 4205 m/z and 5950 m/z in the clinical samples were of much reduced intensity in the QC samples (Figure 5.5). The QC sample is a pool of 10 donors' serum and no other details of handling were available from the suppliers. Thus, the differences are likely to be caused by differences in sample handling leading to differential proteolysis rather than differences in the proteomes of the donors.



**Figure 5.5 Heat maps of peak profiles for all samples.** The peak profiles of QC samples were compared with UKOPS clinical samples using ClinProTools software in A) LMR and B) HMR.

Peak distribution analysis of the QC and clinical samples confirmed these differences. The ellipses represent the standard deviation of the average peak area. A cluster representing the QC samples grouped away from the clinical samples in both mass ranges (Figure 5.6).



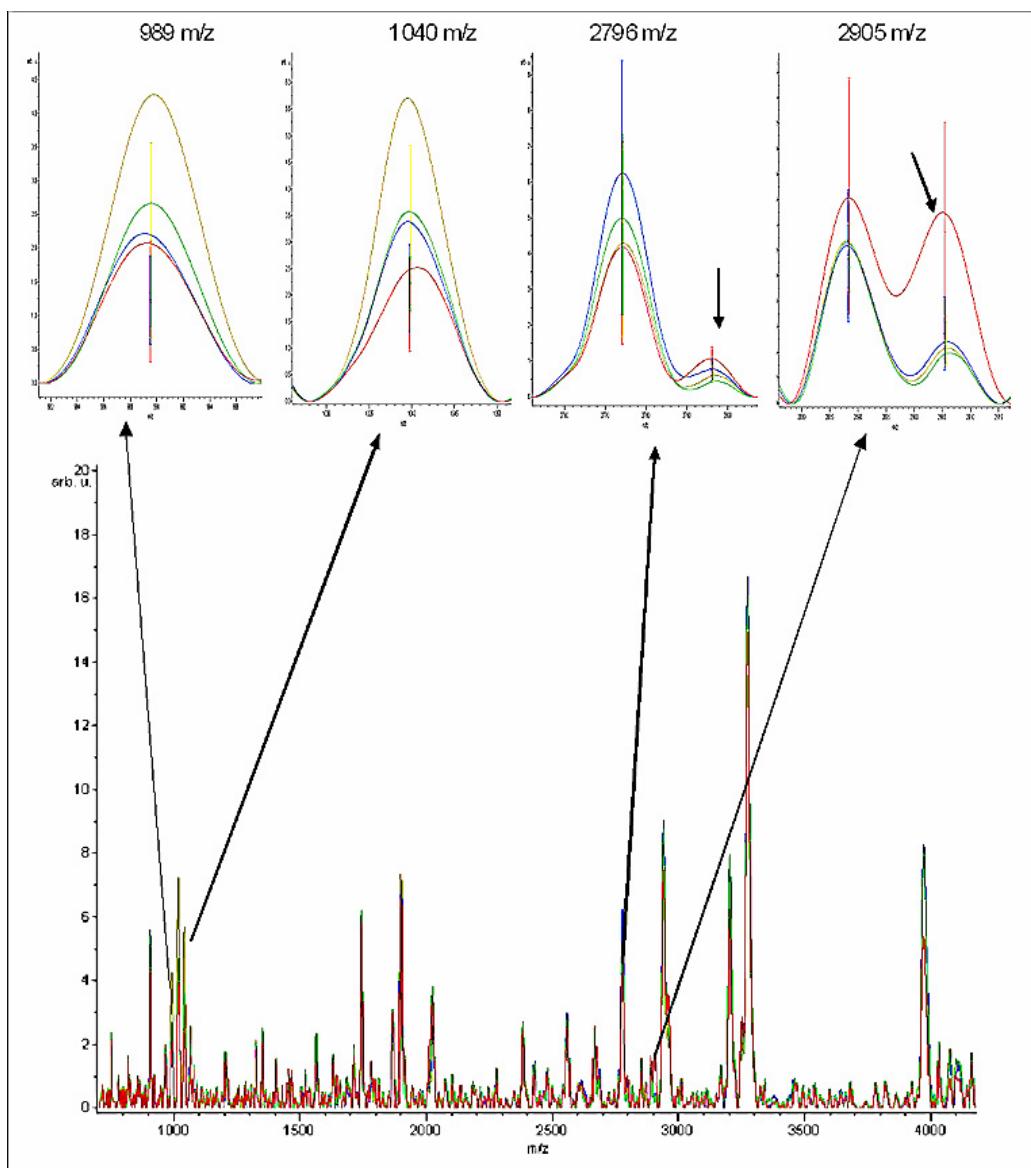
**Figure 5.6 2D peak distributions of the top two discriminatory peaks.** The distribution of peak areas from the top two discriminatory peaks in the A) LMR and B) HMR from the healthy (gold), benign (blue), malignant early (green), malignant late (red) and QC samples (purple) are shown.

### 5.3.3 Discriminatory peak analysis for clinical samples

For discriminatory peak analysis, spectra from the first duplicate spot on the MALDI target were assigned to a training set ('set01') which was used to determine statistically significant discriminatory peaks and to create classification models. Spectra from the second duplicate spot were assigned to a test set ('set02'), which were later used to test the classification algorithm's ability to correctly assign spectra to each of the clinical conditions. Comparison of all four conditions was performed using 179 common peaks ( $S/N > 3$ ) in the LMR and peak data was sorted according to Wilcoxon T-test p-values (Table 5.2). Results demonstrated that seven peaks had a statistically significant difference in the average peak area between the clinical conditions using a cut-off of  $p=0.05$ . The peak at 2905 m/z had an average peak area of 9.31 (arb. u.) in the healthy condition, 10.43 in benign, 9.04 in malignant early and 25.42 in malignant late stage condition. The greatest difference in peak area was found between the malignant early and malignant late at conditions with  $\sim 2.5$ -fold increase in the average peak area ( $p = 0.0003$ ). The second highest scoring peak at 989.5 m/z ( $p = 0.0006$ ) had a higher average peak area in the healthy condition and was similar in the benign, malignant early stage and malignant late stage samples. However, it is important to note that despite these peaks being statistically significant the CVs were rather high, a likely consequence of biological variation across the samples in each condition. Average spectra detailing the top 4 peaks are shown in Figure 5.7.

Mass	Greatest Difference in Ave Peak Area	Wilcoxon T-test	Healthy	Benign	Mal Early	Mal Late	StdDev Healthy	StdDev Benign	StdDev Mal Early	StdDev Mal Late	CV Healthy	CV Benign	CV Mal Early	CV Mal Late
2905.44	16.38	0.000298	9.31	10.43	9.04	25.42	3.63	5.43	2.98	16.31	38.99	52.06	32.96	64.16
989.53	17.11	0.000628	39.27	22.82	25.06	22.15	26.46	11.9	9.32	16.03	67.38	52.15	37.19	72.37
1039.69	26.98	0.00118	60.51	39.61	41.21	33.53	28.06	14.85	8.91	16.15	46.37	37.49	21.62	48.17
2796.19	8.87	0.0114	12.03	13.9	9.85	18.72	3.79	5.77	1.96	7.42	31.50	41.51	19.90	39.64
1561.25	11.24	0.0114	15.9	19.44	27.14	19.95	5.98	6.26	8.87	4.97	37.61	32.20	32.68	24.91
1391.55	2.04	0.0147	7.07	7.69	8.68	9.11	1.45	1.7	1.98	1.76	20.51	22.11	22.81	19.32
1015.66	22.82	0.0148	75.47	56.19	58.4	52.65	28.84	19.75	10.59	14.98	38.21	35.15	18.13	28.45

**Table 5.2 Comparison of average peak areas in the LMR.** Peak areas from the LMR were compared by loading all the conditions against each other in ClinProTools software. Peaks were sorted by the Wilcoxon T-test p-values. The most discriminatory peak is listed first (significant peaks ( $p < 0.05$ ) are shown).

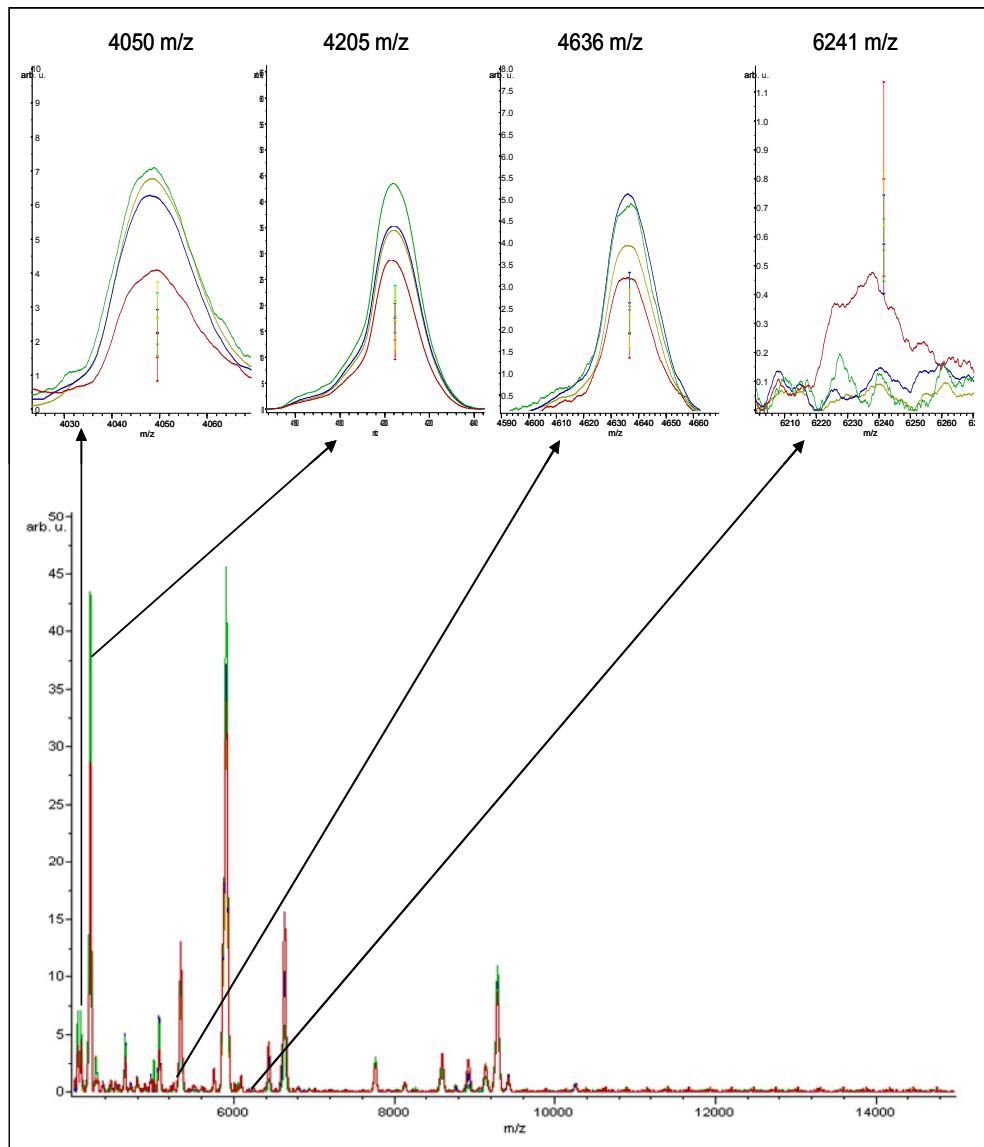


**Figure 5.7 MALDI-TOF spectral overlays illustrating the average LMR (700-4000 Da) peptide profiles.** Clinical samples were processed using the automated bead-based extraction protocol followed by MALDI-TOF MS analysis. Data was analysed with ClinProTools software (V 2.0). Average spectra of healthy (gold), benign (blue), malignant early (green) and malignant late stage (red) samples are shown and representative discriminatory peaks have been enlarged to show the differences in peak area with error bars as standard deviation.

In the HMR, 94 common peaks (SN > 5) were compared between the four conditions (Table 5.3). The most discriminatory peak at 4049.54 m/z had an average peak area 157.78 (arb. u.) in the healthy condition, 134.8 in the benign, 159.98 in the malignant early and 91.38 in the malignant late stage condition. The greatest difference was therefore found between malignant early stage and malignant late stage conditions where there was a difference of ~1.75 fold which was statistically significant at  $p = 0.02$ . Using a cut-off of  $p=0.05$  four discriminatory peaks were found in the HMR. The peak CVs were also high in the HMR, but lower than the LMR (Table 5.3 & Figure 5.8).

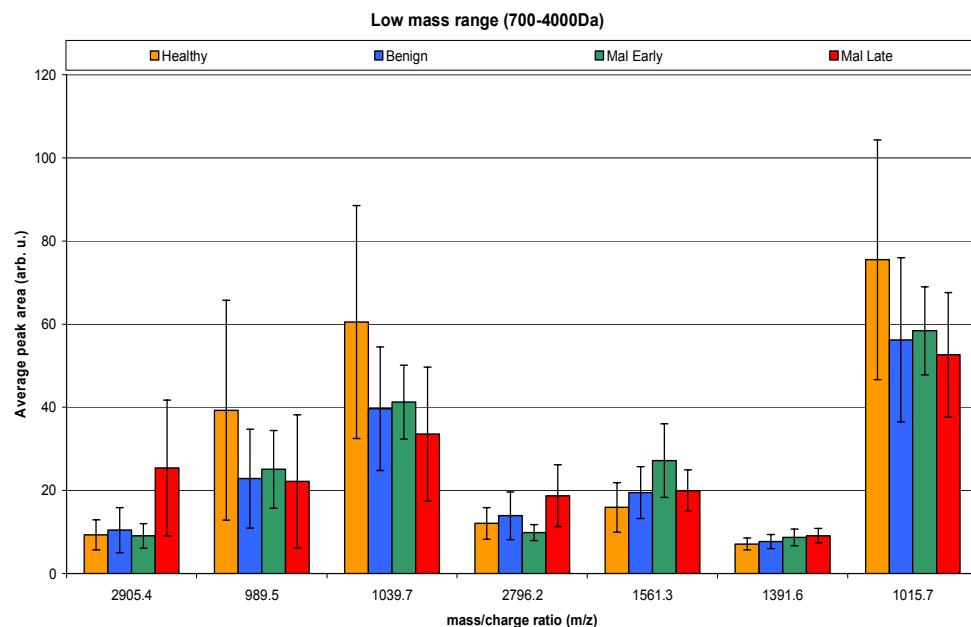
Mass	Difference in Ave Peak Area	Wilcoxon T-test	Healthy	Benign	Mal Early	Mal Late	StdDev Healthy	StdDev Benign	StdDev Mal Early	StdDev Mal Late	CV Healthy	CV Benign	CV Mal Early	CV Mal Late
4049.54	68.6	0.0206	157.78	134.8	159.98	91.38	65.51	40.62	45.17	41.56	41.52	30.13	28.23	45.48
4204.56	451.51	0.0228	1015.34	1052.82	1250.23	798.72	338.93	170.68	178.33	226.22	33.38	16.21	14.26	28.32
6241.38	15.67	0.0228	45.75	40.25	39.07	54.73	13.67	10.88	7.6	20.02	29.88	27.03	19.45	36.58
4636.66	42.92	0.0245	135.78	157.15	152.2	114.24	40.77	41.86	37.5	33.2	30.03	26.64	24.64	29.06

**Table 5.3 Comparison of average peak areas in the HMR.** Peak areas from the HMR were compared by loading all the conditions against each other in ClinProTools software. Peaks were sorted by Wilcoxon T-test p-values. The most discriminatory peak is listed first (only significant peaks ( $p < 0.05$ ) are shown here).

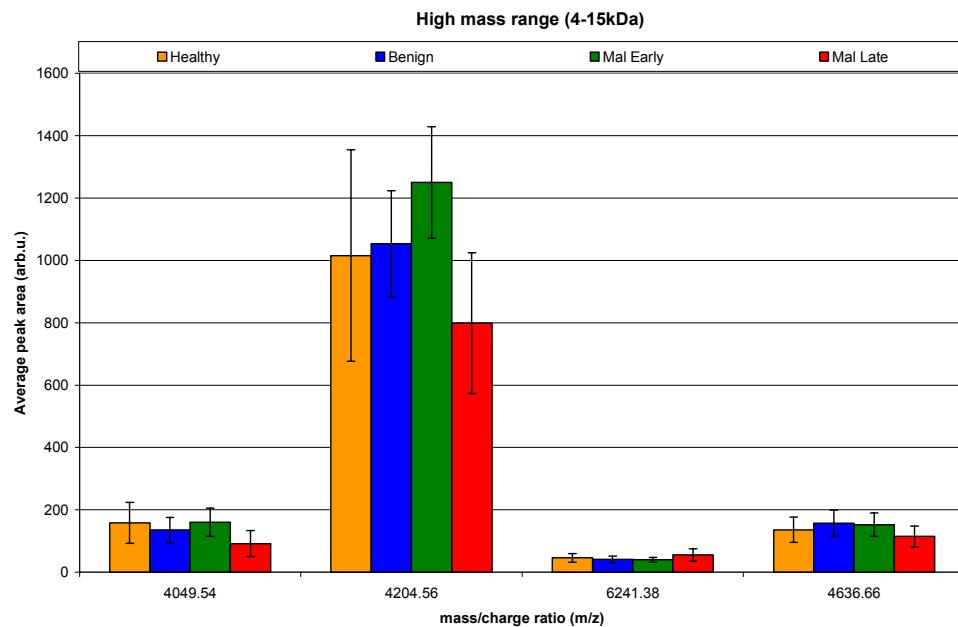


**Figure 5.8 MALDI-TOF spectral overlays illustrating the average HMR (4-15 kDa) peptide profiles.** Clinical samples were processed using the automated bead-based extraction protocol followed by MALDI-TOF MS analysis. Data was analysed with ClinProTools software (version 2.0). Average spectra of healthy (gold), benign (blue), malignant early (green) and malignant late stage (red) samples are shown and representative discriminatory peaks have been enlarged to show the differences in peak area with error bars representing the standard deviation.

Further analysis of the statistically significant discriminatory peaks suggested that fluctuations in the amount of these peptide masses could be related to proteolysis. For example, in the LMR peaks at 2905 m/z and 2796 m/z which showed a greater average peak area in the malignant late stage condition could be fragments of the same polypeptide. Peaks at 989.5 m/z, 1015.3 m/z and 1039.5 m/z which all showed a greater peak area in the healthy condition are approximately 25 Da apart and maybe modified fragments of the same peptide (Figure 5.9). In the HMR peaks at 4049.5 m/z and 4204.5 m/z which showed a greater average peak area in the malignant early stage condition and are approximately 155 Da apart (the amino acid Arginine has a mass of 156 Da). These peaks may also be fragments of the same polypeptide (Figure 5.10).

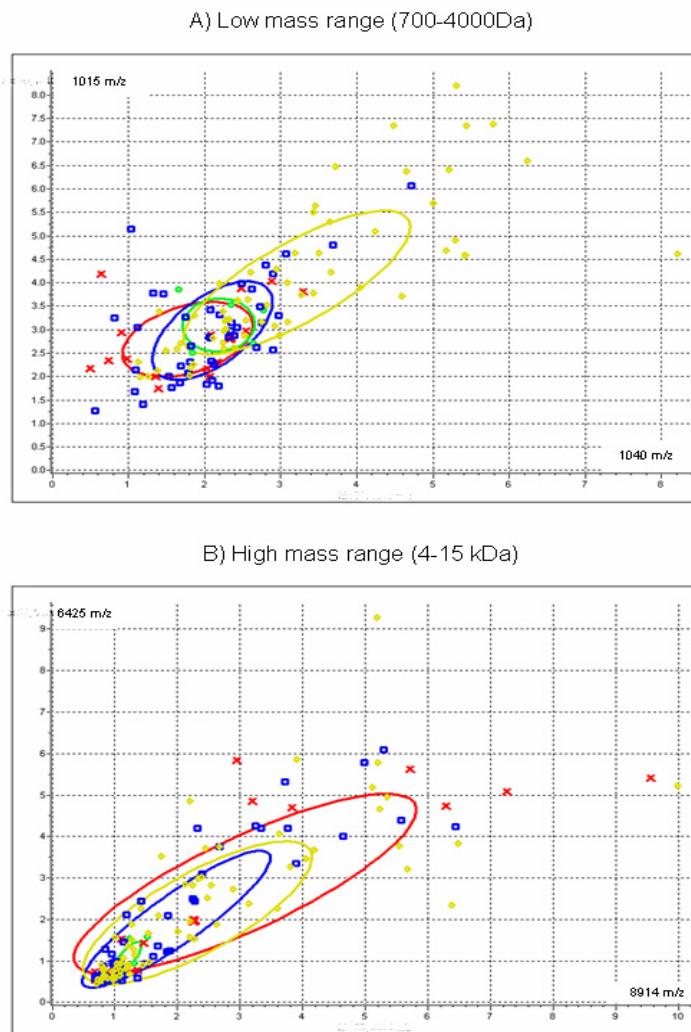


**Figure 5.9 Comparison of discriminatory peaks in the LMR.** Data analysis showed several peaks with differences in average peak area which discriminate clinical samples. Peaks with statistically significant difference ( $p < 0.05$ ) are shown here.



**Figure 5.10 Comparison of discriminatory peaks in the HMR.** Data analysis showed several peaks with differences in average peak area which discriminate clinical samples. Peaks with statistically significant difference ( $p<0.05$ ) are shown here.

Despite this, a peak distribution analysis for pairs of discriminatory peaks revealed poor separation of the healthy, benign, malignant early stage and malignant late stage conditions. The ellipses in Figure 5.11 represent the standard deviation of the average peak area.

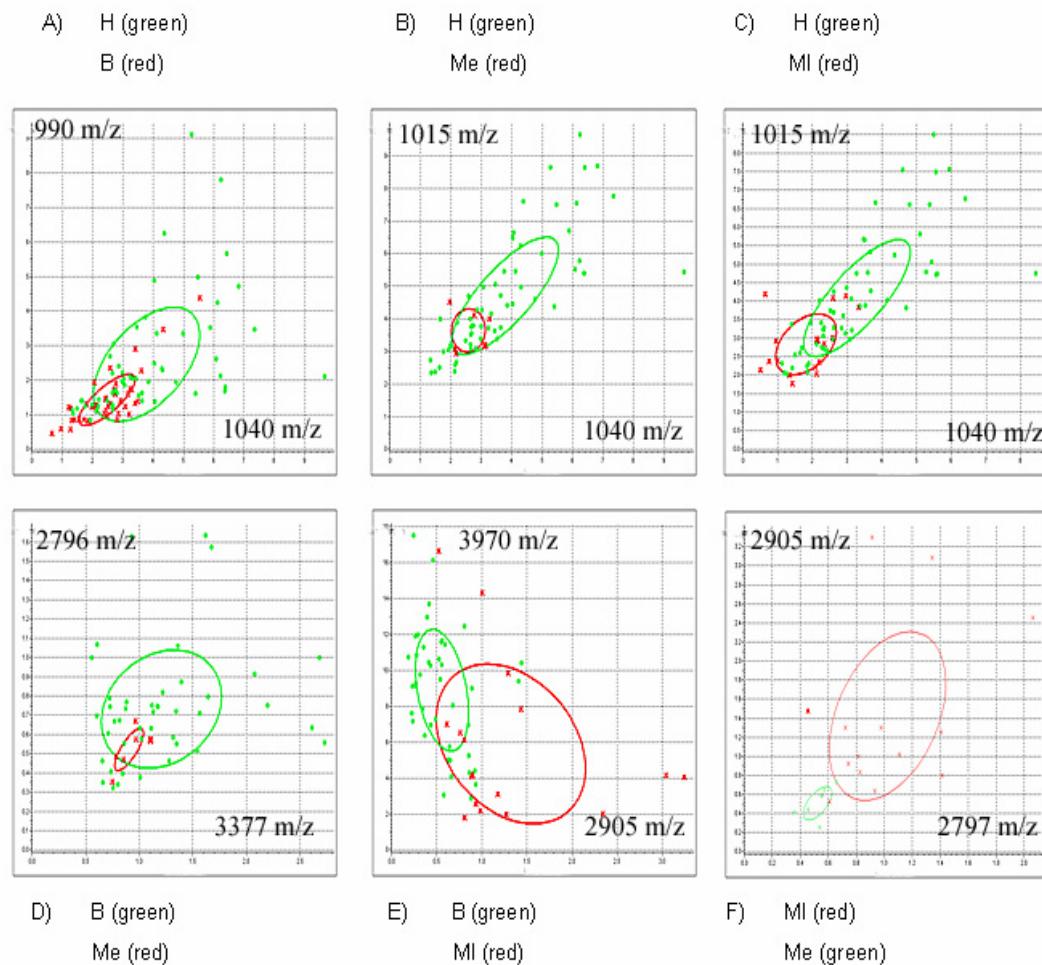


**Figure 5.11 2D peak distributions of the top two discriminatory peaks.** The distribution of peak areas from two discriminatory peaks in the A) LMR and B) HMR from the healthy (gold), benign (blue), malignant early (green), malignant late (red) are shown.

Pair-wise comparisons using the Wilcoxon test between clinical conditions revealed a number of additional discriminatory peaks in both mass ranges. In the LMR, a peak at 904.8 m/z had a 1.5-fold difference in average peak area between the healthy and benign conditions. This peak was significantly up-regulated in the benign condition ( $p=0.04$ ). Peaks at 1203 m/z and 1064 m/z discriminated between the healthy and malignant late stage conditions. The peak at 1203 m/z was up-regulated by 1.4 fold in the malignant late stage condition ( $p=0.03$ ), while the peak at 1064 m/z was up-regulated by 1.5 fold in the healthy condition. In the LMR, the greatest number of differentially expressed peaks were found between the healthy and the malignant late stage conditions.

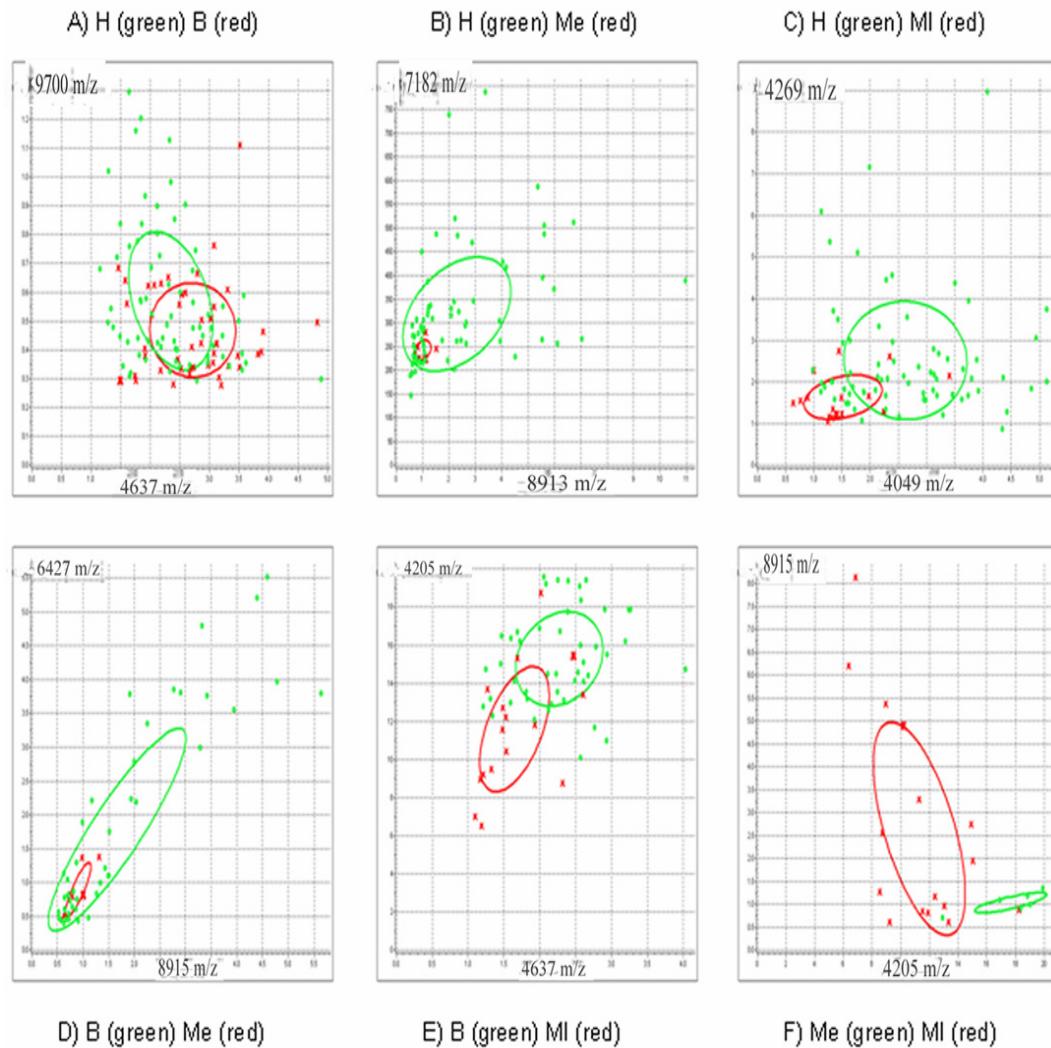
In the HMR, a greater number of differences were found between the benign and the malignant late stage conditions. In addition to the 4 statistically significant peaks found in the four conditions comparison, peaks at 4086.6 m/z and 5062.6 m/z were found to discriminate between the benign and the malignant late stage conditions. Both peaks were up-regulated in the benign condition. The peak at 4086.6 m/z was up-regulated by approximately 1.3-fold ( $p=0.05$ ), and the peak at 5062.6 m/z was up-regulated by approximately 1.4-fold ( $p=0.01$ ).

Peak distribution analysis was performed using pairs of discriminatory peaks (Figure 5.12). In the LMR the ellipses representing the standard deviation for the average peak area for the two most discriminatory peaks showed the large spread of the data.



**Figure 5.12 2D peak distributions of clinical samples in the LMR.** The distributions of the areas of the two most discriminatory peaks in the different clinical conditions are shown. The x-axis shows the peak areas of the most discriminatory peak and the y-axis the peak areas for the second most discriminatory peak. The ellipses represent the standard deviation of the average peak area.

Peak distribution analysis in the HMR showed that the malignant late stage condition separated reasonably well from the healthy, benign and malignant early stage conditions. There was no separation between the healthy, benign and malignant early stage conditions.



**Figure 5.13 2D peak distributions of clinical samples in the HMR.** The distributions of the areas of the two most discriminatory peaks in the different clinical conditions are shown. The x-axis shows the peak areas of the most discriminatory peak and the y-axis the peak areas for the second most discriminatory peak. The ellipses represent the standard deviation of the average peak area.

## 5.4 Classification of clinical samples using SVM

MS spectra consist of high dimensional data which can be used by classification algorithms to classify samples into their respective clinical groups. ClinProTools has a built in function for spectral classification. For the classification of UKOPS samples the Support Vector Machine (SVM) algorithm was chosen. The concept of the SVM was developed by Vladimir Vapnik [Vapnik, 1999]. It has fast become an established pattern recognition tool. In the simplest case, using sophisticated mathematical approaches, the SVM helps to determine an optimal hyperplane separating two clouds of data.

Spectra from the first set of spotting replicates ('set01') were used as a 'training set' to create models. Several tests were done to optimise the recognition capabilities of the model, including the number of peaks used by the model and the number of k-nearest neighbours. The k-nearest neighbours algorithm is amongst the simplest of all machine learning algorithms. Using this algorithm an object is classified by a majority vote of its neighbours, the object is then assigned to the class most common amongst its k nearest neighbors. For spectral recognition, 80% of spectra were used by the model and the remaining 20% were left out for cross-validation as a measure of the reliability of the calculated model (Tables 5.4 & 5.5).

Model name	Number of peaks	Number of k-NN	Recognition (%)	Cross Validation (%)
SVM 1	auto 1-25	3	80.9	44.73
SVM 2	auto 1-25	5	67.25	46.7
SVM 3	50 peaks	3	74.11	49.31
SVM 4	50 peaks	5	60.16	49.74
SVM 5	100 peaks	3	68.75	45.92
SVM 6	100 peaks	5	58.27	46.85

**Table 5.4 Optimisation of the SVM's parameters in the LMR.** The recognition and cross validation capabilities of the SVM used for classification of clinical samples involved the optimisation of the number of peaks and k-nearest neighbours used as shown.

Model name	Number of peaks	Number of k-NN	Recognition (%)	Cross Validation (%)
SVM 1	auto 1-25	3	79.86	73.23
SVM 2	auto 1-25	5	80.78	41.33
SVM 3	50 peaks	3	60.08	42.32
SVM 4	50 peaks	5	62.49	40.75
SVM 5	100 peaks	3	60.49	42.9
SVM 6	100 peaks	5	59.57	40.65

**Table 5.5 Optimisation of the SVM's parameters in the HMR.**

The SVM1 model gave the highest recognition and cross validation scores. This model was initially tested on spectral data which included the QC samples. In the LMR, the SVM algorithm automatically selected 24 discriminatory peaks and the results demonstrate that the overall recognition capability of the algorithm was 80.9% and 100% of QC spectra were recognised and cross-validated correctly (Table 5.6).

<b>A) Model Generation Classes</b>	
Class 1:	MalignantLate\set01
Class 2:	MalignantEarly\Set01
Class 3:	Benign\set01
Class 4:	Healthy\set01
Class 5:	QC\set01

<b>B) Recognition Capability</b>	
<b>Overall:</b>	<b>80.90%</b>
Class 1:	76.92%
Class 2:	50%
Class 3:	82.93%
Class 4:	94.64%
Class 5:	100%

<b>C) Cross Validation</b>	
Percent Leave Out:	20%
Number of Iterations:	10
<b>Overall:</b>	<b>44.73%</b>
Class 1:	21.43%
Class 2:	7.14%
Class 3:	44.29%
Class 4:	50.81%
Class 5:	100%

**Table 5.6 ClinProTools SVM model generation for the LMR.** A) Classes of the clinical conditions, B) the SVM's recognition capability for 80% of spectra from the training set, C) the cross validation results for the remaining 20% of spectra.

D) Integration Regions used for Classification				
Index	Mass	Start Mass	End Mass	Weight
1	708.48	704.89	711.06	0.97
5	742.06	737.45	745.85	1.02
7	771.72	766.89	774.05	0.87
22	921.53	915.64	931.04	0.94
32	1064.03	1050.6	1071.58	0.83
54	1391.49	1384.98	1396.63	1.22
71	1643.45	1637.1	1649.41	1.62
77	1724.82	1720.17	1730.94	1.2
87	1912.03	1906.86	1925	0.75
91	1985.93	1978.75	1993.59	1.29
95	2103.39	2094.57	2113.35	1.1
100	2194.48	2190.47	2204.74	0.85
109	2347.43	2339.11	2356.27	0.75
111	2381.07	2369.61	2393.16	0.74
112	2427.27	2412.5	2438.82	0.74
114	2465.08	2454.65	2469.76	1.03
118	2541.01	2531.82	2545.92	0.8
124	2666.82	2653.5	2677.85	0.83
126	2703.61	2697.63	2710.09	0.76
129	2774.16	2752.19	2789.64	0.86
130	2796.24	2789.64	2806.65	0.95
134	2869	2859.76	2877.93	0.9
135	2888.39	2877.93	2898.73	1.77
136	2905.47	2898.73	2915.9	2.77

**Table 5.6 continued. ClinProTools SVM model generation for the LMR.** D) The integration m/z regions of the 24 peaks automatically selected for classification, here the peak weight refers to the ranking of the peak which is dependent on the separation properties of the peak. Peaks with good separation properties are ranked highly and therefore had a greater weight.

In the HMR, the SVM algorithm automatically selected 23 discriminatory peaks and the results demonstrate that the overall recognition capability of the algorithm was 80.24% all QC spectra were recognised and cross-validated correctly (Table 5.7).

<b>A) Model Generation Classes</b>	
Class 1:	MalignantLate\set01
Class 2:	MalignantEarly\set01
Class 3:	Benign\set01
Class 4:	Healthy\set01
Class 5:	QC\set01

<b>B) Recognition Capability</b>	
<b>Overall:</b>	<b>80.24%</b>
Class 1:	68.75%
Class 2:	66.67%
Class 3:	76.09%
Class 4:	89.71%
Class 5:	100%

<b>C) Cross Validation</b>	
Percent Leave Out:	20%
Number of Iterations:	10
<b>Overall:</b>	<b>44.77%</b>
Class 1:	30.56%
Class 2:	0%
Class 3:	36.71%
Class 4:	56.58%
Class 5:	100%

**Table 5.7 ClinProTools SVM model generation for the HMR.** A) Classes of the clinical conditions, B) the SVM's recognition capability for 80% of spectra from the training set, C) the cross validation results of the remaining 20% of spectra.

D) Integration Regions used for Classification				
Index	Mass	Start Mass	End Mass	Weight
1	4052.64	4023.84	4071.76	1.53
2	4085.21	4071.76	4108.98	0.77
3	4204.57	4146.51	4243.28	0.79
6	4460.16	4431.15	4498.18	0.74
7	4517.76	4498.18	4543.45	1.24
9	4636.69	4591.79	4667.16	1.82
13	4913.91	4905.28	4931.07	1.29
15	5061.92	5034.37	5113.05	2.13
20	5433.5	5396.42	5454.76	0.85
22	5586.23	5552.22	5607.79	1
24	5745.73	5698.63	5778.98	1
27	6080.9	6054.53	6120.97	0.83
29	6240.24	6213.51	6257.29	2.74
34	6626.33	6551.84	6680.79	1.11
36	6793.12	6756.81	6844.78	1.12
42	7217.61	7198.09	7256.2	0.84
47	7629.24	7617.61	7686.81	1.05
52	8227.55	8176.56	8239.04	1.06
53	8340.4	8306.8	8366.41	0.86
55	8585.3	8498.62	8647.2	0.98
57	8757.14	8718.24	8821.78	1.46
58	8916.4	8821.78	8986.36	0.78
66	9789	9752.14	9804.02	0.95

**Table 5.7 continued. ClinProTools SVM model generation for the HMR.** D) The integration m/z regions of the 24 peaks automatically selected for classification, here the peak weight refers to the ranking of the peak which is dependent on the separation properties of the peak. Peaks with good separation properties are ranked highly and therefore had a greater weight.

For the classification of clinical spectra (without the QC samples), the SVM algorithm automatically selected 24 peaks in the LMR, based on the T-test p-values to give 86% overall recognition capability for 80% of spectra from the training set and was able to correctly recognise 75%, 100%, 81.4% and 88.3% of the malignant late stage, malignant early stage, benign and healthy samples (Table 5.8). For cross-validation the remaining 20% of the spectra were classified by the model giving an overall score of 29.39% which is considered poor. The algorithm was able to recognise more of the healthy spectra (61.9%) than either of the benign and malignant late stage spectra (33.8% and 21.9%; Table 5.8). Of the 24 peaks selected by the SVM model peaks at 1391.5 m/z, 2796 m/z and 2905 m/z were also reported in Table 5.2 which showed peaks ranked according to Wilcoxon p-values.

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<b>A) Model Generation Classes</b>	
Class 1:	MalignantLate\set01
Class 2:	MalignantEarly\set01
Class 3:	Benign\set01
Class 4:	Healthy\set01

<b>B) Recognition Capability</b>	
<b>Overall:</b>	<b>86.18%</b>
Class 1:	75%
Class 2:	100%
Class 3:	81.40%
Class 4:	88.33%

<b>C) Cross Validation</b>	
Percent Leave Out:	20%
Number of Iterations:	10
<b>Overall:</b>	<b>29.39%</b>
Class 1:	21.88%
Class 2:	0%
Class 3:	33.77%
Class 4:	61.90%

**Table 5.8 ClinProTools SVM model generation for the LMR.** A) Classes of the clinical conditions, B) the SVM's recognition capability for 80% of spectra from the training set, C) the cross validation results of the remaining 20% of spectra.

D) Integration Regions used for Classification				
Index	Mass	Start Mass	End Mass	Weight
1	708.48	704.89	711.06	0.97
5	742.06	737.45	745.85	1.02
7	771.72	766.89	774.05	0.87
22	921.53	915.64	931.04	0.94
32	1064.03	1050.6	1071.58	0.83
54	1391.49	1384.98	1396.63	1.22
71	1643.45	1637.1	1649.41	1.62
77	1724.82	1720.17	1730.94	1.2
87	1912.03	1906.86	1925	0.75
91	1985.93	1978.75	1993.59	1.29
95	2103.39	2094.57	2113.35	1.1
100	2194.48	2190.47	2204.74	0.85
109	2347.43	2339.11	2356.27	0.75
111	2381.07	2369.61	2393.16	0.74
112	2427.27	2412.5	2438.82	0.74
114	2465.08	2454.65	2469.76	1.03
118	2541.01	2531.82	2545.92	0.8
124	2666.82	2653.5	2677.85	0.83
126	2703.61	2697.63	2710.09	0.76
129	2774.16	2752.19	2789.64	0.86
130	2796.24	2789.64	2806.65	0.95
134	2869	2859.76	2877.93	0.9
135	2888.39	2877.93	2898.73	1.77
136	2905.47	2898.73	2915.9	2.77

**Table 5.8 continued. ClinProTools SVM model generation for the LMR.** D) The integration m/z regions of the 24 peaks automatically selected for classification, here the peak weight refers to the ranking of the peak which is dependent on the separation properties of the peak.

In the HMR (without the QC samples), the SVM automatically selected 24 peaks based on the T-test p-values to give 76.29% overall recognition capability of 80% of the spectra from the training set. For cross-validation the remaining 20% of spectra were classified with an overall score of 32.97% (Table 5.9). Of the 24 peaks selected by the SVM model, peaks at 4049.5 m/z, 4204.6 m/z, 4636.7 m/z and 6241.4 m/z were also reported in Table 5.3 where peaks were ranked according to Wilcoxon p-values.

<b>A) Model Generation Classes</b>	
Class 1:	MalignantLate\set01
Class 2:	MalignantEarly\set01
Class 3:	Benign\set01
Class 4:	Healthy\set01

<b>B) Recognition Capability</b>	
<b>Overall:</b>	<b>76.29%</b>
Class 1:	56.25%
Class 2:	83.33%
Class 3:	78.26%
Class 4:	87.32%

<b>C) Cross Validation</b>	
Percent Leave Out:	20%
Number of Iterations:	10
<b>Overall:</b>	<b>32.97%</b>
Class 1:	14.29%
Class 2:	6.67%
Class 3:	46.25%
Class 4:	64.67%

**Table 5.9 ClinProTools SVM model generation for the HMR.** A) Classes of the clinical conditions, B) the SVM's recognition capability for 80% of spectra from the training set, C) the cross validation results of the remaining 20% of spectra.

D) Integration Regions used for Classification				
Index	Mass	Start Mass	End Mass	Weight
1	4049.54	4024.58	4068.91	1.69
2	4085.83	4068.91	4108.55	0.96
3	4204.56	4148.45	4243.37	0.97
4	4269.99	4244.24	4325.33	0.9
8	4520.07	4495.67	4544.24	1.27
10	4636.66	4590.98	4667.54	1.8
13	4884.69	4859.62	4904.08	0.93
14	4915.69	4904.08	4934.56	1.19
17	5061.53	5024.29	5107.07	2.27
18	5129.26	5109.12	5141.4	0.91
24	5481.79	5453.73	5503.71	0.75
25	5584.98	5555.3	5607.82	1.03
27	5745.26	5677.33	5779.39	0.96
32	6241.38	6203.12	6280.6	2.13
34	6426.38	6391.45	6472.98	0.73
36	6623.96	6552.53	6679.81	1.16
38	6792.77	6756.07	6843.53	0.94
50	7647.82	7620.49	7648.96	1.19
56	8231.32	8175.47	8238.88	1.04
57	8343.05	8307.01	8371.67	1
60	8586.01	8498.54	8644.07	1.19
62	8753.87	8717.49	8819.1	1.64
63	8913.51	8819.1	8976.27	0.77
70	9791.25	9746.89	9803.73	0.79

**Table 5.9 continued. ClinProTools SVM model generation for the HMR. D)** The integration regions of the 24 peaks automatically selected for classification.

The SVM algorithm was then used to classify a second set of data from the other duplicate spots. Results showed that for the LMR data 77% of the healthy, 51% of the benign, 16% of the malignant early stage and 31% of the malignant late stage spectra were classified correctly, this represents sensitivity of the algorithm. In the HMR 63% of the healthy, 67% of the benign, 0% of the malignant early stage and 63% of the malignant late stage spectra were classified correctly. In addition, 92% of QC spectra from both mass ranges were correctly classified (Table 5.10).

Clinical condition	LMR % of spectra classified correctly	HMR % of spectra classified correctly
Mal Late	31	63
Mal Early	16	0
Benign	51	67
Healthy	77	63
QC	92	92

**Table 5.10 SVM Classification results.** The SVM algorithm was used to classify a ‘test-set’ of spectral data from all conditions. Results for the LMR and HMR are shown.

During the initial model generation stage the SVM results showed that 100% of the QC data were recognised and cross-validated correctly. The SVM was then tested on a second data set from the duplicate spot and results showed that 92% of QC spectra in both the LMR and HMR were classified correctly. This suggests that the sensitivity of the algorithm is greater than 90%. Results from the clinical conditions suggest that the classification algorithm may have been limited by the number of spectra available and the relatively large variation across samples within the conditions. The overall scores for the healthy and benign conditions were better than the scores for the malignant stage conditions where there were fewer samples. In summary, this data shows that the spectra do not contain information for reliably predicting the clinical conditions under investigation.

## 5.5 Discussion

The human serum proteome is an extremely complex biological sample containing information on numerous biological processes that takes place in the body. Cancer cells can release proteins into the extracellular fluid through secretion of intact or cleaved proteins in response to changes taking place in the cancer tissue microenvironment and due to cancer cell-host interactions. Many of these products will end up in the bloodstream and hence serve as potential serum biomarkers. Therefore, studying the serum proteomes of healthy, benign and malignant donors is the logical starting point for identifying diagnostic biomarkers and therapeutic targets for cancer [Grizzi and Chiriva-Internati, 2006; aoui-Jamali and Xu, 2006]. In recent years, many advances have been made in the field of proteomics. In particular, the use of high-throughput mass spectrometry methods for analysing complex proteomes (e.g. human serum) has become widespread.

The aim of the work presented in this chapter was to analyse clinical samples from the UKOPS collection to determine statistically significant discriminatory peptide/protein peaks and to determine if these peaks could be used for the classification of ovarian cancer. This aim was tackled by processing samples collected in accordance with a standardised protocol on a semi-automated and optimised bead-based serum polypeptide extraction platform followed by MALDI-TOF MS profiling.

Firstly, the intra-assay reproducibility was calculated using QC samples which had been processed alongside the clinical samples. Results demonstrated that the intra-assay reproducibility did not exceed 20% variance. In fact 85% of LMR peaks and 75% of HMR peaks were found to be below a 15% threshold. Despite this, spot-to-spot variations in peak profiles of the same sample were evident. Indeed, one of the major drawbacks in using MALDI-TOF MS for serum profiling is the inherent variability of the sample preparation process including automated sample spotting and inconsistencies in crystallisation [Cohen and Chait, 1996]. The co-crystallisation of the analyte with the matrix is a prerequisite for uniform ionisation of biomolecules.

A major issue is the non-homogeneous distribution of the analyte in the co-crystallite. To minimise the effects of non-homogeneous distribution of the analyte, spectra were generated by accumulating 400 laser shots over 8 different locations on the spots. The QC sample was included in the assay to account for the technical variability of the semi-automated platform at the time of clinical sample analysis.

Herein the comparison of MALDI-TOF MS spectral peak profiles has shown that the intra-condition variation was relatively high (30-60%) which reflects the combination of technical error and the biological heterogeneity between samples. In the LMR, there were significant differences in the abundance of certain peaks between the healthy and malignant late stage, healthy and benign, and benign and malignant late stage conditions. Of these only one statistically significant peak was found to discriminate between the malignant early and late stage. However, no statistically significant peaks were found to discriminate the healthy and benign conditions from malignant early stage condition. In the HMR, no statistically significant peaks were found to discriminate the healthy condition from the benign or malignant early stage conditions, though 5 peaks were found to change significantly between the benign condition and the malignant late stage conditions.

Interestingly, several peaks were found to be common in discriminating clinical conditions. In the LMR, peaks at 989 m/z and 2905 m/z were common discriminatory peaks between the clinical conditions. The average peak area of peak 989 m/z was higher in the healthy condition compared with benign and malignant conditions and the average peak area of 2905 m/z was higher in malignant late stage compared with the other conditions. However, the CVs of both these peaks were high. For the peak at 989 m/z the CV of the average peak area ranged from 37% to 72% and for peak at 2905 m/z from 33% to 64% between the clinical conditions. In the HMR, peaks at m/z 4050 and 4205 were found to be common discriminatory peaks and on average the peak areas of both of these peaks were lower in the malignant late stage condition. Again the CVs of the average peak area were high. For the peak at 4050 m/z the CV ranged from 28% to 46% and for peak at 4205 m/z from 14% to 33% between clinical conditions. The limited number of samples for the malignant conditions and the intra-condition biological variation which was found to be highest in the healthy and

benign conditions in both mass ranges could explain the lack of discrimination between the conditions.

Using a combination of peaks it was possible to classify spectra into their respective clinical groups. The results from the SVM analysis demonstrated that in the LMR 77% of healthy, 51% benign, 17% malignant early stage and 31% malignant late stage spectra were classified correctly. In the HMR, 63% healthy, 67% benign, 0% malignant early stage and 63% malignant late stage spectra were classified correctly. These poor classification results could be attributed to the limited number of samples for the malignant conditions as well as a lack of robust discriminatory peaks. Interestingly, none of the benign and malignant early spectra were classified as malignant late stage and none of the malignant late stage as malignant early stage spectra. This was found to be true in both mass ranges.

Results from the discriminatory peak and SVM analysis suggest that a panel of peptide masses at 989 m/z, 1064 m/z, 1392 m/z, 2796 m/z, 2905 m/z, 4049 m/z, 4205 m/z, 4637 m/z, 5062 m/z and 6241 m/z could be potentially useful markers of disease, albeit with poorer performance relative to the existing marker CA125. For CA-125 sensitivities of 85% and specificities of 65% are reported. Combining the discriminatory peaks with CA-125 values could provide better sensitivities and specificities. The average peak area of these masses changed depending on clinical condition. Although not identified, these peaks are likely to be fragments of acute-phase, complement and clotting proteins that are commonly found in serum.

In conclusion, the results demonstrate the feasibility of the technology platform for discriminating clinical samples. However, the intra-condition variation was a major limitation. A larger sample set with more malignant samples would be needed to better validate test results. Standardised operating procedures for donors would also be required to minimise biological variation. Furthermore, direct mass spectrometric serum profiling has a limited dynamic range and difficulties in providing the identification of the distinctive peptides and proteins. It is most likely that the distinctive profiles may result from the differential expression of relatively abundant serum proteins and their fragments associated with the host response to tumours and

generated by exoproteases as previously reported by Villanueva et al. However, in the case of ovarian cancer, it appears that these surrogate markers are less informative than for other cancer types. This may be due to different or lower exopeptidase activities in ovarian cancer samples compared with breast, prostate and bladder cancer.

Attempts to isolate masses of interest using 10kDa ultrafiltration devices followed by 1D-SDS PAGE separation for identification of masses of interest were unsuccessful and only very low levels of peptides could be recovered. It is speculated that many low molecular weight peptides and proteins are bound to the high molecular weight and high abundance carrier proteins such as albumin [Lowenthal et al., 2005]. MALDI-QTOF MS analysis is a good alternative method for peptide identification as this allows direct MS/MS sequencing of discriminatory masses. Work is underway to identify these peaks using MALDI-QTOF, although it should be noted that the sensitivity of the technique is lower than that of MALDI-TOF MS with fewer peptides detected, and the observed mass range is reduced.

Finally, MS-based peak pattern recognition is a useful tool for discovery phase research with target masses being identified and characterised prior to the possible translation to the clinic. MALDI-TOF protein profiling however, provides only a limited mass window for putative biomarker analysis. Sensitivity of detection and coverage in clinical proteomics can be effectively improved with extensive pre-fractionation strategies to remove high abundant proteins which can mask the detection of lower abundance protein species. This is the main focus of the next chapter.

**Chapter 6: Fluorescence Two-Dimensional Difference Gel Electrophoresis-based profiling of case-control sera for the identification of putative ovarian cancer biomarkers.****6.1 Introduction**

Work from the previous chapter demonstrated that the direct analysis of human serum using MALDI-TOF MS profiling has several limitations. Firstly, for serum the method has a limited dynamic range of detection ( $10^2$ - $10^6$ ). Secondly, only low mass polypeptides are sampled in the MS. Thirdly accuracy of quantification may be compromised by the inherent variability of the crystallisation and ionisation processes. Fourthly, it is difficult to directly identify discriminatory masses of interest without using online tandem MS which is inherently less sensitive. It is well documented that the serum proteome is an extremely complex protein mixture and conceivably contains all proteins (and fragments thereof) that are expressed in the cells and tissues of an organism. The serum proteome also has an exceptionally large dynamic range of protein expression with protein concentrations spanning 10 orders of magnitude [Liang and Chan, 2007]. For putative biomarker discovery it is imperative to employ separation techniques which will facilitate the analysis of differentially expressed proteins across a broad dynamic range.

While two-dimensional electrophoresis (2-DE) is limited in the ability to detect low abundance and hydrophobic proteins, it still remains a valuable method for the separation and profiling of complex mixtures of proteins. Fluorescence two-dimensional Difference Gel Electrophoresis (2D-DIGE) was developed for improved multiplex proteomic profiling based on the spectrally resolvable fluorescent dyes Cy2, Cy3 and Cy5 [Tonge et al., 2001; Gharbi et al., 2002]. Fluorescence 2D-DIGE was employed to complement the MALDI-TOF MS serum profiling work from the previous chapters by extending the mass range of proteins detected and hopefully to increase the dynamic range of detection of serum proteins. However, the complex nature of serum and the presence of a few proteins at very high concentration levels (mg/mL) makes detection of low-abundance proteins by 2-DE challenging, since the

sample loading capacity is limited and the presence of high-abundance proteins can mask the detection of low-abundance proteins [Song and Hanash, 2006]. Consequently, depletion and fractionation strategies have become popular for dividing the serum proteome into smaller and simpler subsets for the detection of as many proteins as possible, including those at lower abundance [Echan et al., 2005]. A highly promising first step for most analysis strategies of serum or plasma is to deplete the major proteins. Classically, Cibacron Blue and protein A/G chromatography methods have been used to deplete serum of albumin and the immunoglobulins respectively [Kim and Kim, 2007]. Ideally, for biomarker discovery it is desirable to deplete as many high-abundance proteins as possible while minimising incidental losses of non-targeted proteins. In recent years, a range of methods to deplete high-abundance proteins have been evaluated. For example, a recently commercialised HPLC polyclonal antibody column and its spin column version (MARS, Agilent Technologies) are very promising methods for depleting human serum or plasma samples. Polyclonal antibodies are more likely to deplete multiple structural forms of a protein and thus, these columns enabled 10- to 20-fold higher amounts of depleted serum samples to be applied to 2-D gels [Bjorhall et al., 2004; Echan et al., 2005; Sriyam et al., 2007; Liu et al., 2006]. Alternatively, strategies for compressing the protein dynamic range have also been commercialised. An example of this is the ProteoMiner protein enrichment technology (BioRad), which is based on treatment of complex protein samples with a large, highly diverse library of hexa-peptides bound to chromatographic supports [Guerrier et al. 2006; Guerrier et al. 2008; Boschetti et al. 2008]. In theory, the hexa-peptides can bind to all unique protein sequences in the mixture. Because the bead volume limits binding capacity, high-abundance proteins quickly saturate their ligands and excess protein can be washed out. In contrast, low-abundance proteins are concentrated on their specific ligands, thereby decreasing the dynamic range of proteins in the sample. When analysed using downstream proteomic applications, the number of protein species detected is dramatically increased.

The main focus of this chapter is the use of a 2D-DIGE based protein profiling strategy for the differential analysis of pooled clinical serum samples. Two different fractionation strategies were used to enrich the lower abundance proteins prior to 2D-

DIGE including a commercialised HPLC column containing antibodies to seven of the most abundant serum proteins, and a protein enrichment kit for “dynamic range compression”. Each of these fractionation methods were compared with the analysis of unfractionated sera and case control samples (UKOPS) were compared for the discovery of putative biomarkers of ovarian cancer. Differentially expressed protein features were identified using MALDI-TOF peptide mass fingerprinting (PMF) and LC-MS/MS analysis.

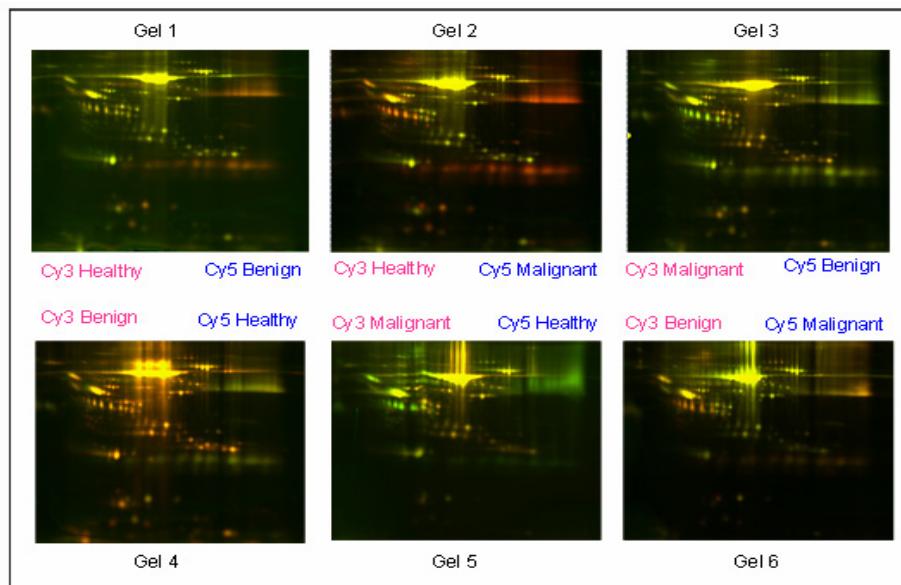
## 6.2 Pooled UKOPS clinical sera

Due to the limited availability of clinical samples equal volumes of each serum sample from the UKOPS collection were pooled into their respective clinical groups. Thus, serum pools were created for the healthy, benign and malignant late stage conditions. In addition, since only a very limited number of malignant early stage samples ( $n=6$ ) were available, this condition was excluded from the 2D-DIGE experiments. Pooling of biological samples is one method that can allow many samples to be studied simultaneously, while preventing false conclusions based on a limited number of individual samples. However, pooling strategies hide the underlying variation across sample sets and may reveal average data that is possibly skewed by outliers. The obvious advantage of pooling is to save time and money. Analysis of all samples individually could not be accomplished using 2D-DIGE.

The protein concentration of each pool was determined using the Pierce BCA protein assay using BSA to generate a standard curve. For accurate measurement within the linear range of the assay, pooled sera from each clinical condition were diluted 1:100 with HPLC grade deionised water. Results showed that the protein concentrations of the healthy, benign and malignant late stage pools were 93.9 mg/mL, 91.9 mg/mL and 85.3 mg/mL respectively. All pools were then equalised to 85.3 mg/mL with HPLC grade deionised water.

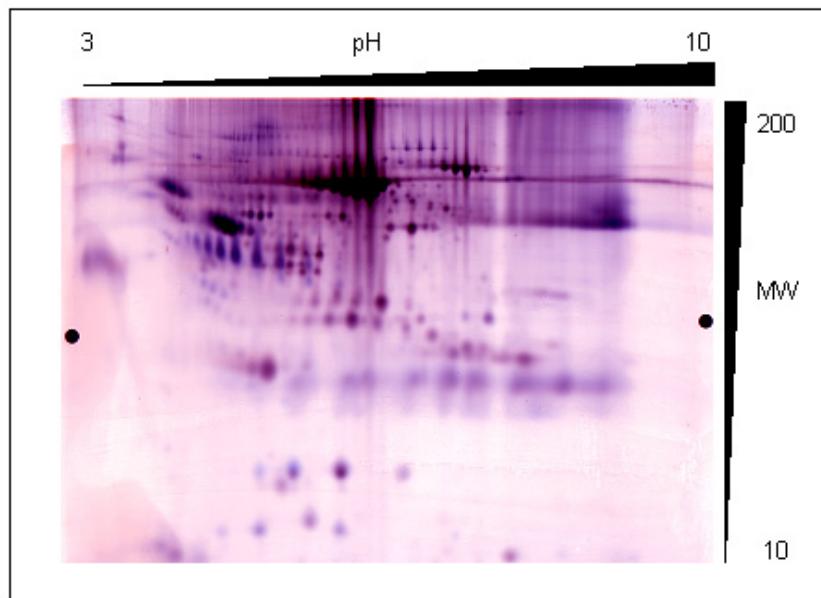
### 6.2.1 2D-DIGE analysis of pooled serum samples.

The depletion of major proteins is typically accompanied with a significant loss of components of potential interest. For instance, the removal of serum albumin can result in the removal of a multitude of proteins and peptides bound to it, which might be valuable for diagnostic purposes [Granger et al., 2005]. With this in mind, a 6 gel experiment was initially performed to compare the number of differentially expressed protein features between the unfractionated clinical pools. 50 $\mu$ g of protein was labelled with Cy3 or Cy5. In addition, to avoid any protein-specific dye effects, dye swaps were performed and samples were run in quadruplicates as shown in Figure 6.1.



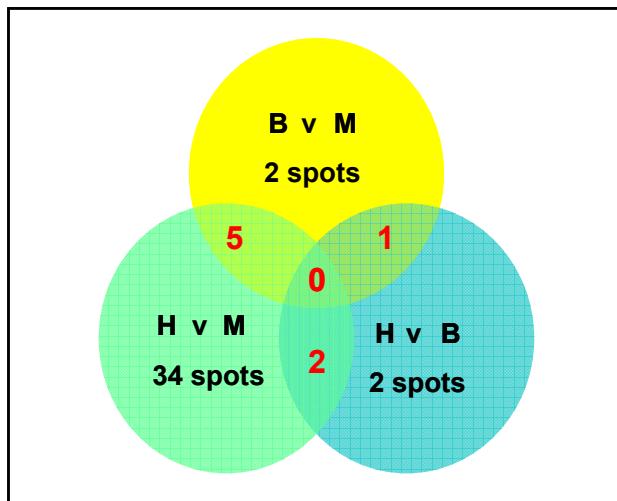
**Figure 6.1 Experimental design of DIGE labelling to compare protein profiles across pools of unfractionated UKOPS serum samples.** Clinical samples were pooled into healthy, benign and malignant groups and then prepared in NHS-lysis buffer. Equal amounts of protein (50  $\mu$ g) were labelled with 200 pmol of Cy3 or Cy5 as shown. Cy3 and Cy5 labelled samples were then mixed appropriately and run on six individual 2-D gels and fluorescence images captured. The figure shows the labelling strategy used for the 6 gels analysing unfractionated sera (50 $\mu$ g protein per dye) and superimposed images generated of each of the six gels (using Image Quant software). The same labelling strategy was later used for the 6 gel analyses of MARS fractionated sera.

Samples were diluted in a urea and CHAPS-based 2D-lysis buffer and subjected to 2D-DIGE analysis, as described in Chapter 2. Briefly, equal amounts of protein (50 µg) from each clinical condition were labelled with Cy3 and Cy5 in quadruplicates. The samples were mixed and run on 24 cm pH 3-10 non-linear IPG strips in the first dimension, followed by 12% SDS-PAGE in the second dimension. The gels were scanned at two different excitation/emission wavelength combinations generating two fluorescent images of proteins labelled with Cy3 and Cy5. Images were imported into DeCyder software for image analysis and quantitative comparison of differentially expressed proteins. Paired fluorescent images were processed using the differential in-gel analysis (DIA) module of the software; gel images were normalised and spot boundaries defined to calculate spot abundances and fold-ratios of abundance calculated between the superimposable paired images. The matched images were then imported into the biological variance analysis module (BVA), where protein features from a selected master gel were matched with the corresponding features across the other gel images. A representative superimposed image of two Cy dye images from the unfractionated pooled serum samples is shown in Figure 6.2.

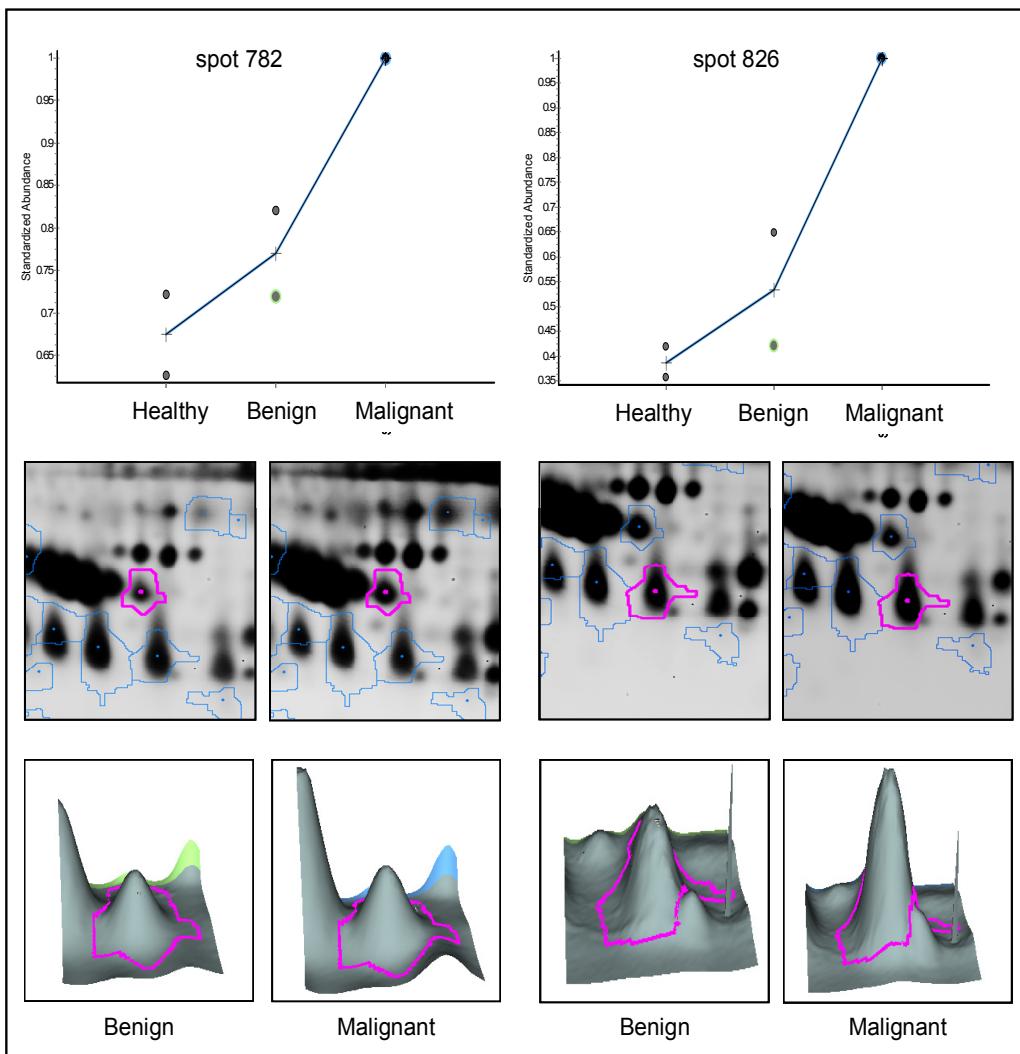


**Figure 6.2 Gel image of unfractionated sera used as the ‘master’ gel in DeCyder image analysis.** This figure represents the overlaid fluorescent images derived from the unfractionated pooled sera labelled with Cy3 (red-healthy) and Cy5 (blue-malignant). This figure was prepared using Adobe Photoshop.

A total of 934 protein features were detected in the master gel of the unfractionated sera. To keep the cost of the experiment to a minimum, no internal Cy2-labelled control was used. However, this made matching of protein features across the gels more difficult. Despite this, quantitative analysis showed that 39 protein features were up-regulated and 2 were down-regulated in the malignant condition versus the healthy condition ( $\geq 1.5$  average fold-change in abundance,  $p < 0.05$ ,  $n = 4$ ). Five protein features were found to be differentially expressed between the healthy and benign conditions with all 5 down-regulated in the benign condition. Eight protein features were differentially expressed between the benign and malignant conditions, all of which were up-regulated in the malignant condition. The number of differentially expressed protein features and overlap is represented in Figure 6.3. A total of 48 differentially expressed protein features were found between the 3 conditions out of the 934 detected and matched features. Examples are shown in Figure 6.4.

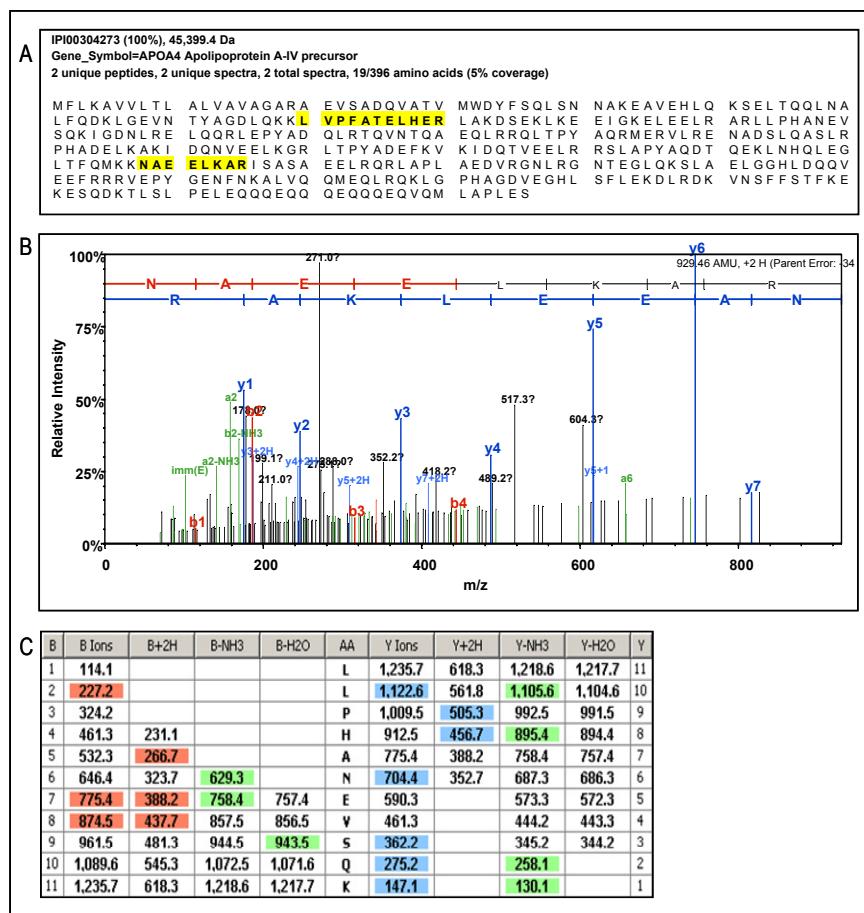


**Figure 6.3 Venn diagram showing the number of differentially expressed protein features and their overlap between the three clinical conditions.** The ratio in abundance of each protein feature was calculated between each clinical condition. Pairwise comparisons of the clinical conditions were performed i.e. healthy (H) / malignant (M), benign (B) / malignant (M) and healthy (H) / benign (B) and the numbers of differentially expressed spots that displayed a  $\geq 1.5$  average fold-change in abundance ( $p < 0.05$ ) are shown. The numbers shown in red represent protein spots which overlap between the three comparisons.



**Figure 6.4 Examples of protein features displaying clinical condition-dependent changes in expression from unfractionated samples.** Protein spots 782 and 826 displayed clinical stage-dependant differential expression. The peptide mixtures of the trypsin digestion from each of these protein spots were analysed by LC-MS/MS and the experimental peptide fragment masses were searched against theoretical masses using Mascot. Both spots yielded multiple protein identities including haptoglobin (HP), albumin (ALB) and apolipoprotein AIV (APOA4). Graphs were derived from DeCyder image analysis and data points are shown for replicate measurements with lines joining the average values. 3D images of spots are shown for the benign and malignant conditions.

Gels were stained with CCB and protein spots were excised from gels and subjected to trypsin digestion. The peptide mixtures obtained from each trypsin digest were then subjected to PMF by MALDI-TOF MS. When MALDI-TOF PMF analysis and database searching did not return any significant “hits” for a sample, the peptide mixtures were additionally analysed by LC-MS/MS. Of the 48 differentially expressed protein features, 35 were identified with high confidence (Figure 6.5 & Table 6.1). Of the 13 unidentified protein features, most were of low abundance and gave poor spectra, and thus could not be identified from database searches.



**Figure 6.5 An example of a differentially expressed protein feature identified by LC-MS/MS.** The trypsin digested peptide mixture of spot number 826 from the unfractionated pooled sera experiment was analysed by LC-MS/MS. A) Apolipoprotein AIV was identified by two unique peptides, (highlighted in yellow in the protein sequence). B) The MS/MS spectrum of peptide NAEELKAR and C) table indicating the masses of identified fragment ions (data produced using Scaffold software, more examples are shown in Appendix 2).

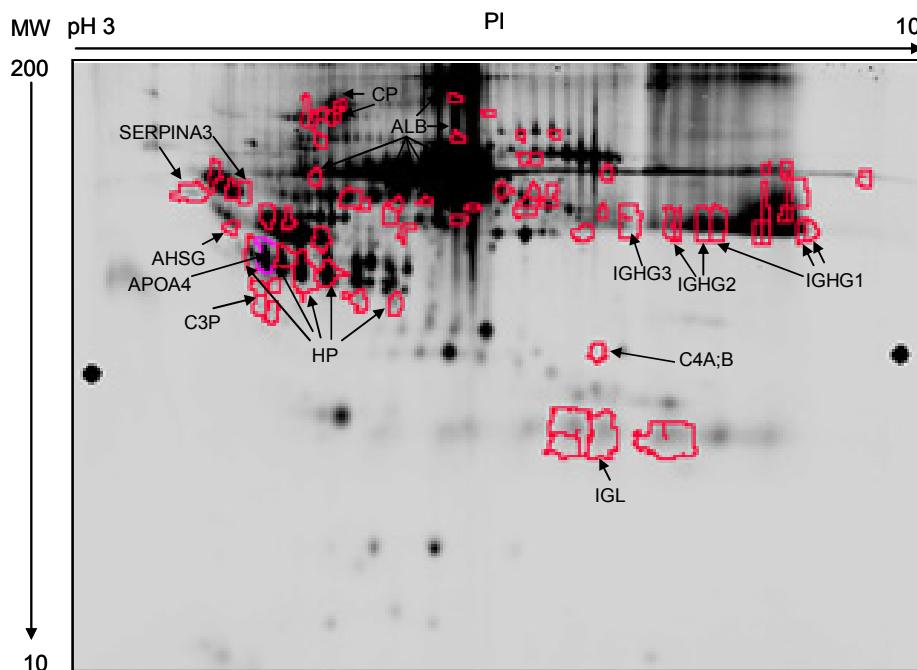
Spot No.	Protein AC	IPI No.	Score	Seq. Cov (%)	No. peptides	Mw	pI	Av. Ratio	T-test	Healthy / Malignant		Av. Ratio	T-test
										Healthy/Benign	Malignant		
232	Ceruloplasmin 97 kDa protein (CP)	IP00794184	40	2	2	97007	5.31	-2.88	0.0095	-1.34	-	-1.51	-
232	Albumin (A1B)	IP00022434	30	8	5	73881	6.33	-2.88	0.0095	-1.34	-	-1.51	-
233	Ceruloplasmin precursor (CP)	IP00047601	38	2	2	122983	5.44	-2.59	0.0047	-	-	-	-
282	Not identified							-2.62	0.002	-1.1	0.4	-1.69	0.035
283	Not identified							-2.4	0.0095	-1.09	0.59	-1.58	0.081
284	Albumin (A1B)	IP00022434	29	3	2	73881	6.33	-2.86	0.007	-	-	-	-
303	Not identified							-2.04	0.044	-1.07	0.72	-1.46	0.32
307	Not identified							-2.08	0.0062	-1.4	-	-1.99	-
361	Not identified							-1.63	0.0054	-1.12	-	-1.79	-
392	Albumin (A1B)	IP00022434	560	39	23	73881	6.33	-1.63	0.015	-	-	-	-
458	Immunoglobulin heavy constant mu protein (IGHM)	IP00385284	54	8	3	43543	5.13	-2.01	0.043	-1.62	0.26	-1.18	0.77
462	Not identified							-1.92	0.011	-1.76	0.21	1.07	0.76
499	Not identified							-1.39	0.025	-2.65	0.015	-2.72	0.031
611	Alpha-1-antichymotrypsin precursor Isoform 1 (SERPINA3)	IP00847635	65	12	6	47792	5.33	-1.55	0.0092	-1.17	0.28	-1.93	0.03
611	Kininogen-1 precursor Isoform LMW (KNG1)	IP00215894	37	4	2	48936	6.29	-1.55	0.0092	-1.17	0.28	-1.93	0.03
614	Albumin (A1B)	IP00022434	261	21	13	71317	5.92	1.6	0.028	-1.03	-	-1.02	-
618	Alpha-1-antichymotrypsin Isoform 1 (SERPINA3)	IP00550991	65	4	2	50737	5.42	-2.95	0.0093	-1.5	0.21	-1.31	0.34
636	Albumin (A1B)	IP00022434	229	15	11	71317	5.92	-2.04	0.026	-2.53	-	-1.31	-
636	Immunoglobulin heavy chain constant region alpha 1 protein (IGHA1)	IP00719233	106	7	4	54150	6.78	-2.04	0.026	-2.53	-	-1.31	-
646	Not identified							-4.09	0.0085	-2.12	-	-1.9	-
648	Albumin (A1B)	IP00022434	322	24	18	73881	6.33	-1.8	0.17	-1.89	0.04	-1.13	0.67
648	Keratin, vimentin, intermediate filament	IP00019359	68	5	2	62131	-1.8	0.17	-1.89	0.04	-1.13	0.67	-
654	Immunoglobulin heavy chain constant region alpha 1 protein (IGHA1)	IP00719233	65	8	5	54150	6.78	-1.99	0.036	-2.2	-	-1.22	-
654	Albumin (A1B)	IP00022434	51	5	7	73881	6.33	-1.99	0.036	-2.2	-	-1.22	-
678	IGHM protein	IP00472610	73	4	2	52665	-2.4	0.0065	-2.12	0.15	1.04	0.82	-
691	IGHG3	IP00829940	128	11	4	38759	8.36	-4.45	0.0011	-3.62	-	-2.57	-
691	Immunoglobulin heavy constant gamma 3 (IGHG3)	IP00472610	140	13	4	52665	-4.45	0.0011	-3.62	-	-2.57	-	-
693	Immunoglobulin heavy constant gamma 1 (IGHG1)	IP00423464	220	16	8	53011	8.84	-4.69	0.0096	-	-	-	-
693	Immunoglobulin heavy constant mu protein (IGHM)	IP00472610	105	8	3	52665	-4.69	0.0096	-	-	-	-	-
710	Not identified							-2.05	0.041	-1.41	0.18	-1.29	0.37
734	Alpha-2-HS-glycoprotein precursor (AHSG)	IP00022431	136	16	6	40098	5.43	-1.65	0.01	-1.36	-	1	-
740	Immunoglobulin heavy constant gamma 2 (IGHG2 Fragment)	IP00389007	32	5	2	46776	7.63	-3.24	0.012	-3.25	0.051	-1.28	0.5
749	Not identified							-1.58	-	-1.9	0.029	-1.14	-

**Table 6.1 2D-DIGE based analysis of the unfractionated pooled clinical sera and LC-MS-based protein identification.** Protein features displaying differential expression are shown. Values are the average ratio of abundance between different clinical conditions (healthy/malignant, healthy/benign and benign/malignant). T-test  $p$  values are given as a measure of confidence for each ratio measured. Protein name, IPI accession number, database search score, sequence coverage (%) and the number of matched peptides for each of the identified proteins are shown.

Spot No.	Protein AC	IP1 No.	Score	Seq. Cov (%)	No. peptides	Mw	pI	Av. Ratio	T-test	Healthy / Malignant	Healthy / Benign	Av. Ratio	T-test	Benign / Malignant
750	Immunoglobulin heavy constant gamma 2 (IgG2 Fragment)	IP00399007	166	12	5	46716	7.63	-3.78	0.0033	-3.13	0.042	-1.42	0.33	
750	Factor VII active site mutant immunocoagulate	IP00382606	120	5	8	77386	6.6	-3.78	0.0033	-3.13	0.042	-1.42	0.33	
750	Immunoglobulin heavy constant mu protein (IGHM)	IP00472610	107	7	3	52665	-	-3.78	0.0033	-3.13	0.042	-1.42	0.33	
753	Immunoglobulin heavy constant mu protein (IGHM)	IP00472610	80	13	4	52633	7.5	-3.87	0.007	-3.94	-	-1.92	-	
753	Factor VII active site mutant immunocoagulate	IP00382606	67	8	6	77386	6.6	-3.87	0.007	-3.94	-	-1.92	-	
753	Immunoglobulin heavy constant mu protein (IGHM)	IP00472610	101	9	4	52665	-	-3.87	0.007	-3.94	-	-1.92	-	
759	Not identified							-4.34	0.0078	-2.85	0.059	-1.8	0.18	
763	Immunoglobulin heavy constant gamma 1 (IgG1)	IP00384638	97	7	3	53503	8.74	-4.91	0.014	-2.14	0.17	-2.02	0.24	
763	Immunoglobulin heavy constant mu protein (IGHM)	IP00472610	245	9	5	52665	-	-4.91	0.014	-2.14	0.17	-2.02	0.24	
765	Immunoglobulin heavy constant gamma 1 (IgG1)	IP00423464	425	29	13	53011	8.84	-4.32	0.0081	-2.67	0.076	-1.85	0.19	
765	Immunoglobulin heavy constant mu protein (IGHM)	IP00472610	315	22	7	52665	-	-4.32	0.0081	-2.67	0.076	-1.85	0.19	
766	Not identified							-4.69	0.0091	-2.17	0.14	-2.02	0.2	
782	Haptoglobin (HP)	IP00431645	98	21	7	31647	8.84	-2.24	0.095	-1.14	0.3	-1.57	0.027	
782	Abolipoprotein A-IV precursor (APOA4)	IP00304273	54	10	4	45371	5.28	-1.24	0.095	-1.14	0.3	-1.57	0.027	
782	Albumin (ALB)	IP0022434	36	4	3	73881	6.33	-1.24	0.095	-1.14	0.3	-1.57	0.027	
800	Haptoglobin (HP)	IP00431645	76	12	5	31647	8.84	-2.92	0.053	-1.29	0.47	-2.58	0.022	
808	Haptoglobin (HP)	IP00431645	363	41	16	31647	8.84	-3.37	0.012	-1.25	0.35	-2.69	0.021	
814	Haptoglobin (HP)	IP00431645	434	41	16	31647	8.84	-2.94	0.019	-1.27	-	-2.43	-	
814	Alpha-1-antitrypsin precursor isoform 1 (SERPINA1)	IP00553177	159	21	6	46878	5.37	-2.94	0.019	-1.27	-	-2.43	-	
822	Haptoglobin (HP)	IP00431645	162	25	10	31647	8.48	-2.71	0.032	-1.38	0.24	-2.35	0.0086	
826	Haptoglobin (HP)	IP00431645	453	43	19	31647	8.48	-2.29	0.072	-1.38	0.32	-2.21	0.018	
826	Albumin (ALB)	IP0022434	93	7	5	73881	6.33	-2.29	0.072	-1.38	0.32	-2.21	0.018	
826	Abolipoprotein A-IV precursor (APOA4)	IP00304273	37	10	4	45371	5.28	-2.29	0.072	-1.38	0.32	-2.21	0.018	
833	Haptoglobin (HP)	IP00431645	555	43	21	31647	8.48	-1.55	0.014	1.21	0.57	1.08	0.72	
842	Complement C2 precursor	IP00739237	53	7	3	45642	4.94	-2.03	0.011	-1.81	0.018	-1.34	0.11	
848	Haptoglobin (HP)	IP00431645	54	8	5	31647	8.48	-2.46	0.014	1.02	0.87	-1.93	0.36	
850	Haptoglobin (HP)	IP00431645	115	21	8	31647	8.48	-2.2	0.024	-1.29	0.26	-2.31	0.036	
850	Albumin (ALB)	IP00745872	39	2	1	69366	5.92	-2.2	0.024	-1.29	0.26	-2.31	0.036	
852	Not identified							-1.55	0.054	1.1	0.65	-2.82	0.025	
855	Not identified							-1.75	0.028	1.12	-	-3.15	-	
898	Not identified							-3.5	0.024	-4.85	-	-1.81	-	
899	Not identified							-3.43	0.015	4.62	-	-1.68	-	
913	Complement C4A precursor (C4AC4B)	IP00032258	18	0	2	192650	6.65	-1.55	0.015	-2.32	-	-1.61	-	
928	Not identified							-3.48	0.022	-4.95	-	-1.97	-	

Table 6.1 continued

Two protein features that were found to be differentially expressed between healthy and benign samples and also healthy and malignant samples were identified as immunoglobulin heavy constant gamma 2 (IGHG2, spot 750 which also contains IGM and factor VII) and complement C3 precursor (spot 842). Three of the five protein features differentially expressed between healthy from malignant and benign and malignant were identified. Of these haptoglobin was identified in two spots (808 & 822) and alpha-1-antichymotrypsin precursor (SERPINA3) and kininogen-1 precursor (Alpha-2-thiol proteinase inhibitor KNG1) were both found in spot 611. The 2D gel migration of the identified differentially expressed protein features is shown in Figure 6.6. Notably, several spots yielded the same protein identification, revealing multiple isoforms of the same gene product.



**Figure 6.6 Representative gel image displaying positions of differentially expressed proteins identified from the unfractionated samples.** Differentially expressed protein features were identified by MS. The locations of several differentially expressed proteins including albumin (ALB), haptoglobin (HP), apolipoprotein AIV (APOA4), isoform 1 of alpha-1-antichymotrypsin (SERPINA3), alpha-2-HS-glycoprotein precursor (AHSG), immunoglobulin heavy (IGHG1) and light chain (IGL), complement factor C4 (C4A;B) are shown.

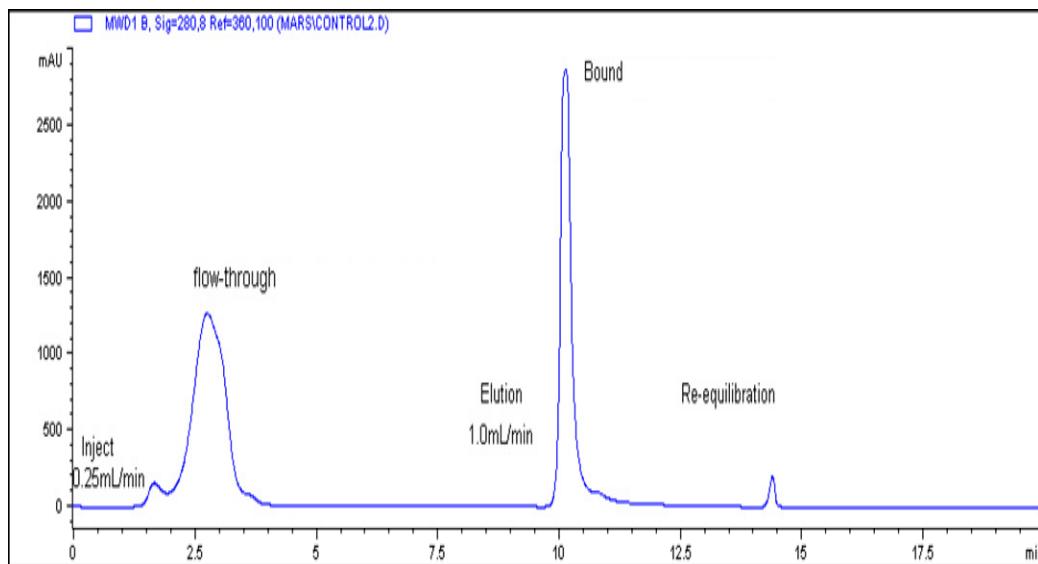
It is apparent from these results that mostly very abundant serum proteins have been identified. Although of interest, these are unlikely to be specific markers of ovarian cancer. The detection of only high abundance proteins in the unfractionated sera is likely to mask lower abundance species and potential disease markers. Indeed, multiple isoforms of the proteins were detected in different spots. Moreover, numerous spots contained more than one protein. The identification of multiple proteins in a single spot makes it very difficult to attribute any changes in spot abundance to a specific protein this is a major drawback of the 2-DE technique. To probe deeper into the serum proteome, the removal of these high-abundance proteins is essential.

### **6.2.2 Multiple Affinity Removal System (MARS)-based depletion of abundant proteins from pooled sera.**

It is known that twenty-two high abundance proteins constitute up to 99% of the total protein content of serum [Fusaro and Stone, 2003]. It is hypothesised that putative biomarkers of interest would be found in the remaining 1%. Thus, to mine deeper into the serum proteome the pooled clinical sera were fractionated with the MARS depletion column (Agilent Technologies), which comprises of polyclonal antibodies designed to effectively remove 85-90% of the top seven most abundant proteins (albumin, IgG, transferrin, haptoglobin, IgA, antitrypsin and fibrinogen) which hinder the detection of lower abundance proteins [Chromy et al., 2004; Echan et al., 2005]. The abundant proteins bind to the column and the unbound fraction of depleted serum was collected as the ‘flow through’. The bound fraction was also recovered by acid elution for analysis.

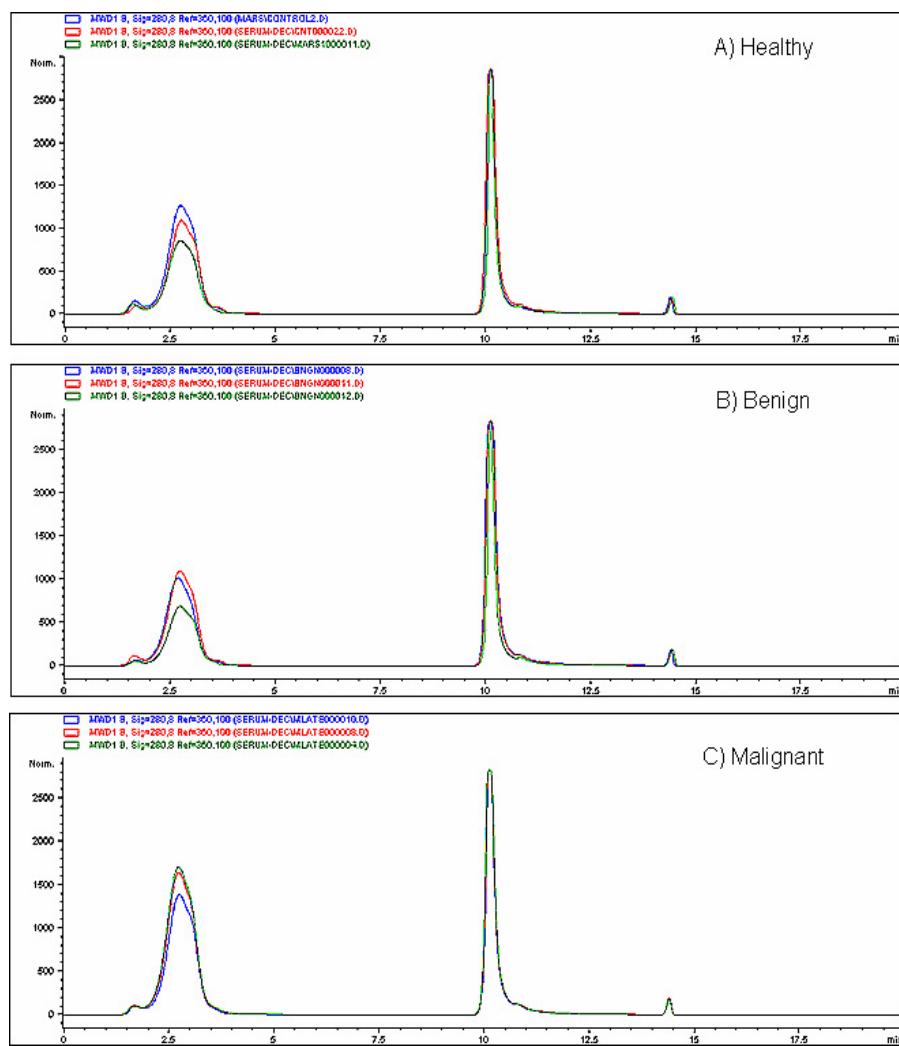
Briefly, from each pool 30  $\mu$ L of serum was diluted five times in Buffer A containing protease inhibitors (COMPLETE, Roche) and spun down at 16,000  $\times$  g at room temperature for 5 minutes. Automated multiple sample injection (2 per run) on an Agilent 1100 HPLC system was set up for 30  $\mu$ L of diluted serum sample per injection in Buffer A at a flow rate of 0.25 ml/min for 9 min. Flow-through fractions

(~0.75 ml per injection) containing the unbound protein species were collected manually at 2-4 min into 1 ml Eppendorf tubes and stored at -20°C until further analysis. The bound fractions were eluted with 100% Buffer B at a flow rate of 1 ml/min for 3.5 min. The column was regenerated by equilibrating with Buffer A for 10 min as shown in Figure 6.7.



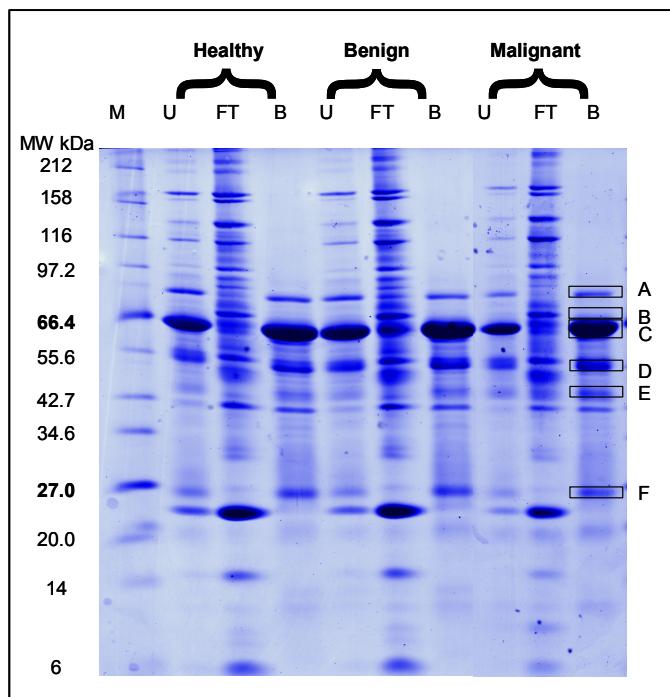
**Figure 6.7 HPLC chromatograph of MARS fractionated sera.** An aliquot of pooled clinical sera was fractionated on a MARS HPLC column (Agilent Technologies). 30  $\mu$ L of sample was injected at a flow rate of 0.25 mL/min in Buffer A. The unbound flow through was collected over 3 min (~0.75 ml) and stored at -20°C prior to downstream 2D-DIGE analysis. The bound proteins were eluted at 1ml/min in Buffer B and collected for 1D SDS-PAGE analysis.

Once the abundant proteins had been removed from each pooled serum sample approximately 10-15% of the starting protein concentration remained in the flow-through fraction. In order to obtain sufficient amounts of the depleted protein fraction for 2D-DIGE analysis, 10 aliquots of each clinical condition were fractionated with the MARS column. Overlaid traces of 3 representative runs from each condition analysed are shown in Figure 6.8. The MARS column was found to be highly reproducible. The variability seen in the flow-through peak can be attributed to inconsistencies in the automated injection on the Agilent 1100 HPLC system.



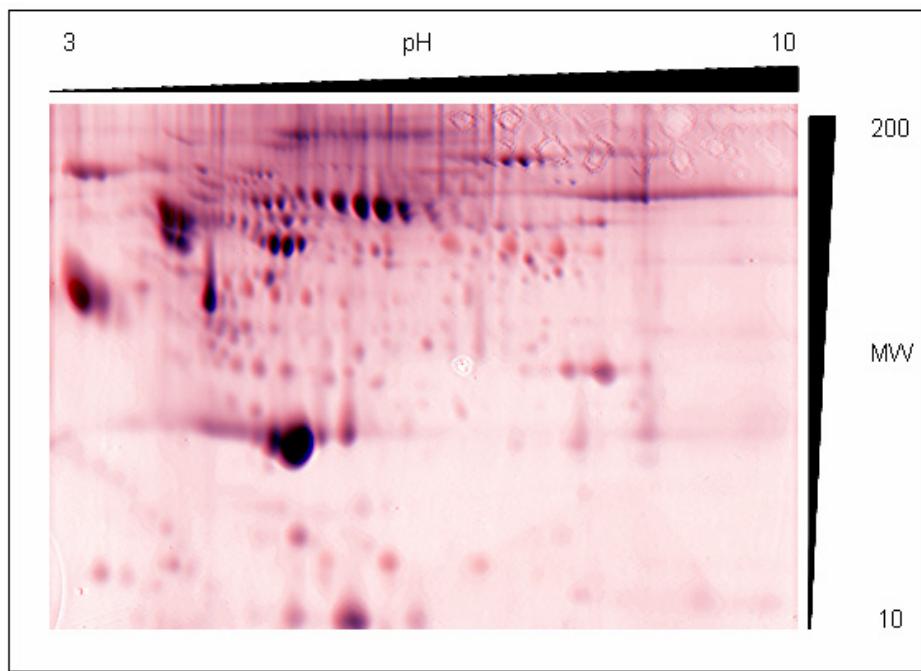
**Figure 6.8 HPLC chromatograph overlays.** MARS depletion of pooled clinical sera was repeated 10 times. Representative overlays of 3 runs for A) healthy, B) benign and C) malignant late stage conditions are shown.

Prior to 2D-DIGE analysis, the unbound fractions from the repeated MARS runs were pooled into their respective clinical groups. The protein concentration was determined using the Pierce BCA assay. Concentrations of 1.02 mg/mL, 1.20 mg/mL and 1.01 mg/mL were recovered for the healthy, benign and malignant conditions respectively. Fractionated samples were separated on a 1D gel to assess the depletion efficiency of the column. Briefly, equal amounts of protein (25 µg) from the unfractionated sera, unbound and bound fractions from the MARS column were separated on a 12% SDS-PAGE gel. The 1D gel showed enrichment of numerous protein bands particularly above 40 kDa and a reduction in the intensity of the 66 kDa albumin band and 80kDa transferrin band as shown in Figure 6.9.

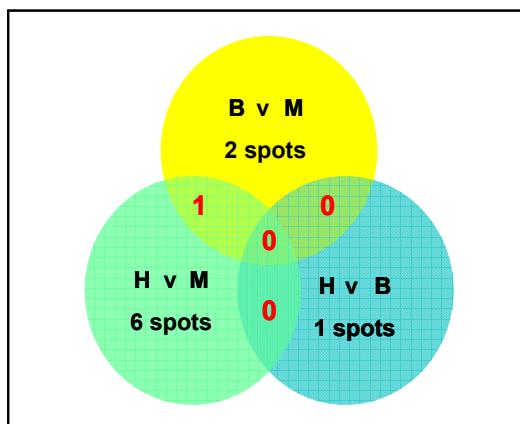


**Figure 6.9 1D SDS-PAGE comparison of MARS fractionated samples.** 25µg of protein from unfractionated (U), flow-through (FT) and bound (B) fractions for each clinical condition were run on a 12% SDS PAGE gel which was then stained with CCB. Lane 1 contained the MW marker (M). Gel bands A) transferrin, B) alpha-1-antitrypsin, C) albumin, D) IgG, E) IgA and F) haptoglobin light chain.

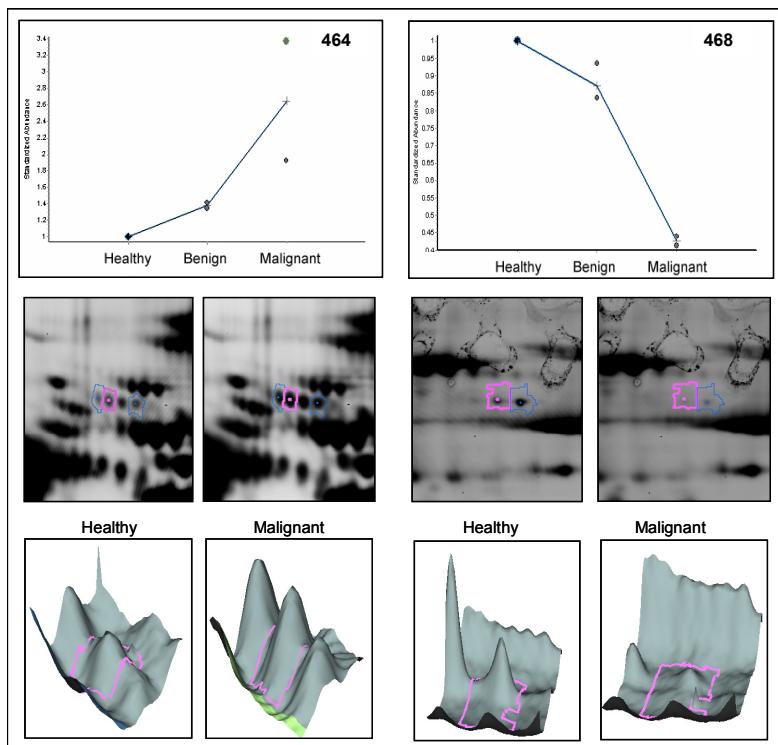
Flow through fractions were desalted and concentrated and then subjected to 2D-DIGE analysis in quadruplicate as previous unfractionated samples. A total of 797 features were detected in the master gel (Figure 6.10). Quantitative analysis showed 4 protein spots were up-regulated in the malignant samples versus the healthy and 3 were down-regulated ( $\geq 1.5$  average-fold change in abundance,  $p < 0.05$ ,  $n = 4$ ). Only 1 protein spot was differentially expressed between the healthy and benign conditions and this was up-regulated in the benign condition. Three protein spots were differentially expressed between the benign and malignant conditions. Of these, 1 was up-regulated in the malignant condition and 2 were down-regulated in the malignant condition versus the benign. In total 10 differentially expressed protein features were found between the 3 conditions (Figures 6.11 and 6.12).



**Figure 6.10 Gel image of MARS fractionated sera used as ‘master’ gel in DeCyder image analysis.** This figure represents the overlaid fluorescent images derived from the MARS fractionated sera labelled with Cy3 Malignant (red) and Cy5 Healthy (blue). This image was prepared using Adobe Photoshop.



**Figure 6.11 Venn diagram showing the number of differentially expressed protein features in MARS depleted sera.** The number of protein features that displayed a  $\geq 1.5$  average fold-change in abundance ( $p < 0.05$ ) and the overlap between the three clinical conditions is shown.

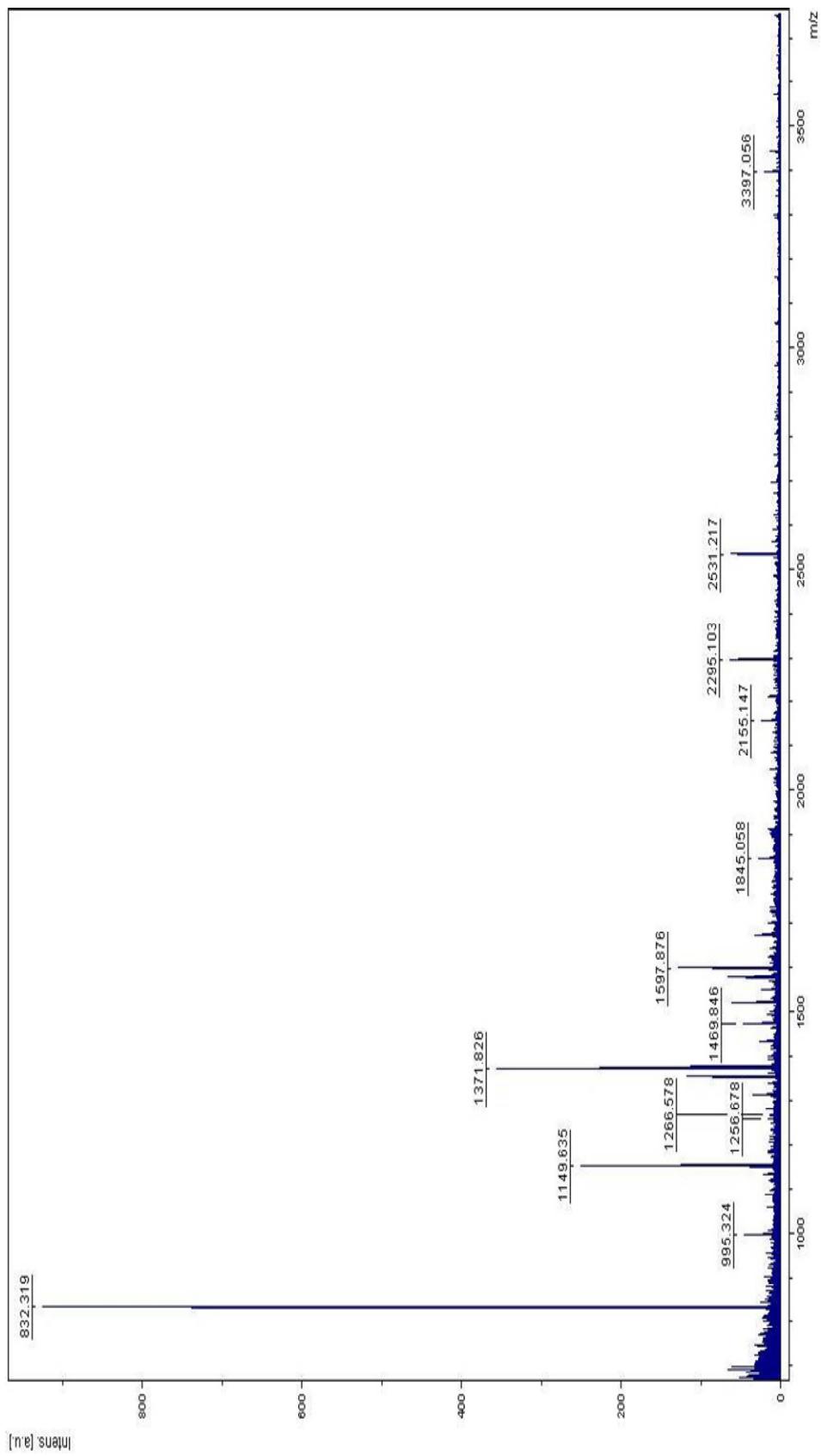


**Figure 6.12 Examples of proteins displaying clinical-stage dependent changes in the MARS fractionated samples.** Protein spots 464 and 468 displayed differential expression between clinical conditions. Graphs were derived from DeCyder image analysis where the standardised abundance is the ratio of the volume of a gel feature from the healthy condition *versus* the volume of the corresponding gel feature in the malignant condition. Data points are shown for quadruplicate measurements with lines joining the average values. 3D images of spots are shown for the healthy and malignant conditions.

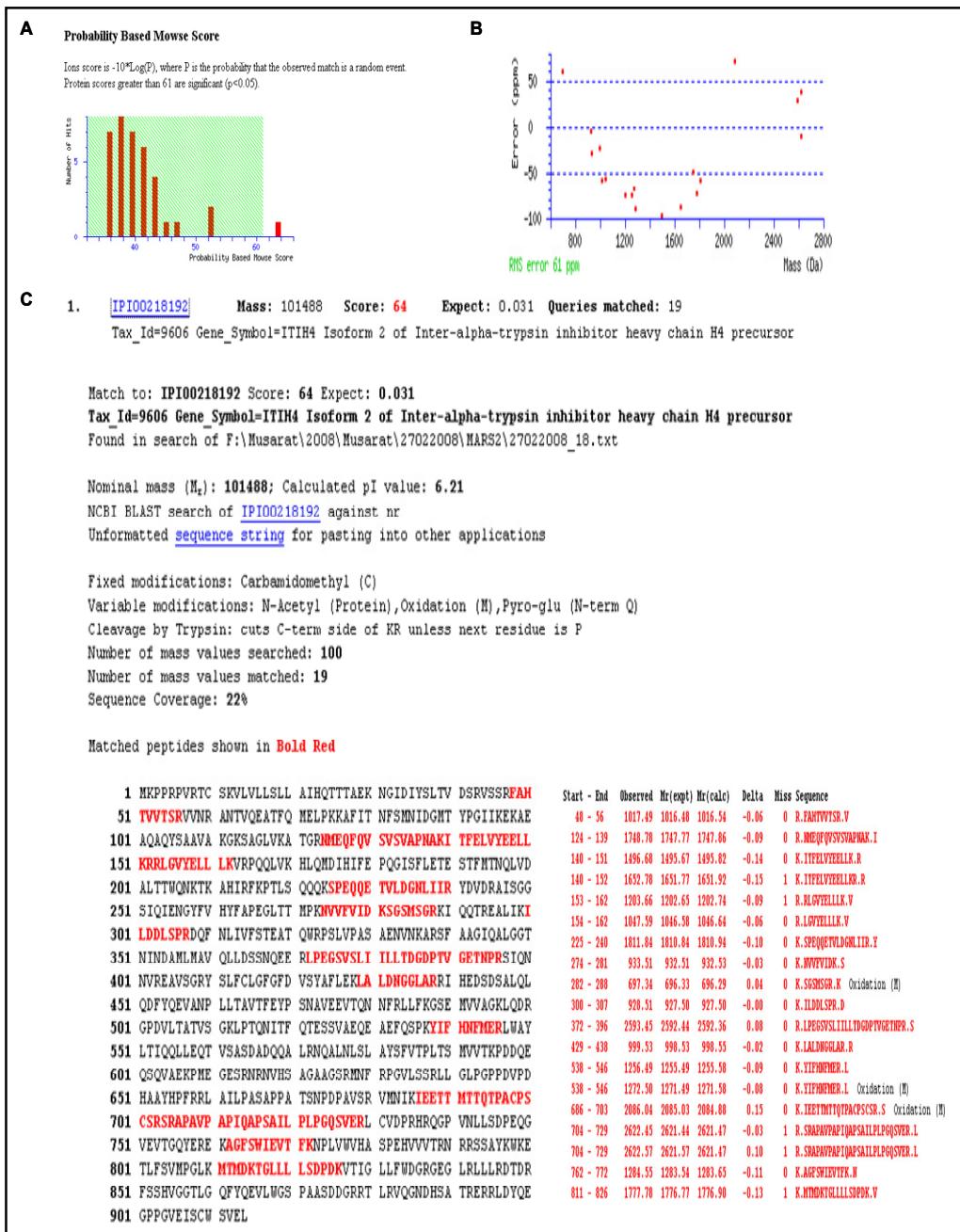
Differentially expressed spots were excised, trypsin digested and the peptide mixtures were analysed by MALDI-TOF PMF or LC-MS/MS. The list of peptide and fragment ions masses generated was then searched against the updated IPI Human database using Mascot. All of the 10 differentially expressed protein features yielded proteins hits of high confidence, although a number yielded more than 1 protein identification (Table 6.3). For example, as shown in Figure 6.12 spot 464 yielded hits for inter-alpha-trypsin inhibitor heavy chain H4 precursor (ITIH4), histidine-rich glycoprotein precursor (HRG), alpha-1B-glycoprotein precursor (A1BG), afamin precursor (AFM), prothrombin precursor (F2 Fragment) and vitamin K-dependent protein S precursor (PROS1). All the differentially expressed protein spots were identified with high confidence (Table 6.2). Examples of MALDI-TOF PMF and LC-MS/MS based protein identifications are shown in Figure 6.13 and 6.14, respectively.

Spot No.	Protein Name	IPI No.	Score	Seq. Cov (%)	No. peptides	Mw	pl	Av. Ratio	Healthy / Malignant		Benign / Malignant
									T-test	Av. Ratio	
242	Ceruloplasmin precursor (CP)	IPI00017601	70	10	7	1229883	5.44	1.05	-	-1.42	0.0086
412	Inter-alpha-trypsin inhibitor heavy chain H4 precursor (ITIH4) Isoform 1	IPI00294193	62	21	20	103489	6.51	-2.07	0.018	-	-
459*	Inter-alpha (Globulin) inhibitor H4 (Plasma Kallikrein-sensitive glycoprotein)	IPI00556036	401	22	16	78971	5.72	-2.51	0.023	-1.15	0.67
459*	Histidine-rich glycoprotein precursor (HRG)	IPI00022371	137	10	5	60510	7.09	-2.51	0.023	-1.15	0.67
459*	Prothrombin precursor - (F2 Fragment)	IPI00019568	95	7	4	71475	5.64	-2.51	0.023	-1.15	0.67
459*	Alpha-1B-glycoprotein precursor (A1BG)	IPI00022895	52	7	2	54809	5.58	-2.51	0.023	-1.15	0.67
459*	Vitamin K-dependent protein S precursor (PROS1)	IPI00294004	46	4	3	77127	5.48	-2.51	0.023	-1.15	0.67
464*	Inter-alpha-trypsin inhibitor heavy chain H4 precursor (ITIH4) Isoform 1	IPI00294193	289	11	12	103489	6.51	-2.65	0.015	-1.3	0.44
464*	Histidine-rich glycoprotein precursor (HRG)	IPI00022371	242	19	9	60510	7.09	-2.65	0.015	-1.3	0.44
464*	Alpha-1B-glycoprotein precursor (A1BG)	IPI00022895	189	17	6	54809	5.58	-2.65	0.015	-1.3	0.44
464*	Afamin precursor (AFM)	IPI00019943	92	8	3	70963	5.64	-2.65	0.015	-1.3	0.44
464*	Prothrombin precursor, (F2 Fragment)	IPI00019568	86	7	4	71475	5.64	-2.65	0.015	-1.3	0.44
464*	Vitamin K-dependent protein S precursor (PROS1)	IPI00294004	61	4	3	77127	5.48	-2.65	0.015	-1.3	0.44
468*	Complement Factor B precursor (CFB Isoform 1 of Fragment)	IPI00019691	123	5	4	88847	6.67	2.43	0.0056	1.09	0.22
468*	Alpha-2-macroglobulin precursor, (A2M)	IPI00478003	102	5	6	164600	6	2.43	0.0056	1.09	0.22
471*	Histidine-rich glycoprotein precursor (HRG)	IPI00022371	364	21	11	60510	7.09	-1.89	0.044	1.21	0.33
471*	Inter-alpha (Globulin) inhibitor H4 (Plasma Kallikrein-sensitive glycoprotein)	IPI00556036	261	13	10	78971	5.72	-1.89	0.044	1.21	0.33
471*	Complement component C9 precursor	IPI00022395	196	16	9	66615	5.43	-1.89	0.044	1.21	0.33
471*	Alpha-1B-glycoprotein precursor (A1BG)	IPI00022895	86	10	4	54809	5.58	-1.89	0.044	1.21	0.33
472	Inter-alpha-trypsin inhibitor heavy chain H4 precursor (ITIH4) Isoform 2	IPI00218192	64	22	19	101488	6.21	3.83	0.029	-1.78	0.36
566	Alpha-1B-glycoprotein precursor (A1BG)	IPI00022895	72	37	16	54809	5.58	-1.38	0.068	-1.08	0.43
566	Complement component C9 precursor	IPI00022395	63	24	18	66615	5.43	-1.38	0.068	-1.08	0.43
657	Complement factor B precursor (CFB Fragment) Isoform 1	IPI00019691	116	3	7	86847	6.67	1.43	0.087	-1	0.99
766	Alpha-2-macroglobulin precursor, (A2M)	IPI00478003	62	13	19	164600	6	1.73	0.037	1	0.99
										-1.13	0.48

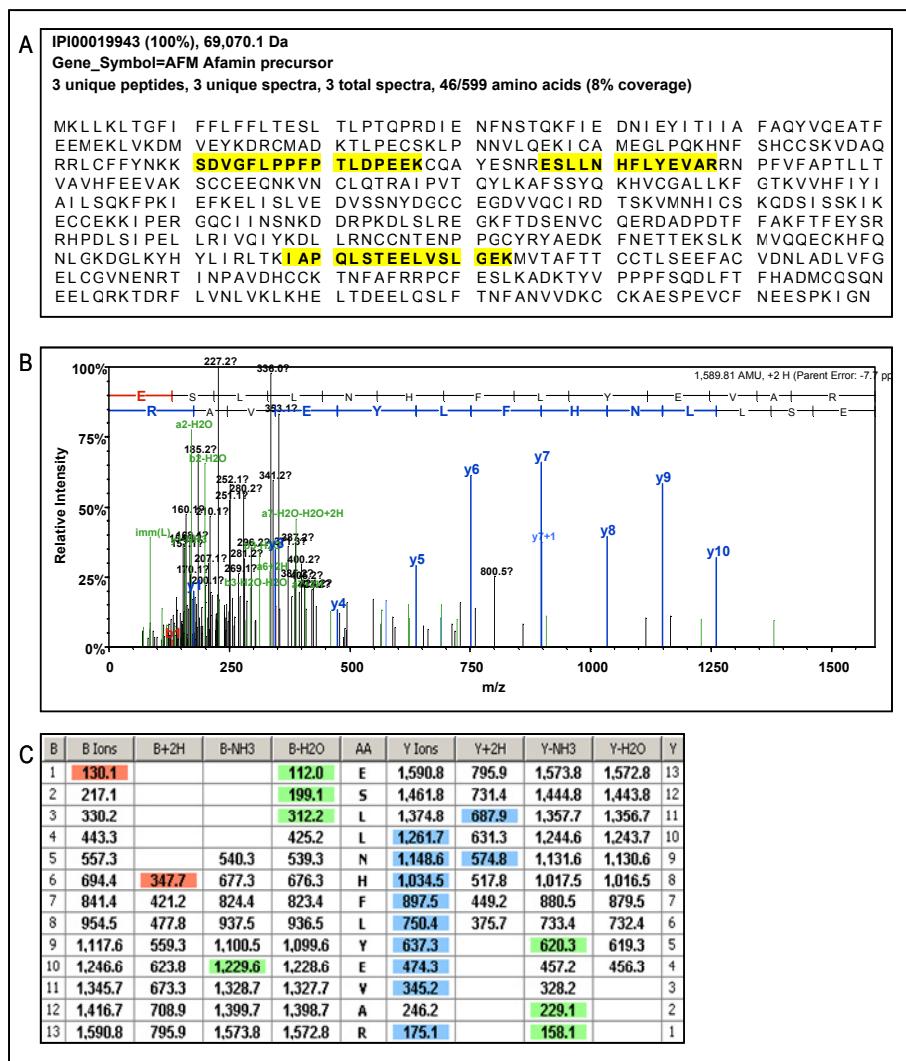
**Table 6.2 2D-DIGE based analysis of the MARS-depleted sera and MS-based protein identifications.** Protein features displaying differential expression are shown. Values are average ratio of abundance between different clinical conditions (healthy/malignant, benign/malignant, and healthy/benign). T-test p values are given as a measure of confidence for each ratio measured. Protein name, IPI accession number, Mascot score, sequence coverage (%) and number of matched peptides for each of the identified proteins are shown. Those marked with \* were identified by LC-MS/MS

**Figure 6.13 A. An example of a differentially expressed protein feature from the MARS fractionated sera identified by MALDI-TOF PMF.**

The trypsin digested peptides mixture from spot number 472 was analysed by MALDI-TOF PMF. The resulting spectrum was internally calibrated with trypsin autolysis peaks (842.51 & 2211.10). Prominent peaks in the mass range 700-4000 were used to generate a peptide mass fingerprint which was searched against the IPI-Human database using the Mascot search engine.

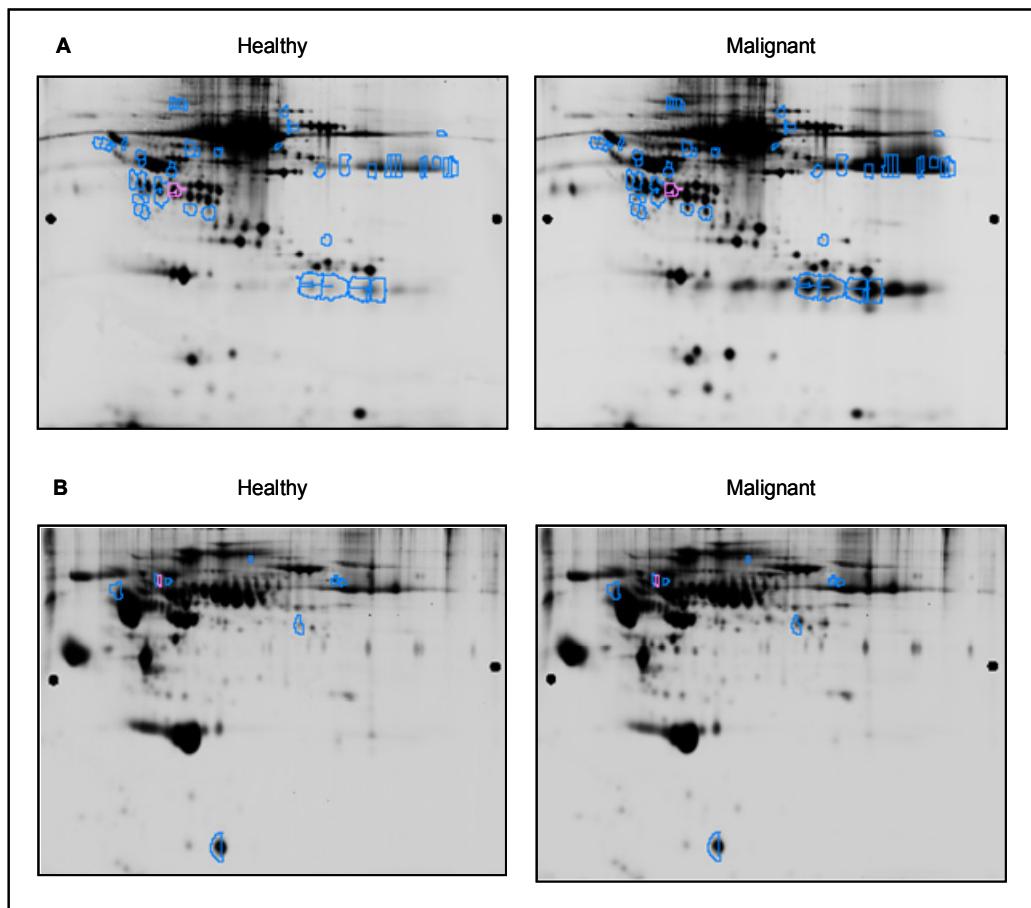


**Figure 6.13B. An example of MALDI-TOF PMF protein identification.** The trypsin digested peptides mixture from spot number 472 was analysed by MALDI-TOF PMF. The resulting spectrum was internally calibrated with trypsin autolysis peaks (842.51 & 2211.10). Prominent peaks in the mass range 700-4000 Da were used to generate a peptide mass fingerprint which was searched against the IPI-Human database using the Mascot search engine. A) Probability based Mowse score, B) RMS based error scores for the peptide mass in the PMF and C) details of the identified protein's score and sequence including matched peptides are shown here (more examples are shown in Appendix 3).



### 6.2.3 Comparison of unfractionated sera and MARS-depleted sera

The numbers of expressed features from the unfractionated clinical sera were compared with the MARS-fractionated sera. Results demonstrated that fewer (~100) protein features were detected in the MARS fractionated gels, suggesting that the depleted proteins exist as multiple isoforms or there is a loss of bound protein species. The removal of the high abundant proteins would be expected to result in an enrichment of lower abundance proteins by facilitating a higher load of these less abundant protein species for 2D-DIGE based analysis (Figure 6.15). However, results show that the number of lower abundant proteins identified was modest.

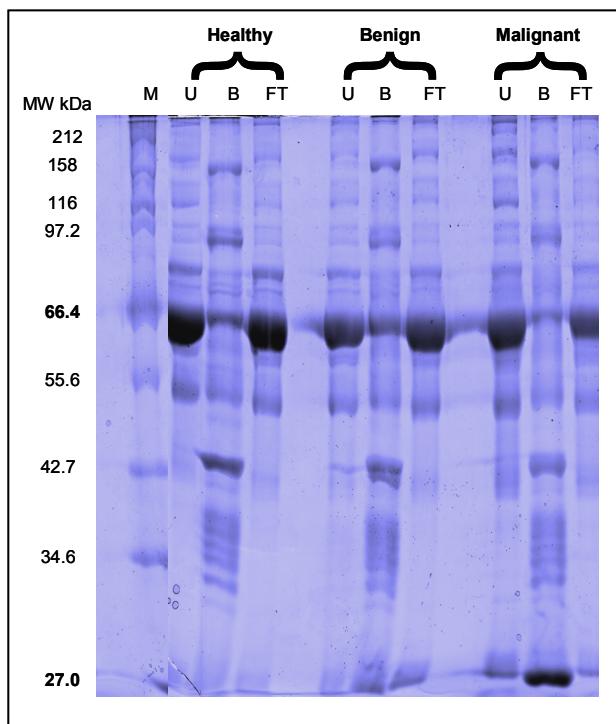


**Figure 6.15 Differentially expressed protein features from MARS-depleted and unfractionated pooled clinical sera.** Quantitative analysis found 48 differentially expressed protein features in A) the unfractionated samples and 10 in B) the MARS depleted fractions. Cy-dye labelled gel images from the healthy and malignant conditions are shown, created using the DIA module of DeCyder.

#### 6.2.4 ProteoMiner based dynamic range compression and protein enrichment.

The ProteoMiner protein enrichment kit is designed to “compress” the serum protein dynamic range and is comprised of a highly diverse combinatorial peptide library immobilised on beads in a spin column format. Theoretically the library contains binding sites for most, if not all, proteins in a sample. The high abundance proteins saturate their affinity ligands and the excess protein is washed away. The medium and lower abundance proteins are concentrated on their specific affinity ligands. Thus, the dynamic range of protein concentrations is reduced, while representatives of all proteins within the original sample remain intact. Briefly, 1 mL of each pooled serum sample incubated with ProteoMiner beads and unbound material collected. The columns were then and the bound proteins were eluted with 100  $\mu$ L of 2D lysis buffer (8 M urea, 2 M thiourea, 4% CHAPS, 0.5% NP40 and 10 mM Tris pH 8.3). The elution step was repeated twice to ensure all bound material was collected and the fractions pooled. Protein yields were 632.4  $\mu$ g, 687.4  $\mu$ g and 786.75 $\mu$ g for the healthy, benign and malignant pools respectively.

Prior to 2D-DIGE analysis the ProteoMiner fractionated samples were separated on a 1D SDS-PAGE gel to assess the enrichment efficiency. Briefly, equal amounts of protein (25  $\mu$ g) from the unfractionated pooled sera, bound and unbound fractions from the ProteoMiner column were separated on a 12 % SDS-PAGE gel. The 1D gel showed enrichment of numerous protein bands particularly below 50 kDa and a reduction in the intensity of the 66 kDa albumin band (Figure 6.16).



**Figure 6.16 1D SDS-PAGE comparison of ProteoMiner fractionated samples.** 25 $\mu$ g of protein from unfractionated (U), flowthrough (FT) and bound (B) fractions for each clinical condition were run on a 12% SDS PAGE gel which was then stained with CCB. Lane 1 contained the molecular weight marker (M).

2D-DIGE analysis of the ProteoMiner fractionated sera was performed in parallel with a repeat analysis of freshly prepared MARS-depleted fractions for comparison of the two strategies. To facilitate spot matching pools of fractionated sera were additionally labelled with Cy2 as an internal standard which was run on all gels as shown in Table 6.3.

**A) ProteoMiner**

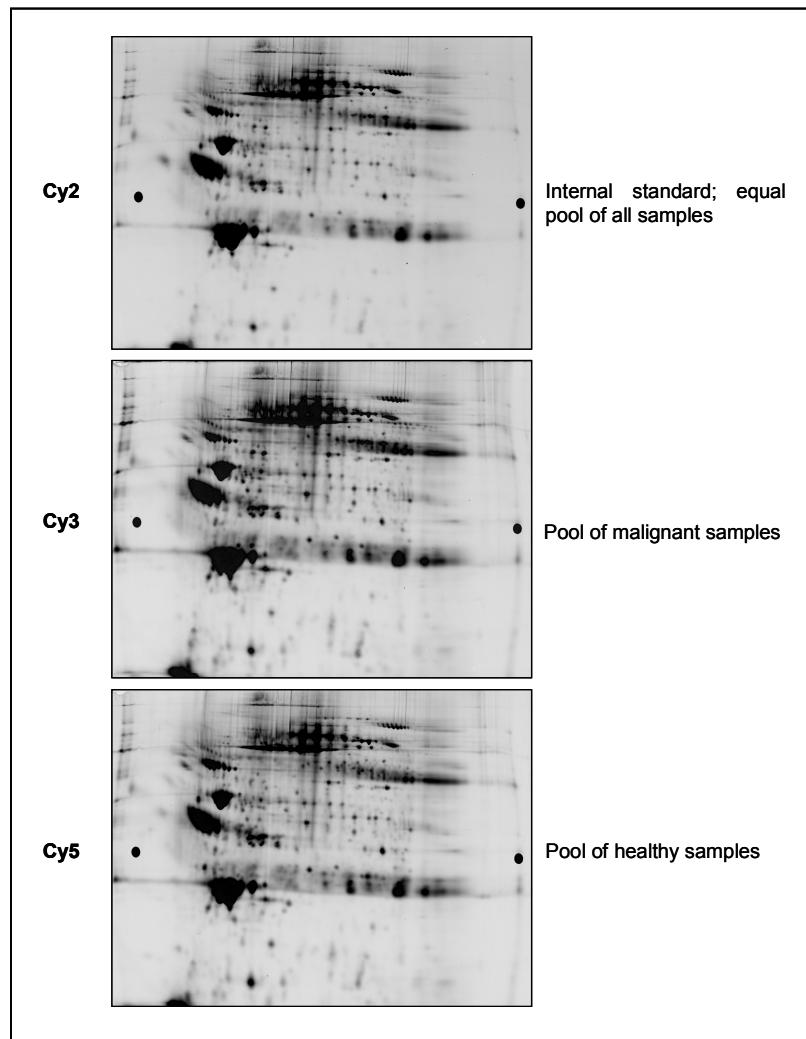
Gel No.	Gel 01	Gel 02	Gel 03	Gel 04	Gel 05	Gel 06
Cy dye						
Cy 3	Malignant	Benign	Healthy	Malignant	Healthy	-
Cy 5	Healthy	Malignant	Benign	Benign	Malignant	-
Cy 2	Pool	Pool	Pool	Pool	Pool	-

**B) MARS**

Gel No.	Gel 01	Gel 02	Gel 03	Gel 04	Gel 05	Gel 06
Cy dye						
Cy 3	Healthy	Healthy	Malignant	Benign	Malignant	Benign
Cy 5	Benign	Malignant	Benign	Healthy	Healthy	Malignant
Cy 2	Pool	Pool	Pool	Pool	Pool	Pool

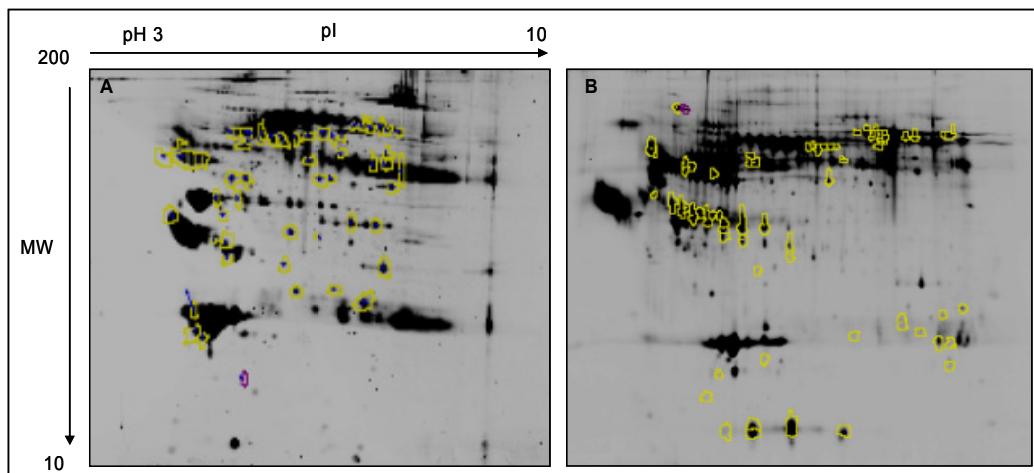
**Table 6.3 Experimental design for 2D-DIGE analysis of fractionated pooled clinical sera.** A) 2D-DIGE based comparison of ProteoMiner fractionation of pooled clinical sera. The table shows the sequence of Cy3 and Cy5 labelled sample triplicates for the healthy and benign conditions and quadruplicates for the malignant condition run on each gel (120 $\mu$ g protein per dye), including the Cy2 labelled pool. B) 2D-DIGE based comparison of MARS fractionated pooled sera. The table shows the labelling of quadruplicate samples from each clinical condition with Cy3 or Cy5 (80 $\mu$ g protein per dye), including the Cy2 labelled pool run on each gel.

Image analysis was carried out using DeCyder software. Briefly, fluorescent images from the same 2D gel were automatically curated, normalised, matched and spot abundances calculated in the DIA module. Then, matching and comparison of protein features across different gels was performed in the BVA module using internal landmarks comprising abundant protein features present in all the Cy2 images. Examples of Cy2, Cy3 and Cy5 images from the ProteoMiner set are shown in Figure 6.17.



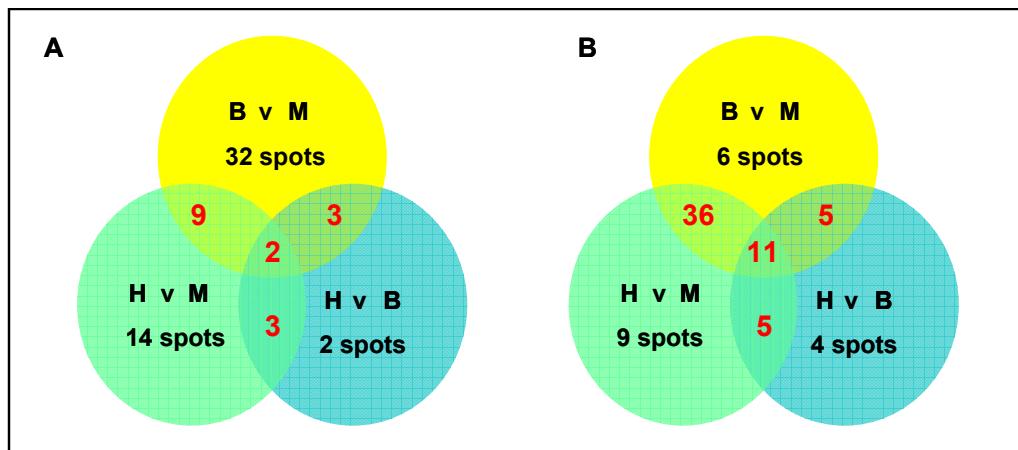
**Figure 6.17 Representative Cy2, Cy3 and Cy5 fluorescence gel images obtained from a single 2D gel in the ProteoMiner 2D-DIGE experiment.** Equal amounts of Cy3 and Cy5 labelled protein samples, derived from pooled clinical sera were mixed with an equal amount of Cy2-internal standard pool. Proteins were separated by 2D gel electrophoresis, and the gel was scanned at the appropriate excitation/emission wavelengths to generate the superimposable set of three images shown.

Statistical analysis was performed where the average abundances of protein features for each condition were compared. In the BVA analysis, 697 and 1468 protein features were found in the master gel of the ProteoMiner and MARS-fractionated samples respectively. However, the high number was due to streaking of gel spots leading to poorer spot definition. Protein features displaying a  $\geq 1.5$  average fold-change in abundance, displaying reproducible changes ( $p < 0.01$ ) and matching on all images, were selected for MS-based identification; These features are marked on the gel images in Figure 6.18 (the selection criteria were made more stringent in this experiment to reduce the number of false positives).



**Figure 6.18 Representative gels displaying the position of differentially expressed proteins.** Protein features displaying  $\geq 1.5$  average fold-change in abundance ( $p < 0.01$ ) are shown in yellow in A) ProteoMiner-fractionated and B) MARS-fractionated samples.

Individual analysis and statistical evaluation of differences between the ProteoMiner-fractionated samples and the MARS-depleted samples revealed a total of 65 and 76 differentially expressed protein features, respectively (Figure 6.19). There was considerable overlap in spot numbers in each pairwise comparison of clinical conditions, particularly for the MARS-fractionated samples. The inclusion of the Cy2 labelled internal standard (pool of all samples) made spot matching across gels much easier and enabled the identification of a high number of differentially expressed proteins features which may have otherwise been missed. Gels were post-electrophoretically stained with CCB and gel images matched to the fluorescent images. A pick list of proteins of interest was generated, spots were excised robotically, trypsin digested and subjected to MS-based protein identification (examples are shown in Appendix 4 and 5 for ProteoMiner and MARS 2, respectively).



**Figure 6.19** Venn diagrams showing the number of differentially expressed protein spots in the fractionated samples and overlapping spots between the three clinical conditions. The average ratio in abundance of each matched protein feature was calculated between clinical conditions. Those displaying a  $\geq 1.5$  average fold-changes in abundance ( $p < 0.01$   $n=3$ ) were selected for identification. Numbers of spots are shown for A) ProteoMiner and B) MARS-fractionated samples with the number of overlapping spots are shown in red.

### 6.2.5 Protein identification by mass spectrometry

Differentially expressed protein spots from the 2D-DIGE experiments were initially subjected to identification by MALDI-TOF MS peptide mass fingerprinting and MASCOT database searching (see Chapter 2). In cases where peptide mass fingerprints could not be confidently matched to available protein sequences, LC-MS/MS was used to obtain peptide sequence information for identification. Of the 65 differentially expressed protein features from the ProteoMiner fractionation, confident protein hits were obtained for 53 of these (Table 6.4). Almost all the protein features yielded single protein identifications, except for 5 spots where 2 protein identifications had significant scores. Of the unidentified protein features, some were of low abundance and gave poor spectra, whilst the others stained well with CCB and gave spectra of good quality, but could not be identified from database searches.

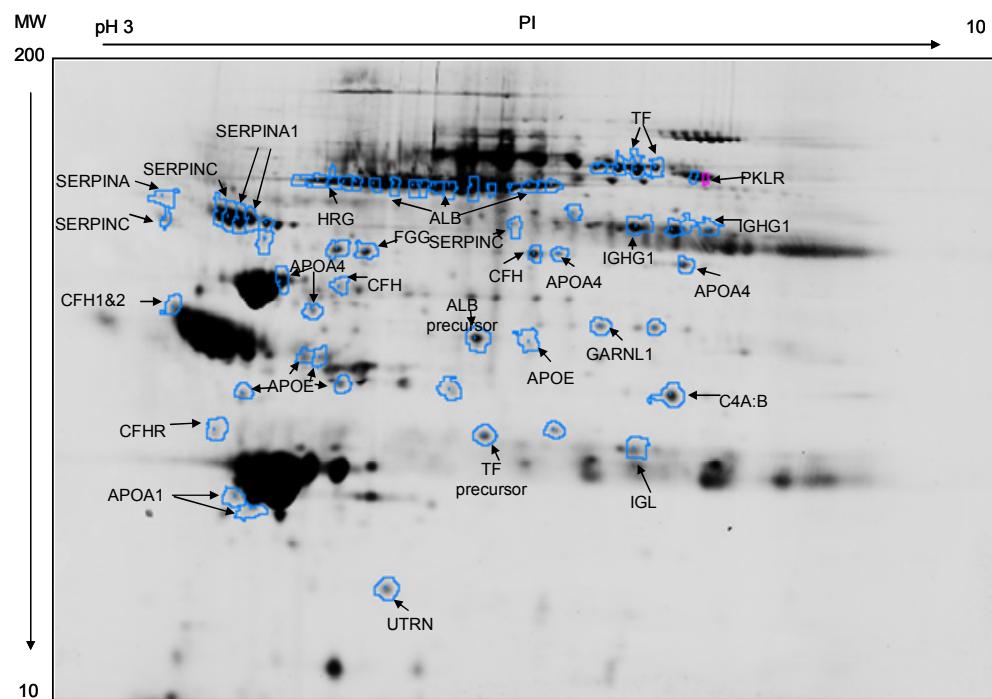
Spot No.	Protein Name	IPI No.	Score	Seq. Cov (%)	No. peptides	Mw	pI	Av. Ratio	T-test	Healthy/Malignant	Healthy/Benign	Av. Ratio	T-test	Benign/Malignant
149	Not Identified													
153	Serotransferrin precursor (TF)	IPI0022463	46	4	2	79280	6.81	1.24	0.051	-1.28	0.018	1.59	0.0019	
157	Not Identified													
160*	Serotransferrin (TF)	IPI0022463	59	22	16	79280	6.81	1.31	0.00016	-1.16	0.17	1.55	0.0012	
164	Not Identified													
165	Histidine-rich glycoprotein precursor (HRG)	IPI0022371	59	30	16	60510	7.09	1.48	0.00021	-1.13	0.25	1.73	0.00047	
174*	Serotransferrin (TF)	IPI0022463	59	20	17	79280	6.81	1.31	0.007	-1.28	0.022	1.9	2.50E-05	
192	Not Identified													
208*	Pyruvate kinase L (PKLR)	IPI00743713	63	23	15	64975	7.6	-1.09	0.5	1.72	0.015	-1.88	0.0038	
215	Serum albumin precursor Isoform 1 (ALB)	IPI00745872	130	10	5	71317	5.92	1.21	0.02	-1.3	0.013	1.57	0.00023	
217	Not Identified													
221	Serum albumin precursor Isoform 1 (ALB)	IPI00745872	716	31	22	71317	5.92	1.29	0.003	-1.24	0.048	1.57	0.0005	
222*	Serum albumin precursor Isoform 1 (ALB)	IPI00745872	94	34	23	71317	5.92	1.33	0.0037	-1.17	0.21	1.56	0.0061	
224*	Serum albumin precursor Isoform 1 (ALB)	IPI00745872	32	167	23	71317	5.92	1.31	0.0036	-1.17	0.13	1.54	0.0021	
226*	Serum albumin precursor Isoform 1 (ALB)	IPI00745872	152	42	30	71317	5.92	1.25	0.00026	-1.26	0.0054	1.58	9.40E-05	
228*	Serum albumin precursor Isoform 1 (ALB)	IPI00745872	145	44	28	71317	5.92	1.25	0.012	-1.41	0.00034	1.75	0.00017	
231*	Serum albumin precursor Isoform 1 (ALB)	IPI00745872	145	46	28	71317	5.92	1.32	0.011	-1.22	0.052	1.61	4.60E-05	
221	Serum albumin precursor Isoform 1 (ALB)	IPI00745872	813	36	23	71317	5.92	1.3	0.0043	-1.34	0.0072	1.74	0.0017	
241	Serum albumin (ALB)	IPI00022434	722	35	20	73881	6.33	1.31	0.0056	-1.28	0.012	1.68	0.0002	
243*	Kinesin-like protein (KIF5)	IPI00024975	68	17	31	161030	5.75	1.29	0.06	-1.37	0.049	1.78	0.0048	
243*	Amyotrophic lateral sclerosis 2 chromosomal region Isoform 2 (ALS2CR12)	IPI00044665	63	26	13	29638	11.67	1.29	0.06	-1.37	0.049	1.78	0.0048	
246*	Serum albumin precursor Isoform 1 (ALB)	IPI00745872	100	38	23	71317	5.92	1.19	0.12	-1.37	0.0037	1.62	0.0011	
247*	Serum albumin precursor Isoform 1 (ALB)	IPI00745872	124	39	26	71317	5.92	1.27	0.066	-1.52	0.01	1.93	0.0007	
248	Serum albumin (ALB)	IPI00022434	1051	45	33	73881	6.33	1.25	0.12	-1.54	0.014	1.91	0.0017	
249	Serum albumin (ALB)	IPI00022434	958	46	29	73881	6.33	1.25	0.033	-1.37	0.015	1.71	1.20E-05	
257	Serum albumin (ALB)	IPI00022434	143	33	21	73881	6.33	1.28	0.033	-1.43	0.028	1.84	0.0021	
269	Alpha-1-antitrypsin precursor Isoform 1 (SERPINA)	IPI00553177	96	19	6	46878	5.37	-2.82	0.0029	-1.28	0.44	-2.2	0.016	
285	Not Identified													
289	Immunoglobulin heavy constant gamma 1 (IGHG1)	IPI00384938	124	11	4	53503	8.74	-2.06	2.90E-05	-1.47	0.0072	-1.49	0.0012	
291	Alpha-1-antitrypsin precursor Isoform 1 (SERPINA)	IPI00553177	297	30	11	46878	5.37	-1.97	0.00038	-1.54	0.00016	-1.28	0.028	
298*	Antithrombin III variant (SERPINC)	IPI00556812	79	37	19	53114	6.11	-1.67	0.0007	-1.2	0.027	-1.39	0.004	
299*	Antithrombin III variant (SERPINC)	IPI00556812	59	33	16	53114	6.11	-1.84	0.00031	-1.55	0.00025	-1.19	0.004	
300	Alpha-1-antitrypsin precursor Isoform 1 (SERPINA)	IPI00553177	193	20	8	46878	5.37	-1.99	0.00027	-1.52	0.0062	-1.31	0.016	
303	Vitamin D-binding protein precursor (GC)	IPI00556812	124	9	6	54526	5.4	-1.89	0.00058	-1.47	0.0033	-1.29	0.02	

**Table 6.4 2D-DIGE based analysis of the ProteoMiner fractionated pooled clinical sera and MS-base protein identification.** Protein features displaying differential expression are shown. Values are the average ratio of abundance between different clinical conditions (healthy/malignant, healthy/benign and benign/malignant). T-test p values are given as a measure of confidence for each ratio measured. Protein name, IPI accession number, database search score, sequence coverage (%) and the number of matched peptides for each of the identified proteins are shown. Those marked with an \* were identified by MALDI-TOF PMF.

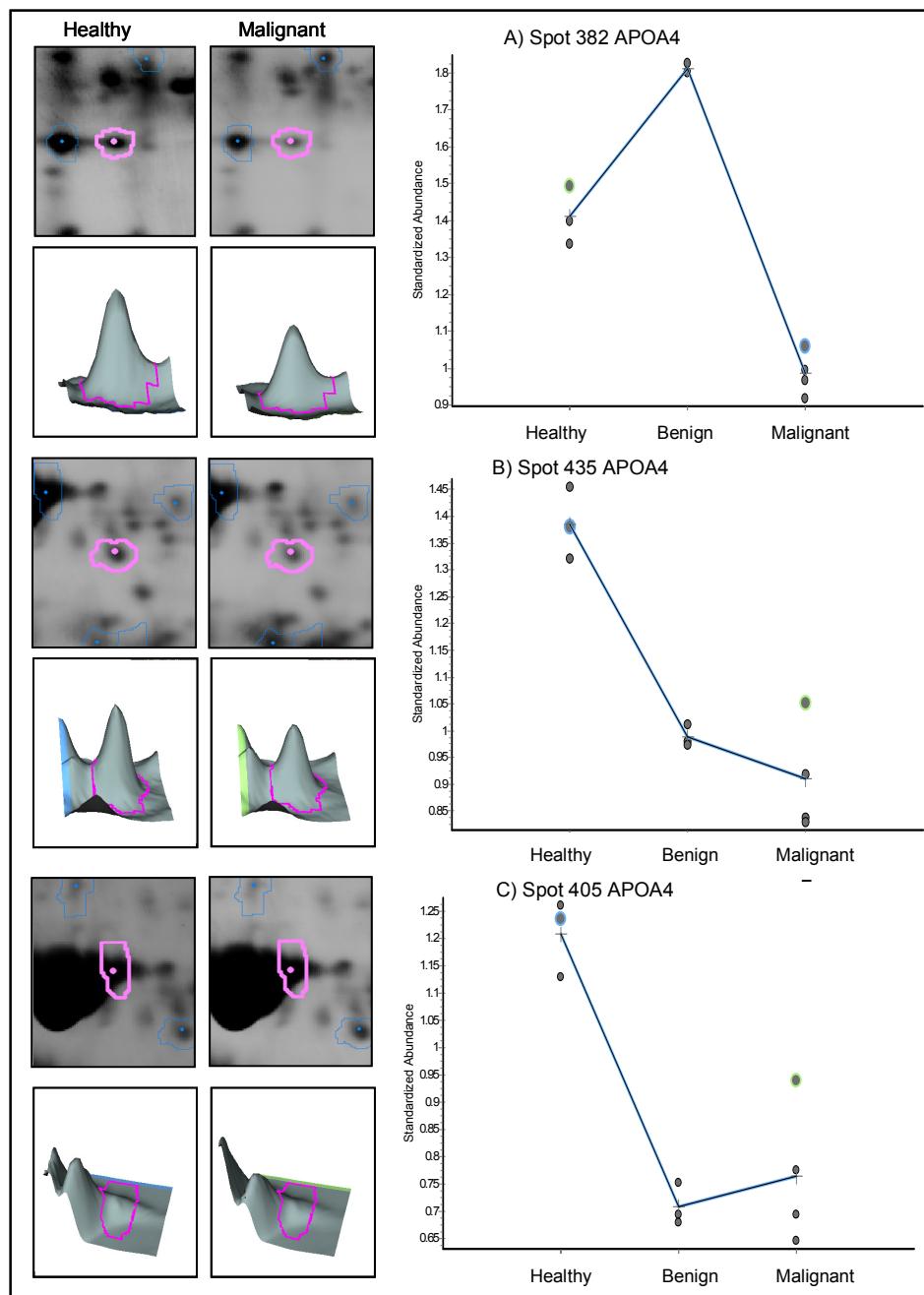
Spot No.	Protein Name	IP1No.	Score	Seq. Cov (%)	No. peptides	Mw	pI	Av. Ratio	T-test	Healthy/Malignant	Healthy/Benign	Benign/Malignant	T-test
306	Antithrombin III variant (SERPINC)	IP00055812	157	11	7	53114	6.11	-1.62	0.0089	-1.03	0.65	-1.57	0.021
319	Not identified												
326	Immunoglobulin heavy constant gamma 1 (IGHG1)	IP00384938	110	6	3	53503	8.74	1.71	0.00039	1.33	0.017	1.29	0.0034
328	Serum albumin	IP00022434	845	35	20	73881	6.33	2.65	0.0002	1.34	0.0085	1.98	0.0008
329	Immunoglobulin heavy constant gamma 1 (IGHG1)	IP00384938	845	35	20	53503	8.74	1.63	0.0011	1.23	0.019	1.32	0.0086
339	Not identified												
360	Not identified												
371	Fibrinogen isoform Gamma A/B (FGG)	IP00021891	206	22	8	52106	5.37	6.69	1.90E-05	1.29	0.00044	1.84	2.70E-05
381	Complement factor H precursor Isoform 2 (CFH)	IP00218998	430	36	16	52106	6.77	1.32	0.0002	-1.28	0.00092	1.68	1.80E-05
382	Apolipoprotein AIV precursor (APOA4)	IP0031042273	877	50	21	45371	5.28	1.43	0.00048	-1.28	0.0015	1.83	1.30E-05
393*	Apolipoprotein AIV precursor (APOA4)	IP0031042273	73	39	15	45344	5.28	-1.26	0.012	1.32	0.012	-1.66	0.0003
405*	Apolipoprotein AIV precursor (APOA4)	IP0031042273	123	45	21	45344	5.28	1.58	0.0056	1.7	0.0031	-1.08	0.54
405*	Kinecin 1 Isoform b (KTN1)	IP00733726	65	17	32	150545	5.59	1.58	0.0056	1.7	0.0031	-1.08	0.54
406*	Complement factor H-related 1 (CFHR)	IP00161093	73	33	14	38766	7.38	1.25	0.0051	-1.29	0.0011	1.61	7.40E-05
406*	Penplakin (PP1)	IP00298057	67	18	33	205096	5.44	1.25	0.0051	-1.29	0.0011	1.61	7.40E-05
431	Complement factor H Isoform 1 precursor	IP00029739	159	5	8	143680	6.21	-1.62	0.0081	-1.23	0.044	-1.32	0.09
431	Complement factor H Isoform 2 precursor	IP00218999	159	14	8	52711	6.77	-1.62	0.0081	-1.23	0.044	-1.32	0.09
435*	Apolipoprotein AIV precursor (APOA4)	IP0031042273	158	57	26	45344	5.28	1.52	0.0017	1.4	0.00037	1.09	0.24
435*	Penicentin (PCNT)	IP00479143	68	10	49	380644	5.39	1.52	0.0017	1.4	0.00037	1.09	0.24
444	GTPase-activating Rap/Ran-GAP domain-like 1 Isoform 3	IP00646904	68	23	15	125169	5.82	-1.24	0.01	1.59	0.00666	-1.97	9.50E-05
445	Not identified												
458	Serum albumin Isoform 2 of precursor	IP00384697	537	25	14	48641	5.97	1.29	0.00035	-1.35	0.0086	1.75	1.10E-05
461*	Apolipoprotein E precursor (APOE)	IP00021842	68	41	16	36246	5.65	1.26	0.0015	-1.21	0.0035	1.53	8.90E-05
461*	Adenonatosis polyposis coli 2 (APC2)	IP00025190	64	11	31	245966	9.08	1.26	0.0015	-1.21	0.0035	1.53	8.90E-05
475	Apolipoprotein E precursor (APOE)	IP00021842	373	32	12	36246	5.65	-1.53	0.00047	-1.13	0.063	-1.35	0.011
478*	Apolipoprotein E precursor (APOE)	IP00021842	91	52	22	36841	5.65	-1.77	0.0059	-1.33	0.065	-1.33	0.047
496	Apolipoprotein E precursor (APOE)	IP00021842	685	48	15	36246	5.65	-1.05	0.021	-1.49	7.00E-05	-1.57	0.00027
499	Apolipoprotein E precursor (APOE)	IP00021842	773	46	14	36246	5.65	-1.2	0.021	1.26	0.017	-1.51	0.0012
500	Not identified												
501	Complement C4-A:B precursor (C4A:B)	IP00032258	168	5	9	194247	6.65	-2.23	5.50E-05	-1.16	0.048	-1.92	0.00016
506	Not identified												
507	Complement factor H-related protein 2 Isoform long of precursor (CFHR)	IP0006154	206	15	4	31543	6	-5.38	0.0019	-1.04	0.75	-5.17	0.00053
507	Complement factor H-related protein 2 Isoform short of precursor (CFHR)	IP0006154	206	17	4	28734	6.52	-5.38	0.0019	-1.04	0.75	-5.17	0.00053
511	Serotransferrin precursor (TF)	IP00022463	325	26	16	79280	6.81	-1.26	0.002	1.67	0.0006	-2.11	1.90E-05
517	Immunoglobulin Lambda protein (IGL)	IP00658130	106	13	4	25347	8.14	-1.96	7.40E-05	1.01	0.91	-1.98	2.70E-05
562*	Apolipoprotein A-I precursor (APOA1)	IP00021841	147	49	15	30759	5.56	1.53	0.0072	1.31	0.094	1.17	0.23
571*	Apolipoprotein A-I precursor (APOA1)	IP00021841	236	85	32	30759	5.56	1.9	0.00088	1.36	0.05	1.4	0.029
577*	Urothrin fragment (UTRN)	IP00009329	70	11	49	396472	5.21	-1.39	0.00045	-1.54	8.70E-05	1.11	0.034

Table 6.4 continued

Furthermore, several spots yielded the same protein identification suggesting multiple isoforms of the same gene product. The 2D gel migration of the identified differentially expressed protein features is shown in Figure 6.20. Abundant serum proteins including apolipoprotein AI, apolipoprotein AIV, apolipoprotein E, alpha-1-antitrypsin precursor, antithrombin III variant, serotransferrin, serum albumin precursor, immunoglobulin heavy and light chain, fibrinogen and several complement factors were identified as differentially expressed protein features in multiple locations. In addition, cellular proteins such as Pyruvate kinase L (PKLR), Vitamin D-binding protein and a fragment of utrophin (UTRN) were also identified. Examples of several spots including yielding hits for apolipoprotein A4 (APOA4) are shown in Figure 6.21.

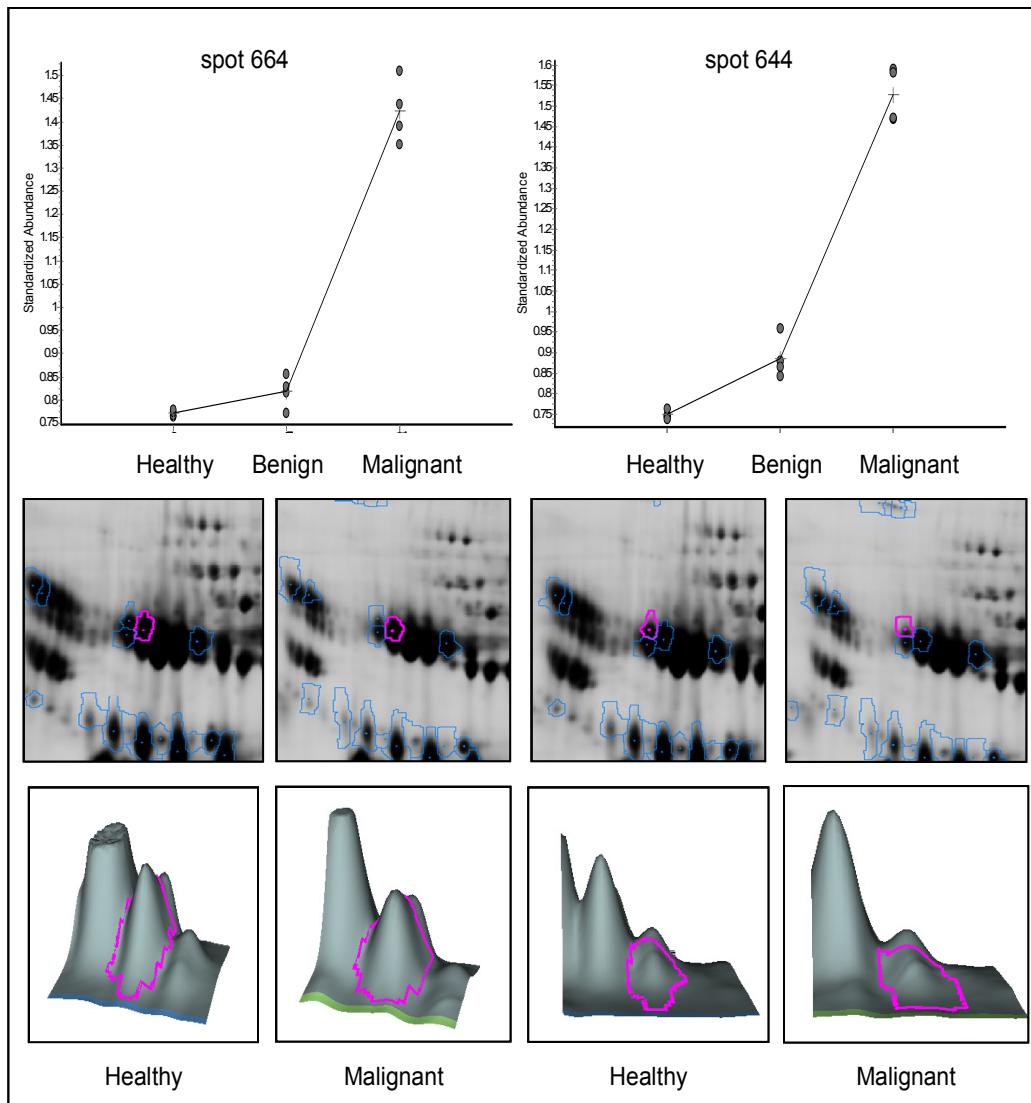


**Figure 6.20 Representative gel image displaying positions of differentially expressed proteins from the ProteoMiner-fractionated samples.** Differentially expressed protein features were identified by MS. The location of differentially expressed proteins including apolipoprotein AI (APOA1), apolipoprotein AIV (APOA4), apolipoprotein E (APOE), alpha-1-antitrypsin precursor (SERPINA), antithrombin III variant (SERPINC), serotransferrin (TF), serum albumin precursor (ALB), the immunoglobulin heavy (IGHG1) and light chain (IGL), fibrinogen (FGG), several complement factors (CFHR, C4A;B), pyruvate kinase L (PKLR), and utrophin (UTRN) are shown.



**Figure 6.21 Examples of multiple spots displaying clinical-sample dependent changes in the ProteoMiner experiment.** Several spots including A) 382, B) 405 and C) 435 yielded hits for Apolipoprotein A4 (APOA4). Differential analysis showed this protein was down-regulated in the malignant condition versus the healthy condition. Graphs were derived from DeCyder image analysis where the standardised abundance is the ratio of the volume of a gel feature in the clinical condition versus the Cy2 standard. Data points are shown for triplicate measurements in the healthy and quadruplicate in the malignant with lines joining the average values. 3D images of spots are shown for the healthy and malignant conditions.

In the second set of MARS-depleted samples, 1468 protein features were detected in the master gel. Quantitative analysis showed 76 differentially expressed protein features ( $\geq 1.5$  average fold-change in abundance,  $p < 0.01$ ). In total, 32 of the 76 differentially expressed protein features were identified with high confidence Table 6.5 examples are shown in Figure 6.22 and MS-based protein identification results are shown in Appendix 5.



**Figure 6.22 Examples of multiple spots displaying clinical-sample dependent changes in the second MARS-fractionated samples.** Protein spots 664 and 644 were both identified as alpha-1-antitrypsin (SERPINA) and displayed differential expression. Graphs were derived from DeCyder image and data points are shown for triplicate measurements for the healthy condition and quadruplicate for the malignant condition with lines joining the average values. 3D images of spots are shown for the healthy and malignant conditions.

Spot No.	Protein name	IPI No.	Score	Seq. Cov. (%)	No. Peptides	Mw	pl	Healthy/Malignant		Av. Ratio	T-test	Av. Ratio	T-test
								Healthy	Malignant				
73*	Alpha-1-antitrypsin precursor Isoform 1 (SERPINA)	IPI00553177	103	40	18	46707	5.37	-1.81	0.0055	-1.09	0.29	-1.66	0.0068
76	Not identified							-1.65	0.0013	-1.06	0.37	-1.55	0.0031
220	Not identified							1.44	0.01	1.66	0.00033	-1.15	0.2
250	Not identified							1.96	7.00E-07	-1.02	0.62	2	2.10E-07
252*	Serotransferrin precursor (TF)	IPI0022463	81	33	24	77000	6.81	2.44	1.70E-08	1.01	0.74	2.41	9.60E-07
279*	Not identified							2.44	4.20E-07	1.1	0.026	2.21	1.10E-06
280*	Serotransferrin precursor (TF)	IPI0022463	114	38	28	77000	6.81	1.87	0.0027	1.02	0.59	1.82	0.0097
281	Serotransferrin precursor (TF)	IPI0022463	272	20	11	79280	6.81	2.27	5.60E-07	1.08	0.032	2.1	3.50E-07
281	Immunoglobulin heavy constant mu protein (IGHM)	IPI00477090	59	8	4	68052	5.89	2.27	5.60E-07	1.08	0.032	2.1	3.50E-07
289	Immunoglobulin heavy constant gamma 1 (IGHG1)	IPI00384938	124	11	4	53503	6.28	2.23	3.00E-07	1	0.91	2.22	5.60E-07
289	Antithrombin III variant (SERPINCl)	IPI0032179	47	9	4	53114	6.11	2.23	3.00E-07	1	0.91	2.22	5.60E-07
296	Not identified							2	1.20E-05	1.01	0.79	1.98	6.80E-06
297	Serotransferrin precursor (TF)	IPI0022463	315	16	10	79280	6.81	2.25	4.20E-06	1.01	0.78	2.22	5.90E-07
323*	Serotransferrin precursor (TF)	IPI0022463	146	45	32	77000	6.81	2.42	3.30E-07	1.02	0.66	2.37	8.90E-09
322*	Serotransferrin precursor (TF)	IPI0022463	140	48	32	77000	6.81	2.52	6.60E-07	1.12	0.0072	2.24	2.80E-06
323*	Serotransferrin precursor (TF)	IPI0022463	56	26	20	77000	6.81	2.78	7.50E-08	1.14	0.0069	2.44	6.50E-08
335	Serum albumin (ALB)	IPI00745872	80	32	22	69321	5.92	2.17	0.00011	1.06	0.2	2.05	0.0018
346	Serotransferrin precursor (TF)	IPI0022463	82	31	22	77000	6.81	2.63	3.20E-07	1.05	0.28	2.51	3.30E-07
352	Not identified							2.14	0.00079	1.27	0.0076	1.68	0.0053
357	Serum albumin (ALB)	IPI00745872	97	7	5	71317	5.92	1.84	2.80E-06	1.36	0.001	1.35	0.0051
357	Serotransferrin precursor (TF)	IPI0022463	92	8	5	79280	6.81	1.84	2.80E-06	1.36	0.001	1.35	0.0051
407	Not identified							1.77	0.00055	1.07	0.06	1.65	0.0084
452	Not identified							1.12	0.24	-1.91	0.00046	2.14	2.30E-05
457	Not identified							-1.7	2.30E-05	-3.34	2.00E-07	1.96	4.70E-07
459	Not identified							-1.42	0.0003	-2.85	9.40E-07	2.01	3.60E-06
461	Serum albumin precursor Isoform 1 (ALB)	IPI00745872	96	32	22	71317	5.92	-1.77	1.50E-06	-3.94	1.40E-08	2.22	1.30E-06
464	Serum albumin (ALB)	IPI0022434	67	26	19	73881	6.33	-1.04	0.44	-2.09	6.30E-05	2.02	2.10E-05
465	Serum albumin (ALB)	IPI0022434	108	36	32	62166	6.33	-1.4	0.0057	-3.07	4.20E-05	2.2	5.50E-05

**Table 6.5 2D-DIGE based analysis of the second MARS-depleted clinical sample set.** Protein features displaying differential expression are shown. Values are average ratio of abundance between different clinical conditions (healthy/malignant, benign/malignant, and healthy/benign). T-test p values are given as a measure of confidence for each ratio measured. Protein were identified by MS Protein name, IPI accession number Mascot score, sequence coverage (%) and number of matched peptides are given for each of the identified proteins are shown. Those marked with an \* were identified by MALDI-TOF PMF.

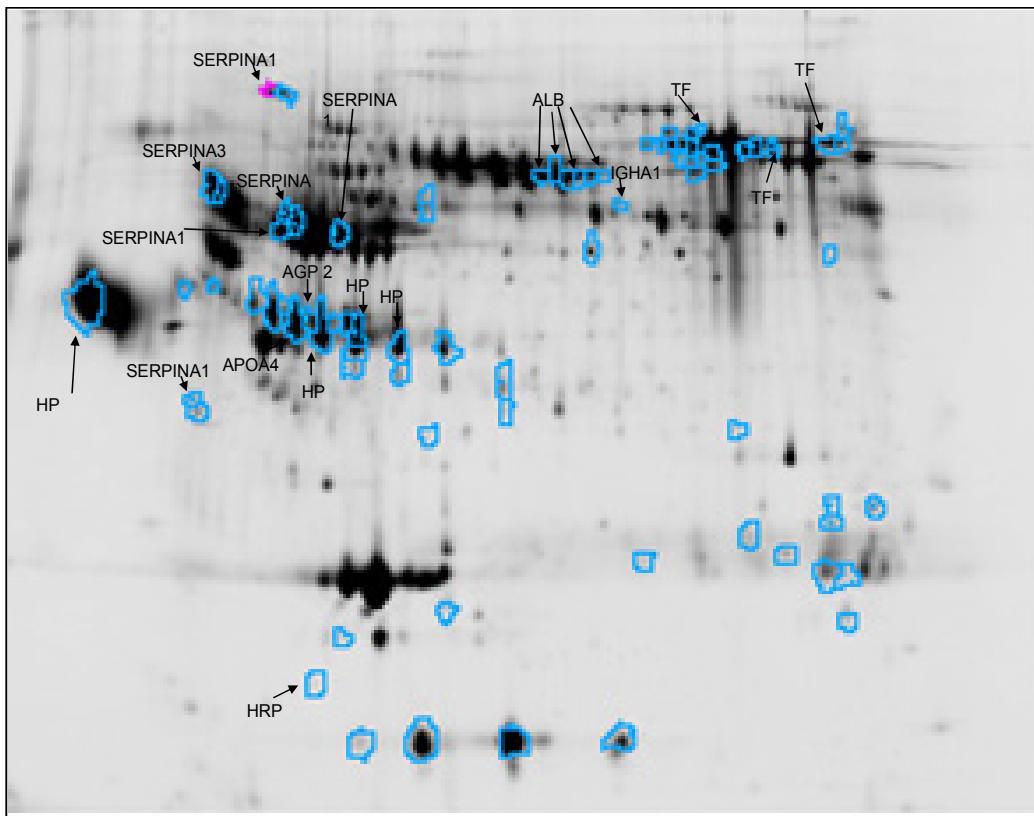
Spot No.	Protein name	IPI No.	Score	Seq. Cov. (%) Peptides	No.	Mw	pI	Healthy/Malignant	Healthy/Denign	Benign/Malignant	
								Av. Ratio	T-test	Av. Ratio	T-test
477	Serum albumin precursor Isoform 1 (ALB)	IP00745872	78	32	61945	5.92	-1.78	1.90E-06	-4.02	1.10E-07	2.26
523	Alpha-1-antichymotrypsin precursor Isoform 1 (SERPINA3)	IP010550991	92	34	60850	5.42	-2	2.90E-07	-1.16	0.0081	-1.73
537	Not identified							-1.56	7.50E-08	1	0.99
541	Not identified							1.76	0.0022	-1.37	0.0084
585	Immunoglobulin heavy chain constant region alpha 1 protein (IGHA1)	IP00386879	97	6	3	54195	6.46	-1.01	0.98	-1.59	0.01
609	Not identified							1.68	0.0065	-1.23	0.00067
644*	Alpha-1-antitrypsin (SERPINA)	IP00790784	72	29	14	40238	4.98	-2.04	7.50E-08	-1.18	0.0011
644*	Phenylalanyl-tRNA synthetase beta chain (phe T)	IP00300074	63	22	18	66715	6.4	-2.04	7.50E-08	-1.18	0.0011
664*	Alpha-1-antitrypsin precursor (SERPINA)	IP00553177	136	43	24	55397	5.37	-1.84	2.60E-07	-1.06	0.041
664*	Protein Dape Isoform 1 (DAPLE)	IP00740019	82	18	37	229215	5.87	-1.84	2.60E-07	-1.06	0.041
664*	Vinculin Isoform 2 (VCL)	IP00307162	71	23	26	124292	5.5	-1.84	2.60E-07	-1.06	0.041
664*	Ras-related protein (Rab-2B)	IP01012896	66	57	11	24427	7.68	-1.84	2.60E-07	-1.06	0.041
680*	Alpha-1-antitrypsin precursor (SERPINA)	IP00553177	69	32	16	46707	5.37	-1.68	1.60E-07	-1.09	0.04
712*	Alpha-1-antitrypsin precursor (SERPINA)	IP00553177	145	49	23	46707	5.37	-1.62	9.90E-07	-1.06	0.17
712*	Isoform 1 of T-box transcription factor TBX3	IP00298944	76	28	18	77529	8.48	-1.62	9.90E-07	-1.06	0.17
712*	Vinculin Isoform 2 (VCL)	IP00307162	70	19	25	124292	5.5	-1.62	9.90E-07	-1.06	0.17
769	Not identified							1.74	6.30E-06	1.39	0.00015
774	Not identified							2.05	0.0015	-1.66	0.0065
885	Not identified							2.28	2.70E-06	-1.07	0.14
888	Not identified							1.41	0.048	-1.44	0.0006
926	Not identified							-3.04	1.60E-05	-1.53	0.0001
930	Haptoglobin precursor (HP)	IP00431645	70	45	16	31362	8.48	-2.09	0.00026	-1.03	0.67
948	Apolipoprotein A-IV precursor (APOA4)	IP00304273	83	9	4	45371	5.28	-1.77	1.80E-05	-1.2	0.0031
950	Not identified							44836	5.14	-2.48	1.60E-07
971	Apolipoprotein A-IV precursor (APOA4)	IP00304273	190	55	24	44044	5.24	-3.25	1.10E-08	-1.82	6.60E-06
973	Haptoglobin precursor (HP)	IP00431645	497	39	17	31647	8.48	-1.99	5.20E-06	-1.22	0.0041
974	Alpha-1-acid glycoprotein 2 precursor (AGP 2)							1.44	0.00017	1.59	0.00019
991*	Haptoglobin precursor (HP)	IP00431645	63	43	14	31647	8.48	-2.81	5.30E-08	-1.52	8.70E-06
1010*	Haptoglobin precursor (HP)	IP00431645	64	38	14	31362	8.48	-2.58	1.10E-07	-1.51	2.60E-05
1021	Not identified							-2.25	3.50E-07	-1.47	6.40E-05
1042*	Haptoglobin precursor (HP)	IP00478493	82	42	17	38941	6.13	-2.69	2.80E-07	-1.51	0.00024
1044*	Haptoglobin precursor (HP)	IP00431645	61	39	14	31362	8.48	-2.03	1.90E-05	-1.48	0.0005
1047*	Haptoglobin precursor (HP)	IP00478493	64	39	14	38427	6.13	-1.74	3.60E-06	-1.43	0.00045
1074	Serum albumin (ALB)	IP0022434	30	3	2	39529	5.38	-2.54	2.90E-05	-1.44	0.0042
1093	Not identified							-2.65	3.10E-08	-1.55	5.20E-05

Table 6.5 continued

Spot No.	Protein name	IPI No.	Score	Seq. Cov. (%)	No. Peptides	Mw	pI	Healthy/Malignant		Healthy/Benign		Av. Ratio	T-test
								Av. Ratio	T-test	Av. Ratio	T-test		
1117	Not Identified							-2.08	4.60E-07	-1.5	2.30E-05	-1.39	0.00027
1137	Alpha-1-antitrypsin Isoform 1 of precursor (SERPINA1)	IPI00553177	631	38	21	46878	5.37	-1.61	9.30E-05	-1.68	0.0002	1.04	0.2
1158	Not Identified							1.4	0.0012	-1.31	0.0014	1.83	5.50E-06
1160	Not Identified							-1.4	7.30E-06	-1.55	3.20E-07	1.1	0.011
1186	Not Identified							1.57	0.00029	1.22	0.0023	1.29	0.0057
1193	Alpha-1-antitrypsin Isoform 1 of precursor (SERPINA1)	IPI00553177	40	6	2	46878	5.37	-1.55	4.50E-05	-1.28	0.0072	-1.21	0.014
1249	Not Identified							1.52	0.0033	-1.16	0.11	1.77	9.80E-05
1253	Not Identified							1.6	0.0076	1.32	0.007	1.21	0.15
1265	Not Identified							1.61	0.00037	-1.27	0.0079	2.05	2.00E-06
1280	Immunoglobulin kappa variable 1-5 (IGKV1)	IPI00430820	57	18	3	26034	5.74	1.22	0.0014	-1.41	1.20E-05	1.71	1.40E-06
1313	Not Identified							1.23	0.4	-5.61	2.70E-05	6.89	0.00026
1325	Not Identified							1.27	0.011	-1.39	0.0017	1.77	5.30E-05
1351	Not Identified							1.35	0.00023	-1.19	0.04	1.61	0.00027
1360	Not Identified							1.44	0.00041	-1.17	0.021	1.69	0.00011
1394	Not Identified							2.07	0.0023	1.17	0.18	1.77	0.0055
1402	Not Identified							-1.52	0.0012	-1.43	0.0003	-1.06	0.37
1417	Not Identified							2.59	7.20E-06	-1.04	0.53	2.69	1.90E-05
1425	Haptoglobin related protein Isoform 1 (HRP)	IPI00477597	178	8	6	39496	6.42	1.79	0.003	1.05	0.3	1.69	0.0047
1439	Not Identified							-2.06	1.00E-06	-1.29	0.00071	-1.6	2.30E-06
1441	Not Identified							-2.15	7.50E-06	-1.88	1.20E-05	-1.14	0.099
1442	Not Identified							-2.53	2.10E-08	-1.73	3.00E-06	-1.46	4.40E-06
1445	Not Identified							-2.39	9.50E-09	-1.53	5.10E-06	-1.56	1.10E-06

Table 6.5 continued

The 2D gel migration of the identified differentially expressed proteins in the second MARS experiment is shown in Figure 6.23. Again several abundant serum proteins including alpha-1-antitrypsin precursor (SERPINA), serotransferrin (TF), serum albumin (ALB), the immunoglobins (IGHA) and haptoglobin (HP) were identified in multiple locations.



**Figure 6.23 Representative gel displaying position of differentially expressed proteins from the MARS-depleted samples.** Differentially expressed protein features were identified by MS. The locations of serum albumin precursor (ALB), the immunoglobin heavy (IGHA1), serotransferrin (TF), haptoglobin (HP), apolipoprotein AIV (APOA4), alpha-1-antitrypsin precursor (SERPINA), alpha-1-antichymotrypsin (SERPINA3), alpha-1-acid glycoprotein 2 precursor (AGP2) and Haptoglobin-related protein precursor (HRP) identified as differentially expressed protein features are shown.

### 6.3 Comparison of 2D-DIGE experiments

Results from the BVA analysis showed that a different number of protein features were detected in each of the 2D-DIGE experiments. The 2D gels showed better protein separation when only 240 µg of protein was loaded (80 µg per Cy dye, second MARS experiment). Indeed, in the second MARS experiment due to streaking 1468 protein features were detected in the master gel used for spot matching. Poor resolution of some peaks e.g. albumin and serotransferrin made it difficult to determine an accurate number of protein features. Furthermore, accurate quantification was often compromised due to the partial co-migration of some protein features. 934 protein features were detected in the unfractionated experiment, while 797 and 697 protein features were detected in the first MARS experiment and ProteoMiner experiments, respectively. Only 32 out of 76 of the differentially expressed features from the second MARS experiment yielded protein identifications compared with 35 out of 48 in the unfractionated, 10 out of 10 in the first MARS and 53 out of 65 in the ProteoMiner experiment. This may be due to the lower protein load used in the second MARS experiment. In the ProteoMiner and second MARS experiments the selection criteria for differentially expressed protein features were made more stringent to reduce the number of false positives [Karp et al., 2007]. The difference in the number of protein features selected for identification using cut-offs of  $p < 0.05$  and  $p < 0.01$  was modest as shown in Table 6.6.

Differentially expressed protein features		
A) ProteoMiner	$p < 0.05$	$p < 0.01$
H v B	12	9
H v M	32	27
B v M	54	46
Total	74	65
B) MARS	$p < 0.05$	$p < 0.01$
H v B	61	61
H v M	25	25
B v M	59	58
Total	77	76

**Table 6.6 Differentially expressed protein features in the ProteoMiner and second MARS experiments.** The number of features displaying  $\geq 1.5$  average fold-changes in abundance at  $p < 0.05$  and  $p < 0.01$  are shown.

Results showed a total of 57 gene products were identified with confidence as shown in Table 6.7 which also shows the direction of regulations (up/down) between clinical conditions and the number of features where the protein was identified in each experiment. Ten proteins (AGP2, AHSG, CP, Factor VII, IGHA1, IGHG2, IGHG3, IGHM, IGL, KHG1) were found only in the unfractionated sample. Eight proteins (AFM, A1BG, A2M, CFB, ITIH4, F2 fragment and PROS) were found only in the first MARS-depleted samples. Thirteen proteins (inc; C4A;C4B, APOE, SERPINC1 and Vitamin D binding protein) were only found in the ProteoMiner-fractionated samples and 7 proteins (AGP2, Phe RS, DAPLE, HRP, Rab-2B, TBX3 and VCL) were found only in the second set of MARS-depleted samples. Three proteins including isoform 1 of  $\alpha$ -1-antitrypsin precursor (SERPINA1), apolipoprotein A-IV precursor (APOA4) and immunoglobulin heavy constant gamma 1 (IGHG1) were found to be commonly differentially expressed in the unfractionated, MARS2 and ProteoMiner fractionated samples. Of these SERPINA1 was up-regulated in the malignant condition versus healthy and benign conditions in all three experiments (Table 6.7). It is important to note that there are a number of multiple hits per spot which is one of the major drawbacks of the 2-DE technique making attribution of differential expression to a specific protein very difficult.

Protein name	Malignant/Healthy		Benign/Healthy		Malignant/Healthy		Benign/Healthy		Malignant/Healthy		Benign/Healthy	
	UnF	MARS1	PM	MARS2	UnF	MARS1	PM	MARS2	UnF	MARS1	PM	MARS2
Albumin (ALB)	+ (10)		+ (3) - (1)	+ (10)		+ (3) - (1)	+ (10)		+ (3) - (1)	+ (10)		+ (1) - (3)
Adenomatosis polyposis coli 2 (APC2)		+ (1)						- (1)				+ (1)
Afamin precursor (AFM1)	+ (1)				+ (1)							+ (1)
Alpha-1-antichymotrypsin precursor (SERPINA3)	+ (2)		+ (1)	+ (2)		+ (1)	+ (2)		+ (1)	+ (2)		+ (1)
Alpha-1-antitrypsin Isoform 1 of precursor (SERPINA1)	+ (1)		+ (3)	+ (7)	+ (1)		+ (3)	+ (7)	+ (1)	+ (3)	+ (6) - (1)	+ (1)
Alpha-1-acid glycoprotein 2 precursor (AGP 2)				- (1)			- (1)					+ (1)
Alpha-1B-glycoprotein precursor (A1BG)	+ (4)				+ (3) - (1)							+ (4)
Alpha-2-HS-glycoprotein precursor (AHSG)	+ (1)			+ (1)					+ (1)			+ (1)
Alpha-2-macroglobulin precursor (A2M)	- (2)		+ (3)	- (1)		- (2)		+ (3)	- (1)		+ (1) - (1)	+ (3)
Antithrombin III variant (SERPINC1)			- (1)			+ (1)		+ (1)				- (1)
Amyotrophic lateral sclerosis 2 chromosomal region (ALS2CR12)		- (1)				+ (1)		+ (1)				+ (3) - (1)
Apolipoprotein A-I precursor (APOA1)		- (2)				- (2)		- (2)				- (2)
Apolipoprotein A-IV precursor (APOA4)	+ (2)		+ (1) - (3)	+ (2)		+ (2)	+ (2)	+ (2)	+ (2)		+ (1) - (3)	+ (2)
Apolipoprotein E precursor (APOE)		+ (4) - (1)				+ (3) - (2)		+ (3) - (2)				+ (2) - (2)
Ceruloplasmin precursor (CP)	+ (2)			+ (2)			+ (2)		+ (2)			+ (1)
Complement C3 precursor (C3)	+ (1)			+ (1)			+ (1)		+ (1)			+ (1)
Complement C4-A precursor (C4A/C4B)	+ (1)		+ (1)		+ (1)		+ (1)		+ (1)			+ (1)
Complement component C9 precursor (C9)	+ (2)	+ (1)		+ (2)	+ (1)		+ (2)	+ (1)	+ (2)	+ (1)		+ (2)
Complement factor B isoform 1 of precursor (CFB Fragment)		- (2)			+ (1) - (1)			+ (1) - (1)		+ (1)		- (2)
Complement factor H isoform 1 of precursor (CFH)		+ (1)				+ (1)		+ (1)		+ (1)		+ (1)
Complement factor H isoform 2 of precursor (CFH)		+ (1) - (1)				+ (1) - (1)		+ (1) - (1)		+ (1) - (1)		+ (1)
Complement factor H-related Isoform short of protein 2 precursor (CFHR2)		+ (1)				+ (1)		+ (1)		+ (1)		+ (1)
Complement factor H-related Isoform long of protein 2 precursor (CFHR2)		+ (1)				+ (1)		+ (1)		+ (1)		+ (1)
Factor VII active site mutant immunonconjugate	+ (2)				+ (2)				+ (2)			+ (2)
Fibrinogen gamma chain isoform Gamma-A precursor (FGG)		- (1)				- (1)		- (1)				- (1)
GTPase-activating Rap/Ran-GAP domain-like 1 isoform 3		+ (1)				- (1)		- (1)				+ (1)
Haptoglobin precursor (HP)	+ (9)		+ (7)	+ (9)		+ (7)		+ (7)		+ (9)		+ (7)
Haptoglobin related protein (HRP)												
Histidine-rich glycoprotein precursor (HRG)	+ (3)	+ (1)			+ (2) - (1)	- (1)		+ (2)	- (1)	+ (3)	- (1)	
Immunoglobulin heavy chain constant region alpha 1 protein (IGHA1)	+ (2)				+ (2)			+ (2)		+ (2)		

**Table 6.7 Differentially expressed proteins identified by MS.** Proteins from all four experiments displaying differential expression are shown. Values are the number of features up-(+) or down-regulated (-) between different clinical conditions (malignant/healthy, benign/healthy, and malignant/benign).

Protein name	Malignant/Healthy						Benign/Healthy						Malignant/Benign						
	UnF	MARS1	PM	MARS2	UnF	MARS1	PM	MARS2	UnF	MARS1	PM	MARS1	PM	MARS1	PM	MARS1	PM	MARS2	
Immunoglobulin heavy constant gamma 1 (IGHG1)	+3	+1(-2)	-1)	+3)	+1(-2)	-1)	+3)	+1(-2)	-1)	+3)	+1(-2)	-1)	+1(-2)	-1)	+1(-2)	-1)	+1(-2)	-1)	+1(-2)
Immunoglobulin heavy constant gamma 2 (IGHG2 Fragment)	+2)			+2)			+2)			+2)			+2)			+2)			+2)
Immunoglobulin heavy constant gamma 3 (G3m marker (IGHG3))	+1)			-1)	+1)		-1)	+1)		-1)	+1)		-1)	+1)		-1)	+1)		-1)
Immunoglobulin heavy constant mu protein (IGHM)	+8)			+8)			+8)			+8)			+8)			+8)			+8)
Immunoglobulin kappa variable 1-5 (IGKV1)					-1)		-1)			+1)			+1)			+1)			+1)
Immunoglobulin lambda locus protein (IGL)	+1)			+1)			+1)			+1)			+1)			+1)			+1)
Inter-alpha (Globulin) inhibitor H4 (Plasma Kallikrein sensitive glycoprotein (ITIH4))	+1)			+1)			+1)			-1)			-1)			-1)			+1)
Inter-alpha-trypsin inhibitor heavy chain H4 Isoform 1 of precursor (ITIH4)	+2)			+2)			+2)			+2)			+2)			+2)			+2)
Inter-alpha-trypsin inhibitor heavy chain H4 Isoform 2 of precursor (ITIH4)	-1)			-1)			-1)			-1)			-1)			-1)			-1)
Kininogen-1 isoform 1 MW precursor (KNG1)	+1)			+1)			+1)			+1)			+1)			+1)			+1)
Kinesin-like protein (KIF15)					-1)		-1)			-1)			-1)			-1)			-1)
Kinectin 1 isoform b (KTN1)					-1)		-1)			-1)			-1)			-1)			-1)
Pericentrin (PCNT)					+1)		+1)			+1)			+1)			+1)			+1)
Periplakin (PPL)					-1)		-1)			-1)			-1)			-1)			-1)
Phenylalanyl-tRNA synthetase beta chain (pheT)					+1)		+1)			+1)			+1)			+1)			+1)
Prothrombin precursor (F2 Fragment)					+2)		+2)			+2)			+2)			+2)			+2)
Protein Dapple (DAPLE) Isoform 2					+1)		+1)			+1)			+1)			+1)			+1)
Pyruvate Kinase L (PKL)					+1)		+1)			+1)			+1)			+1)			+1)
Ras-related protein (Rab-2B)					+1)		+1)			+1)			+1)			+1)			+1)
Serotransferrin precursor (TF)					+3)	-1)	-9)			+3)	-1)	-9)	+1)	-3)	-9)	+1)	-3)	-9)	+1)
Serum albumin precursor Isoform 1 (ALB)					-14)	+1)	+14)			+14)	+1)	+14)	-14)	-14)	-14)	-14)	-14)	-14)	-14)
T-box transcription factor isoform 1 (TBX)						-1)	-1)			-1)			-1)			-1)			-1)
Utriphin (UTRN)						+1)	+1)			+1)			+1)			+1)			+1)
Vinculin (VCL) Isoform 2						+2)	+2)			+2)			+2)			+2)			+2)
Vitamin D-binding protein precursor (GC)					+1)		+1)			+1)			+1)			+1)			+1)
Vitamin K-dependent protein S precursor (PROS)					+1)		+1)			+1)			+1)			+1)			+1)

Table 6.7 continued

#### 6.4 Discussion

The human serum proteome is a complex biological mixture potentially containing an archive of patho-physiological information. Serum proteomics is being increasingly used to discover and characterise candidate biomarkers for disease diagnosis, prognosis and treatment response. The most important lesson that has been learned from protein expression profiling is the difficulty of handling the dynamic range of the serum proteome, which is 9-10 orders of magnitude and greater than the quantitative dynamic range of most analytical techniques [Fung et al., 2005].

For the studies presented in this chapter sera from the UKOPS collection was pooled into clinical groups, since analysis of large numbers of samples individually by 2D-DIGE was not possible. Pooling strategies hide the underlying variation within a group and may reveal average data that is skewed by outliers. By pooling larger numbers of samples this could be overcome [Pitteri and Hanash, 2007]. The dynamic range of the proteome was compressed using two complimentary fractionation strategies prior to fluorescence two dimensional difference gel electrophoresis-based profiling. The MARS depletion technique was used to enrich lower abundance protein species by depleting 7 of the most abundant proteins. Additionally, the ProteoMiner protein enrichment kit was used to reduce the dynamic range and capture ‘equalised’ amounts of all constituent proteins. Differentially expressed protein features from whole sera and fractionated sera were excised and trypsin digested. The resultant peptide mixtures were analysed by MALDI-TOF PMF and LC-MS/MS. One of the advantages of LC-MS/MS is that the tryptic peptides are further fragmented in the mass spectrometer (in the collision cell), allowing the determination of amino acid sequence and resulting in less ambiguous protein identifications compared with peptide mass fingerprinting [Koehn and Oehler, 2007].

The work carried out in this section showed that only a few protein species were consistently differentially expressed between the clinical conditions. The results indicate that some of the proteins are related to immuno-host cell defence responses (acute-phase proteins) and may be protein fragments, possibly produced by

proteolytic enzymes. In all experiments the majority of the differentially expressed features yielded hits for high abundance proteins.

Proteins identified included SERPINA3 and APOA4, and both of these proteins were up-regulated in the malignant condition. SERPINA3 is an alpha globulin glycoprotein which is a member of the serine proteinase inhibitor (serpin) family. This enzyme is produced in the liver and is known to be an acute-phase protein that is induced during inflammation. SERPINA3 has been shown to be up-regulated in human leukocyte antigen (HLA)-positive tumours in cervical cancer [Kloth et al., 2008]. Gene expression profiling experiments have shown a 2-fold increase in the expression of SERPINA3 in mucinous ovarian cancers compared with normal ovarian surface epithelial cells and to other histotypes [Marquez et al., 2005]. In agreement with this results from both the unfractionation and second MARS experiments showed SERPINA3 was up-regulated in the malignant condition. APOA4 belongs to the apolipoprotein family and is primarily produced in the intestine and secreted into the plasma. APOA4's precise function is unknown but it may serve as a lipid-binding protein and has lecithin:cholesterol acyltransferase (LCAT) activating ability. The APOA4 gene was shown to be up-regulated in familial pancreatic cancer, it has been studied extensively in relation to cardio-vascular disease and is a strong candidate as a breast and ovarian cancer susceptibility gene [Zervos et al., 2006].

To enrich the lower abundant protein species sample pre-fractionation was performed with the multiple affinity removal system. Results showed that 7 of the high abundance proteins were removed with high efficiency. One of the major limitations of 2D-gels is the sample loading capacity. Too much protein sample results in poorly resolved gels and too little protein makes MS based protein identification of low abundant protein features difficult [Sriyam et al., 2007; Huang et al., 2005]. Depleting serum of the abundant proteins facilitated the analysis of lower abundant species since more of these proteins could be loaded on the 2D gels.

Quantitative analysis of the first set of MARS-depleted clinical samples showed only 10 differentially expressed proteins features that were significant ( $p < 0.05$ ). Protein identifications were made for all of these with several spots yielding more than one

protein. The identification of more than one protein in a spot is a major limitation of 2D-gel based quantitative analysis, since it is difficult to assign the differential expression to a particular protein found in the spot. It would most likely to have come from the most abundant protein in the spot, particularly if the amount of this protein is far in excess of the others. For example, in the first MARS-depletion experiment spot number 459 yielded multiple identities including ITIH4, HRG, F2, ALGB and PROS1 by LC-MS/MS. Of these ITIH4 was identified by 16 peptides, with a Mascot score of 401. HRG was identified by 5 peptides and a Mascot score of 137, F2 was identified by 4 peptides with a Mascot score of 95, and ALGB was identified by 2 peptides with a Mascot score of 52, and finally, PROS1 was identified by 3 peptides with a Mascot score of 52. This suggests that the likely difference in abundance is attributable to ITIH4. Spot number 459 showed a 2.5-fold increase in the malignant condition versus the healthy conditions, respectively. However, it could be speculated that the co-migration of all these proteins may have generated a false positive.

Interestingly, in the list of proteins identified, ITIH4 and afamin were two proteins which have been previously reported as ‘markers’ for ovarian cancer [Jackson et al., 2007; Zhang et al., 2004]. Both of these were identified in spot number 464 which showed a 2-fold increase in the malignant condition. ITIH4 is an acute-phase protein which is produced by the liver. The levels of ITIH4 have been shown to increase significantly in the sera of patients after different surgical trauma [Pineiro et al., 1999]. Afamin is a vitamin E binding glycoprotein which is part of the albumin super family. Previous studies have reported on the potential of afamin as a putative marker for ovarian cancer recurrence [Jackson et al., 2007]. The study by Jackson et al. showed an inverse relationship between CA-125 and afamin concentrations from the time of treatment to the time of relapse. The potential complementarity of afamin with CA-125 was also shown in three patients in whom CA-125 was relatively uninformative, although the changes in afamin were modest. For diagnostic discrimination, afamin alone was poor, but it was suggested that the potential for the isoforms, in particular isoform 2, for complementing CA-125 or other markers should be explored further in a larger study with an independent test set [Jackson et al., 2007].

The MARS depletion experiment was repeated and several additional proteins which showed differential expression between the clinical pooled sera were identified but there was no overlap between the two MARS experiments. This is likely due to the fact that no Cy2 internal standard was used in the first experiment which made spot matching across gels difficult and only 10 differentially expressed features were identified. The proteins identified in the second MARS experiment included haptoglobin (HP) and isoform 1 of alpha-1-antitrypsin (SERPINA1) both of which were up-regulated in the malignant condition. HP is a blood plasma protein that binds free haemoglobin, preventing the loss of iron through the kidneys and protecting the kidneys from damage by haemoglobin, while making the haemoglobin accessible to degradative enzymes. In the clinic, a haptoglobin assay is used to screen for and monitor haemolytic anemia. HP has been previously reported as an up-regulated marker protein in ovarian cancer patients [Ye et al., 2003]. Previous reports in ovarian cancer have indicated that there is a change of glycosylation on haptoglobin [Turner et al., 1995] and IgG [Gercel-Taylor et al., 2001] in ovarian cancer patients.

SERPINA1 is a plasma protein which acts as an inhibitor of serine proteases. Its primary target is elastase, but it also has a moderate affinity for plasmin, thrombin, trypsin, chymotrypsin and plasminogen activator. The aberrant form increases the rate of coagulation and has proteolytic activity against insulin and plasmin. SERPINA1 has also been previously reported as an acute-phase marker in gynaecological cancers [Kloth et al., 2008; Tatra, 1985]. SERPINA1 was one of three proteins which were differentially expressed in all the unfractionated, MARS2 and ProteoMiner experiments. SERPINA1 was up-regulated in the malignant condition versus the healthy and benign condition in all three experiments. However, HP and SERPINA were in the list of proteins which should have been depleted by the MARS column. In addition, serotransferrin (TF) was identified as a differentially expressed protein feature in a number of locations. This suggested that the depletion efficiency of the column may have declined with repeated use. TF was found to be down-regulated in the malignant condition in 9 different spots. TF is an iron-binding transport protein which is responsible for transporting iron from the sites of absorption and heme degradation to areas of storage and utilisation and has been previously reported to be down-regulated in the serum of ovarian cancer patients [Dumaswala et al., 2000].

Other proteins identified in the second MARS-depletion experiment included alpha-1-acid glycoprotein 2 precursor (AGP2), phenylalanyl-tRNA synthetase beta chain (Phe-RS), protein dapple isoform 2 (DAPLE), haptoglobin related protein (HRP), Ras-related protein (Rab-2B), T-box transcription factor isoforms 1 (TBX3) and vinculin isoform 2 (VCL). AGP2 is expressed by the liver, secreted into the plasma and appears to function in modulating the activity of the immune system during the acute-phase reaction. Phenylalanine-tRNA synthetase (Phe-RS) is localised to the mitochondrion and is an essential enzyme which catalyzes the transfer of the amino acid phenylalanine (Phe) to the Phe-specific transfer-RNA. DAPLE is a negative regulator of the canonical Wnt signalling pathway, acting downstream of dishevelled (Dvl) to inhibit  $\beta$ catenin stabilisation. Wnts are a large family of cysteine-rich secreted glycoproteins that control development. The intracellular signalling pathway of Wnt is also conserved evolutionally and regulates cellular proliferation and differentiation [Bienz and Clevers, 2000; Seidensticker and Behrens, 2000; Wodarz and Nusse, 1998] and several components of Wnt signalling are implicated in the genesis of human cancer.

RAB2B is required for protein transport from the endoplasmic reticulum to the Golgi complex. Pyruvate kinase L (PKLR) was also identified as a differentially expressed protein. Pyruvate kinase, is a homotetramer of 50.60 kDa subunit, with two forms, one liver specific (L), the other erythrocyte specific (R), transcribed from a distinct promoter, glycolysis, energy pathway, generating ATP from ADP. T-box transcription factor isoforms 1 (TBX3) is a transcriptional repressor involved in developmental processes which plays a role in limb pattern formation. Tbx3 transcription is activated by ectopic expression of beta-catenin in mouse liver and in human tumor cell lines. Tbx3 has been indicated as a serological marker for ovarian cancer [Souchelnytskyi et al., 2006]. Finally, VCL is involved in cell adhesion and may be involved in the attachment of the actin-based microfilaments to the plasma membrane. It may also play important roles in cell morphology and locomotion. VCL subcellular locations include the cytoplasm and cytoskeleton. These proteins were predominately found in spots which yielded multiple protein identities it is therefore difficult to attribute any specific changes to them. However, several proteins e.g.

TBX3 and DAPLE have previously been reported as markers for ovarian cancer thus these proteins warrant further investigation.

The ProteoMiner-based fractionation showed that compression of the protein dynamic range could be achieved, although mostly high abundance proteins were found to be differently expressed; namely, TF, APOA1, APOA4, APOE and SERPINA1. The results demonstrated the ProteoMiner kit appeared to have a greater affinity for apolipoproteins as previously reported [Pitteri and Hanash, 2007]. Numerous studies have reported on changes in serum lipid and lipoproteins levels in cancer and other diseases. For example, elevated plasma lipoprotein (A) has been associated with an increased risk of cardiovascular disease and significant elevation of total plasma apolipoprotein (A) levels have also been reported in cancer patients compared with hospitalised control patients and normal healthy blood [Wright et al., 1989]. Furthermore, an APOE genetic polymorphism has been shown to modify the risk for a variety of diseases, including breast cancer [Moore et al., 2006; Zhang et al., 2004; Kuesel et al., 1992]. APOA1 is the major protein constituent of the high-density lipoprotein (HDL). Previous reports suggest aberrant serum levels of APOA1 might be a useful marker of ovarian cancer [Moore et al., 2006; Zhang et al., 2004; Kuesel et al., 1992]. The results demonstrated that APOA1 was down-regulated in the malignant condition in two different spots in the ProteoMiner experiment, APOA4 was up-regulated in the malignant condition in 3 out of 4 spots and down-regulated in the remaining spot in the ProteoMiner experiment and up-regulated in 2 spots in the malignant condition in the unfractionated and MARS 2 experiments. APOE was up-regulated in the malignant condition in 3 out of 4 spots and down-regulated in the remaining spot in the ProteoMiner experiment.

In addition, vitamin D-binding protein (GC) and utrophin (UTRN) were both up-regulated in the malignant condition and have both been previously reported as ‘markers’ for cancer. GC is a secreted multifunctional protein found in plasma, ascitic fluid, cerebrospinal fluid and urine, and on the surface of many cell types. In plasma, it carries the vitamin D sterols and prevents polymerization of actin by binding its monomers. It associates with membrane-bound immunoglobulin on the surface of B-lymphocytes and with IgG Fc receptor on the membranes of T-lymphocytes. Studies

suggest that the exploitation of the unique properties of vitamin D-binding protein could enable the development of important therapeutic agents for the treatment of a variety of diseases [Gomme and Bertolini, 2004]. UTRN may play a role in anchoring the cytoskeleton to the plasma membrane. In normal muscle cells, utrophin is located at the neuromuscular synapse and myotendinous junctions. It is necessary for normal membrane maintenance, and for the clustering of the acetylcholine receptor. Utrophin is known to be intracellular, thus its detection in serum indicates so-called tissue leakage [Souchelnytskyi et al., 2006].

Several cellular proteins were found in spots which yielded multiple hits. These included adenomatosis polyposis coli 2 (APC2), which was identified in a spot with APOE, promotes rapid degradation of cadherin-associated protein and may function as a tumour suppressor and may function in Wnt signalling. Kinectin 1 isoform b (KTN1) which was identified in a spot with APOA4 has been identified as a tumor-associated antigen. The receptor for KTN1 kinesin is involved in kinesin-driven vesicle motility and accumulates in integrin-based adhesion complexes (IAC) upon integrin aggregation by fibronectin. The subcellular locations of KTN1 include the endoplasmic reticulum membrane. High levels of KTN1 are found in peripheral blood lymphocytes, testis and ovary, lower levels in spleen, thymus, prostate, small intestine and colon. Defects in KTN1 may be involved in the onset of cancer [Wang et al., 2004b]. Periplakin (PPL) which was identified in a spot with CFHR is a component of the cornified envelope of keratinocytes. PPL may link the cornified envelope to desmosomes, intermediate filaments and may act as a localisation signal in PKB/AKT-mediated cell signalling pathway. Finally, Pericentrin (PCNT) which was also found with APOA4 may be involved in organisation of microtubules during meiosis and mitosis. Again these proteins were predominately found in spots which yielded multiple protein identities and it is therefore difficult to attribute any specific changes to them. It is important to note that only three proteins including SERPINA1, APOA4 and IGHG1 were found to be commonly differentially expressed in the unfractionated, MARS2 and ProteoMiner fractionated samples.

In summary, results have shown that a panel of putative markers consisting of several apolipoproteins (APOA1, A4 & E), serotransferrin (TF), haptoglobin (HP),  $\alpha$ -1-antitrypsin precursor isoform 1 (SERPINA1), vitamin D-binding protein (GC),

afamin, utrophin and the cellular proteins (APC, Tbx3 and DAPLE) involved in Wnt signalling warrant further investigation. Future experiments may involve a large scale immuno-based study in an independent cohort of UKOPS case control samples which is beyond the time frame of this project. This would be the ideal way to evaluate the diagnostic usefulness of these proteins, in combination with the CA-125 assay, for early detection of ovarian cancer.

## Chapter 7: Conclusions and future directions

The primary hypothesis driving the research presented in this thesis is that the human serum proteome contains a source of proteins whose abundances change with disease state. It is proposed that the identified protein abundance changes between the diseased and healthy state could act as early biomarkers of ovarian cancer giving clinicians the opportunity for earlier intervention. The search for putative markers of ovarian cancer was investigated using polypeptide separation methods and mass spectrometry. As previously detailed several collections of clinically relevant serum samples were available for this investigation. However, due to the low incidence of ovarian cancer the number of diseased samples was limited.

The results achieved are presented in four chapters. Chapter three utilised a previously established magnetic bead-based peptide extraction protocol and MALDI-TOF MS profiling which was then used to analyse case-control samples. Chapter four describes the various steps taken to adapt and optimise this protocol in the host laboratory. Chapter five describes the analysis of case-control samples in the host laboratory using the optimised protocols. Finally, chapter six is concerned with the use of additional protein separation techniques designed to increase the dynamic range of detection of the serum proteome for 2D-DIGE-MS profiling.

In Chapter three, one of the interesting findings from the case-control study where samples pre-dating diagnosis of ovarian cancer and control groups were compared using MS analysis was that peaks 4292.5 m/z and 3171.1 m/z could be used in combination with CA-125 levels to detect ovarian cancer up to 12 months prior to diagnosis. Although these peaks were not identified, it could be speculated that they may be fragments of host immune/acute phase proteins (e.g. inter- $\alpha$ -trypsin inhibitor heavy chain (ITIH4)) generated by exo-peptidases as previously reported by Villanueva et al. (2005). Several groups have reported on the use of a combination of host immune/acute phase proteins as potential disease markers [Chen et al., 2005]. It is clear that the presumption of the existence of a single cancer-specific biomarker is outdated and investigations concentrating of finding panels of markers have the potential to produce greater sensitivity and specificity. The fact that cancer cells are

themselves ‘deranged’ host cells, tends to suggest that the existence of single and specific cancer biomarkers is improbable. In contrast, the complex proteomic pattern of the tumour–host microenvironment may be unique and may constitute a biomarker amplification cascade. In fact, the most important biomarkers may be normal host response proteins that are aberrantly cleaved through cancer-specific protease activities. Such a proposal lends itself to a pattern analysis approach to investigate the loss or gain of peptide ions within the spectra of disease versus normal samples.

Having identified protocols suited to the high-throughput analysis of serum-based spectral patterns, the overall aim of the experiments presented in chapter 4 was to identify sources of error which may affect the reproducibility of the selected technology platform. Although automation allowed the processing and analysis of a greater number of samples the initial reproducibility of the platform was poor. The reproducibility was improved by reducing the bead loss during the wash steps and diluting the eluate before MS analysis. Interestingly, the beads chosen for general use were found to bind highly abundant proteins including HSA and apolipoproteins which are common serum proteins. It is speculated that the presence of these proteins led to competition and suppression effects during peptide extraction and MALDI ionisation. Diluting the eluate led to improved spectral quality, presumably by improving crystallisation and reducing peptide ion suppression but did not facilitate peptide identification. Subsequent studies showed that despite attempts to deplete the abundant proteins they continued to mask the detection of lower abundant protein species.

In addition, different clinically feasible sample handling and processing protocols were assessed. An interesting finding was that samples kept on ice after collection with a transport time of less than 6 hours were more stable (as defined by serum peptide inter sample profile comparison) than those which had not been kept on ice prior to transport. This provides support for the exopeptidase activity hypothesis [Villanueva et al., 2006]. This states that disease-specific exopeptidases are active on serum proteins after blood samples have been left to clot with the fragmentation patterns generated by these exoprotease activities providing diagnostic information. Fragments of fibrinopeptide A (FPA) and complement 3f (C3f), among others have been identified and reported as surrogate markers of cancer [Villanueva et al., 2006].

More importantly, several groups have also reported on differential expression of abundant serum proteins (or fragments thereof) as markers of disease [Villanueva et al., 2006; Ye et al., 2003; Zhang et al., 2004].

There was also support for the use of older sample collections where samples have been in transit and storage for prolonged periods of time. Case-control studies can be performed as long as all samples have been handled identically. Exopeptidase activity may come to an end point after a certain period depending on the transit and storage conditions. Placing samples on ice would serve to lower the rate of exopeptidase activity and thus, sample integrity remains intact for MS-based analysis. The peptides are themselves the product of specific enzymatic activities, and careful qualitative and quantitative measurements may therefore yield some insights in the protease activities at work. However, steady state measurements can only provide some quantitative estimates of enzyme activity when contributing factors such as specific activity and half-life of the product or metabolite are known. Proteases are well-established components of tumour progression and invasiveness [Matriesian et al., 2003]. As such, enzymes, inactive proteolytic fragments of enzymes or protease inhibitors have become important and promising cancer biomarkers [Landis-Piwowar et al., 2006]. Some efforts are being made towards activity-based proteomic profiling involving the use of chemical probes that selectively label, on a whole-proteome background, certain classes of active enzymes but not their inactive forms [Kato et al., 2005]. Furthermore, a test to compare defined exopeptidase activities by quantifying the peptide products of such enzymes within individual proteomes of two or more groups of biological samples has recently been reported [Villanueva et al., 2008].

The experiments described in chapter 5 utilised the optimised magnetic bead-based serum profiling platform and a panel of peptide masses were found to be useful in (poorly) discriminating between the clinical conditions. However despite defining a cut-off for the technical variance, the biological heterogeneity innate in human-derived clinical samples resulted in large variation within the clinical conditions. The SVM classification algorithm was also limited by the small number of diseased samples. A larger sample set needs to be analysed to validate these results. It would have been ideal to identify some of the discriminatory masses. However, as

previously mentioned, direct peptide identification using MALDI-TOF/TOF MS suffers from several limitations. This is especially true for a complex sample such as serum where in the presence of numerous proteins the separation of the parent ion of interest is often difficult. As the data in chapter 4 showed the beads used for peptide extraction also captured larger proteins making the sample eluate complex and generating crystallisation heterogeneity and ion suppression. Although the peaks of interest were not identified it is most likely that the distinctive MS profiles have resulted from the differential expression of relatively abundant serum proteins and their fragments associated with (the response to) tumours, which may have been further cleaved by disease specific ex-vivo exoprotease activity [Villanueva et al., 2008]. Work on isolating and identifying peaks of interest is ongoing. A larger sample set from UKOPS has been analysed using the automated bead-based fractionation protocol in the host laboratory and data is being analysed in collaboration with Professor Gammerman's group at Royal Holloway University. On their own the peptide peaks identified performed poorly when used to classify a test set of samples, but sensitivity is improved when used in combination with CA-125, data analysis is on-going.

The next step would involve the validation of these markers. Validation of biomarkers would require robust diagnostic performance on independent case-control sets. To this end, the platform developed herein could be expanded to incorporate an antibody-based enrichment strategy for capturing peptides on magnetic beads coated with an array of antibodies for several proteins coupled to mass spectrometry-based multiple reaction monitoring (MRM) quantification. Since the majority of markers reported from proteomic studies to date have predominately included host-response (acute-phase) proteins, this would be an ideal way to quantitatively analyse peptides associated with the host immune response [Whiteaker et al., 2007].

The experiments described in chapter six permitted the identification of several proteins that were differentially expressed between pools of clinical sera. In the unfractionated serum experiment, several host response/acute-phase proteins including the immunoglobins and proteins from the SERPIN family were identified as differentially expressed protein features. Of these the SERPIN proteins which are

commonly known as positive acute-phase reactants were up-regulated in the malignant condition. SERPIN proteins are involved in down regulation of local inflammation. The inflammatory cascade includes a multitude of constituent proteins with varying functions, including structural proteins, clotting factors, angiogenesis and transport proteins. The host response is generally mediated by the innate immune system and the host response proteins exist at substantially high concentrations within the tumour microenvironment. According to the host-response protein amplification cascade concept, proteins synthesized in the liver enter the circulation and when exposed to a localized disease area, they are processed by the local host response, and modified forms of the proteins re-enter the general circulation. This is the source of amplification of a localised disease signal. Specificity of this process is made possible by the fact that each disease generates a different type of local host response. This may be due to the fact that each disease expresses a different set of antigens (e.g. tumour markers) or that the recruitment of specific inflammatory mediators differs based on the inciting event. However, it is likely that these markers may not be specific for ovarian cancer.

Using an antibody-based enrichment strategy for quantitative measurements of such host response proteins and the peptides associated with them may provide detailed insights on tumour progression and invasiveness. Numerous proteomic studies published to date have identified relatively abundant host response proteins as candidate biomarkers [Moore et al., 2006; Zhang et al., 2004; Zhang et al., 2007]. It would be interesting to measure how their levels fluctuate with tumour progression and to determine if the changes are disease and/or stage specific in samples pre-dating diagnosis.

The systematic detection of low abundance proteins in human blood is complicated by the extremely wide dynamic range of protein abundances. The depletion of major proteins is a popular strategy for enhancing detection sensitivity in serum or plasma. The low abundance proteins enrichment strategies employed herein enabled additional protein species to be detected on 2-DE, although the increase was modest, and most newly visualized spots were minor forms of relatively abundant proteins. The inability to detect low abundance proteins near expected 2-D staining limits was

probably due to both the highly heterogeneous nature of most serum proteins and masking of low abundance proteins by the next series of medium abundance proteins, which included the apolipoproteins. Due to the wide dynamic range of the serum proteome, even removing the top 20 most abundant proteins would probably not allow the detection of the lowest abundant proteins. In reality the removal of the top seven proteins enhances mid-range rather than low-range proteins and additional fractionation is required.

Not surprisingly, in both the MARS and ProteoMiner experiments, a number of gel spots yielded identities for the apolipoproteins (APOA1, APOA4 & APOE). Of these APOA4 was also identified in the unfractionated serum experiment. The precise function of APOA4 is unknown. Interestingly, the ProteoMiner protein enrichment kit showed a greater affinity for these ‘medium’ abundant proteins. APOA1 and APOE were only found in the ProteoMiner experiment and both proteins were found to be down-regulated in the malignant condition. APOE is synthesized principally in the liver and is the lipoprotein component of very low-density lipoproteins (VLDLs). APOE combines with lipids and is involved in cholesterol transport, lipid metabolism and protein synthesis. APOE is expressed in significant amounts in the ovaries, testes and the brain, is synthesised by a wide variety of peripheral cells, including macrophages. Its production by extra-hepatic cells has also raised questions regarding its role in peripheral tissues. In addition, APOE is involved in numerous other functions, including tissue repair, the immune response and regulation of cell growth and differentiation. The levels of these proteins in diseased samples may be related to tumour size and future follow up investigations should be able to confirm this as long as the relevant clinical data is available. In summary, the results from chapter 6 showed that a panel of putative markers consisting of several apolipoproteins (APOA1, A4 & E), serotransferrin (TF), haptoglobin (HP),  $\alpha$ -1-antitrypsin precursor isoform 1 (SERPINA1), vitamin D-binding protein, afamin and utrophin warrant further investigation. As Table 7.1 shows many of these proteins have previously been reported as markers for ovarian and other cancers.

Biomarker	Cancer type	References
Apolipoprotein A1	Ovarian, pancreatic	Zhang et al., 2004; Kozak et al., 2005
Haptoglobin $\alpha$ -subunit	Ovarian, pancreatic, lung	Ye et al., 2003
Transthyretin fragment	Ovarian	Kozak et al., 2005
Inter-alpha-trypsin inhibitor fragment	Ovarian, pancreatic	Zhang et al., 2004
Vitamin D-binding protein	Prostate, breast	Corder et al., 1993; Pawlik et al., 2006
Serum amyloid A	Nasopharyngeal, pancreatic, ovarian	Orchekowski et al., 2005; Moshkovskii et al., 2005; Hellerman et al., 2007
$\alpha$ 1-antitrypsin and $\alpha$ 1-antichymotrypsin	Pancreatic	Orchekowski et al., 2005; Yu et al., 2005
Haemoglobin-alpha & -beta subunits	Ovarian	Woong-Shick et al., 2005
EPCA-2	Prostate	Leman et al., 2007
Afamin	Ovarian	Jackson et al., 2007

**Table 7.1 Examples of putative serum biomarkers.** Adapted from aoui-Jamali and Xu, (2006).

In addition, several cellular proteins involved in Wnt-signalling were found in spots which yielded multiple hits. Wnts are a large family of cysteine-rich secreted glycoproteins that control development and several components of Wnt signalling are implicated in the genesis of human cancer. These included adenomatosis polyposis coli 2 (APC2; identified in a spot with APOE), which promotes rapid degradation of cadherin-associated protein and may function as a tumour suppressor. Protein Daple Isoform 2 (DAPLE) is a negative regulator of the canonical Wnt signalling pathway, acting downstream of Dvl to inhibit  $\beta$ -catenin stabilisation. In addition, Kinectin 1 isoform b (KTN1; identified in a spot with APOA4) has been identified as a tumor-associated antigen. Kinesin, the receptor for KTN1 is involved in kinesin-driven vesicle motility and accumulates in integrin-based adhesion complexes upon integrin aggregation by fibronectin. Previous reports have suggested that defects in KTN1 may be involved in the onset of cancer [Wang et al., 2004].

In conclusion, the work presented in this thesis has revealed several candidate markers that need to be tested on a larger sample set in combination with CA-125 using immuno-based assays. The proteome of an organism, in this case human, is defined as the complete set of proteins that can be expressed by the genetic material. Based on the number of proteins found in the extensive separation and analysis shown by this work, the number of disease specific-biomarkers may well be lower than the postulated number in the literature.

To further improve the chances of finding serum markers for ovarian cancer, a number of parameters could be improved. The proteome could be divided into smaller ‘sub-proteomes’. For example, using fractionation techniques to separate the glycoproteins and phosphoproteins or 2D-LC separation of tryptic peptides would facilitate more detailed analysis of the serum proteome. In addition, quantitative analysis using stable isotope labelling techniques such as isotope-coded affinity tags (ICAT) or isobaric tags for relative and absolute quantitation (iTRAQ) could be performed on these fractions. The use of such sub-proteome fractionation techniques would permit a simplification of the proteome while providing practical steps towards the ultimate dissection of the entire proteome. In essence, these methods are capable of capturing fairly accurately the relative quantitative information from two or more samples in a single analysis, thereby reducing the analysis time and the effect of technical variability. The MARS or ProteoMiner fractionation strategies could also be extended to an LC-MALDI label-free quantitation platform. Additional analysis of the bound fraction from the MARS depletion studies could also yield useful data. As previous studies on the analysis of albumin-associated peptides and proteins from ovarian cancer patients have shown, low-abundance nuclear proteins linked to cancer susceptibility, including BRCA2, were represented in sera as a series of specific fragments bound to albumin [Lowenthal et al., 2005].

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**Smooth**

```
function [X_new] = smooth(X,windowSize)
start = windowSize+1;
for i=start:size(X,1)-start+1 % changed from size(X,1) - start
X_new(i-start+1,:) = [X(i,1) mean(X(i-
windowSize:i+windowSize,2))];
end
```

---

**Baseline correction**

```
function [point_present] =
baseline_correction(base,point_present,X,pd)
% base - baseline function
% pd - percentage difference
counting = 0;
min_X = inf;
for i = 1:size(X,1)
if base(i,2) > X(i,2)
if X(i,2) < min_X
min_X = X(i,2);
min_X_index = i;
end
counting = 1;
else
if counting
counting = 0;
min_X = inf;
for j = 1:size(X)
if point_present(j)
if abs(X(j,1) - X(min_X_index))/X(min_X_index) < pd
point_present(j) = 0;
end
end
end
point_present(min_X_index) = 1;
end
end
end
if counting
counting = 0;
min_X = inf;
for j = 1:size(X)
if point_present(j)
if abs(X(j,1) - X(min_X_index))/X(min_X_index) < pd
point_present(j) = 0;
end
end
end
point_present(min_X_index) = 1;
end
```

```

function [B,point_present] = splinefun(B,point_present)
index = 1;
B1 = B(:,1);
B2 = B(:,2);
xx = B1;
X = B1(point_present==1);
Y = B2(point_present==1);
for i=1:size(B,1)
xx(i) = B(i,1);
if point_present(i)
X(index) = B(i,1);
Y(index) = B(i,2);
index = index + 1;
end
end
yy = pchip(X,Y,xx);
s = size(B,1);
clear B;
B(:,1) = xx(:);
B(:,2) = yy(:);
for i=1:s
B(i,1) = xx(i);
B(i,2) = yy(i);
end

```

---

### Normalise

```

function [X] = normalise(X,C)
point_sum = sum(X(:,2));
%C = 5*10^8;
X(:,2) = (X(:,2)/point_sum)*C;
for i=1:size(X,1)

t = (X(i,2)/point_sum)*C;
X(i,2) = t;
end
%plot(X(:,1), (point_sum/size(X,1))*ones(size(X,1),1), '-')

```

---

### Peak identification

```

function p=peak_finder(X,ws,thold,sample_index)
% sw - singal-to-noise ratio window size
thold - minimum intensity threshold
% The output 'p':
p(:, 1)      sample index;
p(:, 2)      number of the peak in the initial array;
p(:, 3)      m/z-ratio;
% p(:, 4)  signal-to-noise ratio (intensity divided by the
average intensity in the window);
p(:, 5)      intensity.
if nargin == 3
    sample_index = 0;
end

```

```

slopeSign = diff(X(:,2))>0;
slopeSignChange = diff(slopeSign)<0;
h = find(slopeSignChange) + 1;
h(X(h,2) < thold) = [];
p(:,1) = h;
p(:,2) = X(h,1);
XX = X(:,1);
X2 = X(:,2);
index = 1;
for i=h'
wst = min(ws,length(XX) - i);
wst = min(wst,i-1);
q = find(XX<=(XX(i+wst)));
q1 = find(XX>=(XX(i-wst)));
q2 = intersect(q,q1);
p(index,3) = X(i,2)/mean(X2(q2));
index = index + 1;
end
p(:,4) = X(h,2);
p = [sample_index*ones(size(p(:,1))) p];

```

---

### Peak list

```

function peak_list =
genPeakList_001(proc_spec_LMR,proc_spec_HMR,peak_set,lab,peakGroups,pd)
% peakGroups - max or mean values of the peakalign2-function
% output
% pd - mass separation parameter, must be the same as in
% peakalign2.m function
% peak_set, lab - not used parameters
peak_list = zeros(1,size(peakGroups,1));
for j = 1:size(peakGroups,1)
    if size(peak_set,1) == 0
        h=[];
    else
        h1 = find(peak_set(:,2)<peakGroups(j,1));
        h2 = find(peak_set(:,2)>peakGroups(j,1));
        h = intersect(h1,h2);
    end
    if size(h,1) == 0
        if 1%peakGroups(j) < max(proc_spec_LMR(:,1))
            h1 = find(proc_spec_LMR(:,1)<peakGroups(j,1) +
peakGroups(j,1)*pd);
            h2 = find(proc_spec_LMR(:,1)>peakGroups(j,1) -
peakGroups(j,1)*pd);
            h = intersect(h1,h2);
            ep = max(proc_spec_LMR(h,2));
            if length(ep) == 0
                ['no signal, setting to -1, m/z=' num2str(peakGroups(j)) ]
                peak_list(1,j) = -1;
            else
                peak_list(1,j) = ep;
            end
        end
    end
end

```

```

end
else
h1 = find(proc_spec_HMR(:,1)<peakGroups(j,1) +
peakGroups(j,1)*pd);
h2 = find(proc_spec_HMR(:,1)>peakGroups(j,1) -
peakGroups(j,1)*pd);
h = intersect(h1,h2);
ep = max(proc_spec_HMR(h,2));
if length(ep) == 0
['no signal, setting to -1 m/z = ' num2str(peakGroups(j)) ]
peak_list(1,j) = -1;
else
peak_list(1,j) = ep;
end
end
else
if size(h,1) == -1
peak_list(1,j) = peak_set(h,5);
else
if size(h,1) > 1
peak_list(1,j) = max(peak_set(h,5));
end
end
peak_list(1,j+1) = lab;

```

---

### Peak alignment

```

function peak_groups = peakalign2(pk, first_SNR, second_SNR,
massSep)

Input: pk - spectrum ID
peak location in clock ticks
peak location in mass units
signal-to-noise ratio of the peak
normalized baseline-corrected intensity of the peak
first_SNR - Minimum signal-to-noise ratio for new cluster
second_SNR - Minimum signal-to-noise to be included in
existing cluster
this is not used in this version as it adds no extra peaks
to a cluster just increments the count
massSep - Mass separation param
Output:
peak_groups - PeakID
Highest peak mass location
Mean Mass location
Min mass
Max mass
Number of pk
Max Intensity
%%%%%
pk = sortrows(pk,-5); % descending order of the 5th column
group_index = 1;
peak_groups = [];

```

```

spec_at_peak = zeros(size(pks,1),1);
pks_second_SNR = pks(pks(:,4)<first_SNR,:);
pks_second_SNR(pks_second_SNR(:,4) < second_SNR) = [];
pks(pks(:,4)<first_SNR,:) = [];
size(pks)
for i=1:size(pks,1)
if mod(i,100)==0
i /size(pks,1)
end
if pks(i,4) >= first_SNR
if size(peak_groups,1) == 0
peak_groups(group_index,:) = [ group_index pks(i,3) pks(i,3)
pks(i,3) pks(i,3) 1 pks(i,5)];
spec_at_peak(i) = group_index;
group_index = group_index + 1;
spec_list(group_index).list = pks(i,1);
else
h = [];
for j=1:size(peak_groups,1)
if abs((peak_groups(j,2) - pks(i,3))/peak_groups(j,2)) <=
massSep
h = [h j];
end
end

if size(h,1) == 0 %create new group
peak_groups(group_index,:) = [group_index pks(i,3) pks(i,3)
pks(i,3) pks(i,3) 1 pks(i,5)];
spec_at_peak(i) = group_index;
group_index = group_index + 1;
spec_list(group_index).list = pks(i,1);
else
if size(h,1) >= 1 %add to existing group;
if size(h,1) > 1 then choose closest group
if size(h,1) > 1
ind = h(1);
for j=h
if abs((peak_groups(j,2) - pks(i,3))/peak_groups(j,2)) <=
abs((peak_groups(ind,2) - pks(i,3))/peak_groups(ind,2))
ind = j;
end
end
else
ind = h(1);
end %
end
if size(h,1) > 1
hsp1 = find(spec_at_peak == ind);
hps2 = find(pks(hsp1,1) == pks(i,1));
if size(hps2,1) == 0
%add peak to peak_groups(ind,:)
peak_groups(ind,3) = (peak_groups(ind,6)*peak_groups(ind,3) +
pks(i,3))/(peak_groups(ind,6)+1);
peak_groups(ind,6) = peak_groups(ind,6) + 1;
if pks(i,3) < peak_groups(ind,4)

```

```

peak_groups(ind,4) = pks(i,3);
end
if pks(i,3) > peak_groups(ind,5)
peak_groups(ind,5) = pks(i,3);
end
spec_at_peak(i) = ind;
spec_list(ind).list = [spec_list(ind).list; pks(i,1)];
end %
end
if size(hps2,1) == 0
end %
end
size(h,1) == 0
end
end
size(peak_groups,1) == 0
end %
end
pks(i,4) >= first_SNR
end %
end
for i=1:size(pks,1)
for i=1:size(pks_second_SNR,1)
h= [];
for j=1:size(peak_groups,1)
if abs((peak_groups(j,2) -
pks_second_SNR(i,3))/peak_groups(j,2)) <= massSep
h = [h j];
end
end
if size(h,1) == 0 %do nothing
elseif size(h,1) >= 1
ind = h(1);
if size(h,1) > 1
for j=h
if abs(peak_groups(j,2) - pks_second_SNR(i,3)) <=
abs(peak_groups(ind,2) - pks_second_SNR(i,3))
ind = j;
end
end
end
end
hsp1 = find(spec_list(ind).list == pks_second_SNR(i,1));
if size(hsp1,1) == 0
peak_groups(ind,6) = peak_groups(ind,6) + 1;
spec_list(ind).list = [spec_list(ind).list;
pks_second_SNR(i,1)];
end
end

```

---

**Peak intensity list**

```
function [peak_list f_list] = make_peak_int_list(pg, massSep,
proc_path)

pg - peak_groups, output of peakalign2.m
pg = pg(:, 2); % max value
%pg = pg(:,3); % mean value
%proc_path = '/rmt/csnewton/pgrads/brian/UKCTOCS_GW/proc/';
%proc_path = '/rmt/csnewton/pgrads/brian/Current/D-
drive/Tempst/proc_cal/';
if nargin < 3
    proc_path = [pwd '\res\processed\']
end
f_list = file_finder(proc_path);
%f_list_ctr = file_finder([proc_path 'Ctr\'],'*_1*');%'*_2'
%f_list_bre = file_finder([proc_path 'Bre\'],'*_1*');%'*_2'
%f_list_pro = file_finder([proc_path 'Pro\'],'*_1*');%'*_2'
%f_list_bla = file_finder([proc_path 'Bla\'],'*_1*');%'*_2'
%l = length(f_list_ctr) + length(f_list_bre) +
length(f_list_pro) + length(f_list_bla);
l = length(f_list);
massSep = 0.0015;

peak_list = [];
c=0;
for i=1:length(f_list)
c=c+1;
c/l
    X = dlmread([proc_path f_list(i).fname]);
    peak_list = [peak_list;
    genPeakList_001(X,[],[],0,pg,massSep)];
end
%{
for i=1:length(f_list_ctr)
c=c+1;
c/l
    X = dlmread([proc_path 'Ctr\' f_list_ctr(i).fname]);
    peak_list = [peak_list;
    genPeakList_001(X,[],[],0,pg,massSep)];
end
for i=1:length(f_list_bre)
c=c+1;
c/l
    X = dlmread([proc_path 'Bre\' f_list_bre(i).fname]);
    peak_list = [peak_list;
    genPeakList_001(X,[],[],1,pg,massSep)];
end
for i=1:length(f_list_pro)
c=c+1;
c/l
    X = dlmread([proc_path 'Pro\' f_list_pro(i).fname]);
    peak_list = [peak_list;
    genPeakList_001(X,[],[],2,pg,massSep)];
end
```

```

for i=1:length(f_list_bla)
c=c+1;
c/l
X = dlmread([proc_path 'Bla\' f_list_bla(i).fname]);
peak_list = [peak_list;
genPeakList_001(X, [], [], 3, pg, massSep)];
end
%
```

---

### Spectral calibration

```

function Xc = cal_spec(raw, cal, cal_peaks, massSep, ws)
SNR_low = 1.5;
%ws = 50;
%cal_peaks = [782.402 1047.20 1297.51 1348.66 1620.88 2094.46
2466.73 ...
%            3149.61 6181.05 8565.89 12361.09];
cal_peaks = sort(cal_peaks);
index = 1:length(cal_peaks);
%LMR_index = [1 2 3 7];
%
HMR_index = [10 12 13];
TOFs = sqrt(cal_peaks);
use = [];
length(cal_peaks)
for j = 1:length(cal_peaks)
inds = intersect(find(cal(:,1) > cal_peaks(j)*(1 - massSep)),
find(cal(:,1) < cal_peaks(j)*(1 + massSep)));
[m_1 h_1] = max(cal(inds,2));
peak_mz(j) = cal(inds(h_1),1);
max_point_index = inds(h_1);
XX = cal(:,1);
X2 = cal(:,2);
q = find(XX<=(XX(max_point_index)+ws));
q1 = find(XX>=(XX(max_point_index)-ws));
q2 = intersect(q,q1);
snr(j) = cal(max_point_index,2)/mean(X2(q2));
if cal(max_point_index,2)/mean(X2(q2)) > SNR_low
use = [use 1];
else
use = [use 0];
end
end
initial = [1; 1];
1
[peak_mz' snr']
use = find(use == 1);
x = lsqnonlin(@(x)fun1(x, peak_mz(index(use))),
TOFs(index(use))), initial);
raw_mz = ((x(1)*ones(size(raw,1),1) +
sqrt(raw(:,1)/x(2)))).^2;
Xc = [raw_mz raw(:,2)];
```

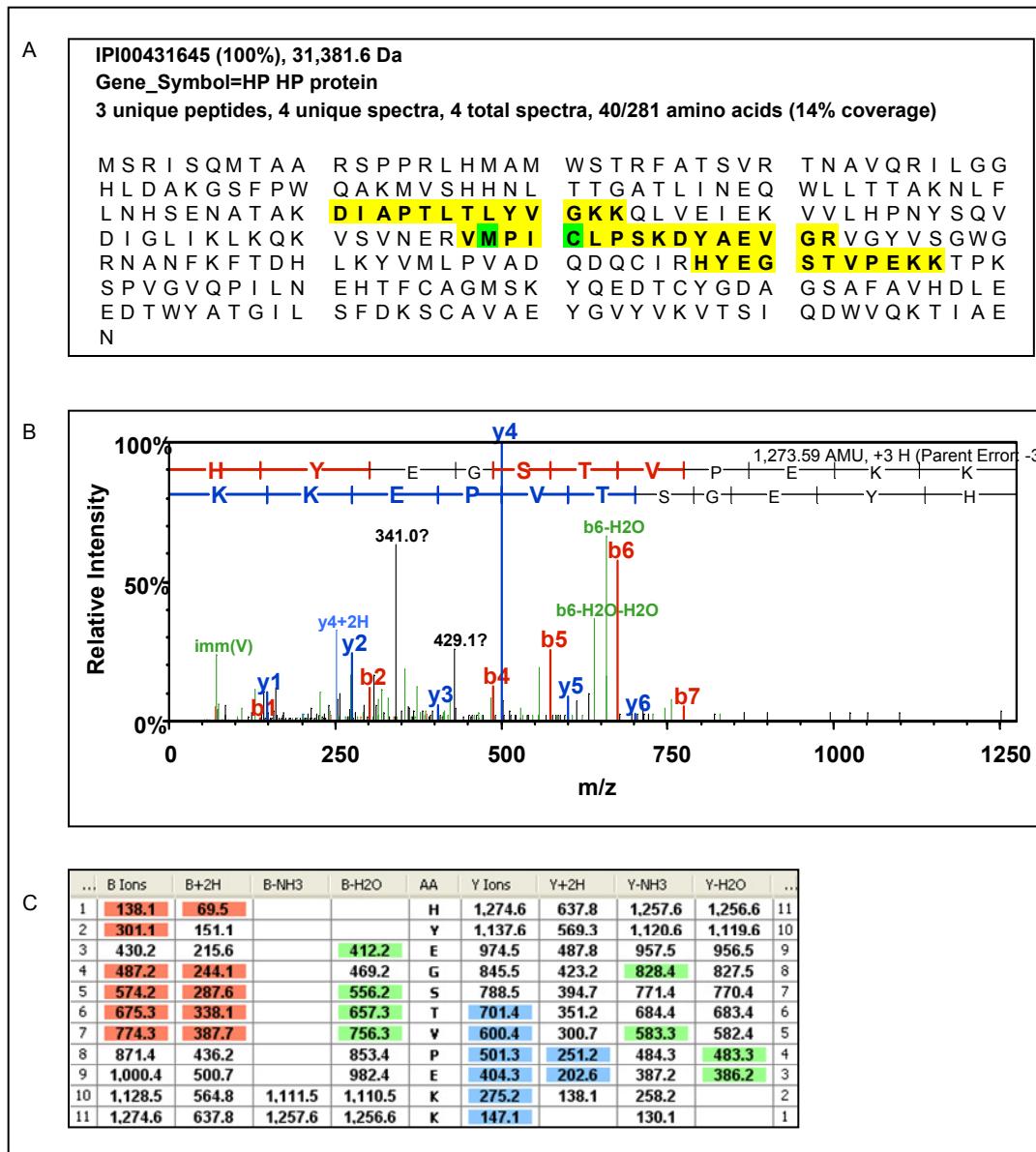
---

**Graphical output**

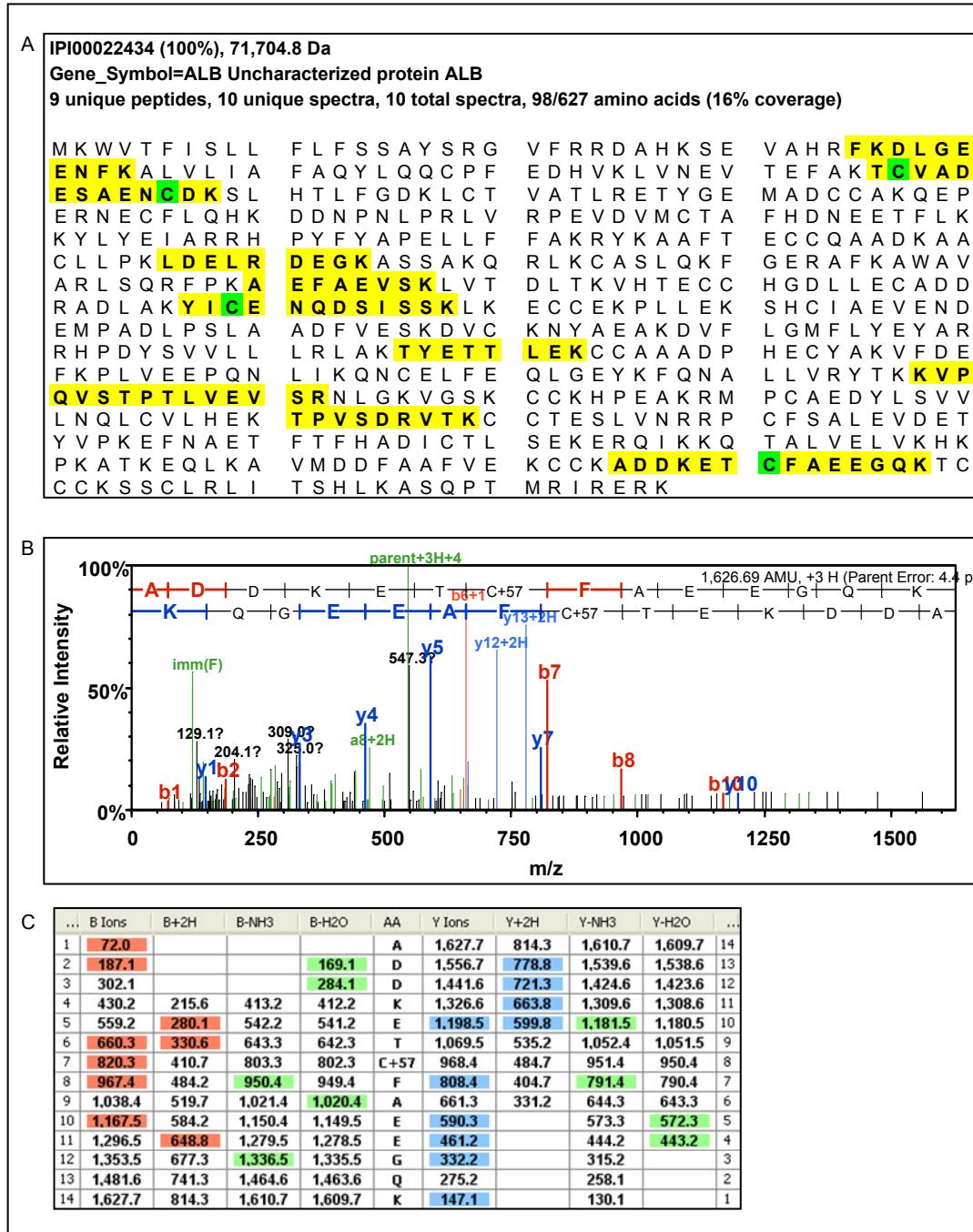
```
function plot_all(pg,plot_path)
pg = pg(:, 2); % max value %
pg = pg(:,3); % mean value
if nargin < 2
plot_path = [pwd '\res\plots\'];
end
if ~isdir(plot_path)
mkdir([pwd '\res\'], 'plots');
end
if ~isdir([plot_path 'fig\'])
mkdir(plot_path, 'fig');
end
if ~isdir([plot_path 'eps\'])
mkdir(plot_path, 'eps');
end
proc_path = [pwd '\res\processed\'];
proc_path_c = [proc_path 'Ctr\'];
proc_path_bla = [proc_path 'Bla\'];
proc_path_pro = [proc_path 'Pro\'];
proc_path_bre = [proc_path 'Bre\'];
for i=1:length(pg)
figure
plot_peak(pg(i),50,proc_path_c,'m')
plot_peak(pg(i),50,proc_path_bla,'g')
h = gcf; % returns the current figure handle
saveas(h,[plot_path 'eps\' num2str(pg(i)) '_bla.eps'])
saveas(h,[plot_path 'fig\' num2str(pg(i)) '_bla.fig'])
close(h); % deletes the figure
figure % created the figure object
plot_peak(pg(i),50,proc_path_c,'m')
plot_peak(pg(i),50,proc_path_pro,'b')
h = gcf;
saveas(h,[plot_path 'eps\' num2str(pg(i)) '_pro.eps'])
saveas(h,[plot_path 'fig\' num2str(pg(i)) '_pro.fig'])
close(h);
figure
plot_peak(pg(i),50,proc_path_c,'m')
plot_peak(pg(i),50,proc_path_bre,'r')

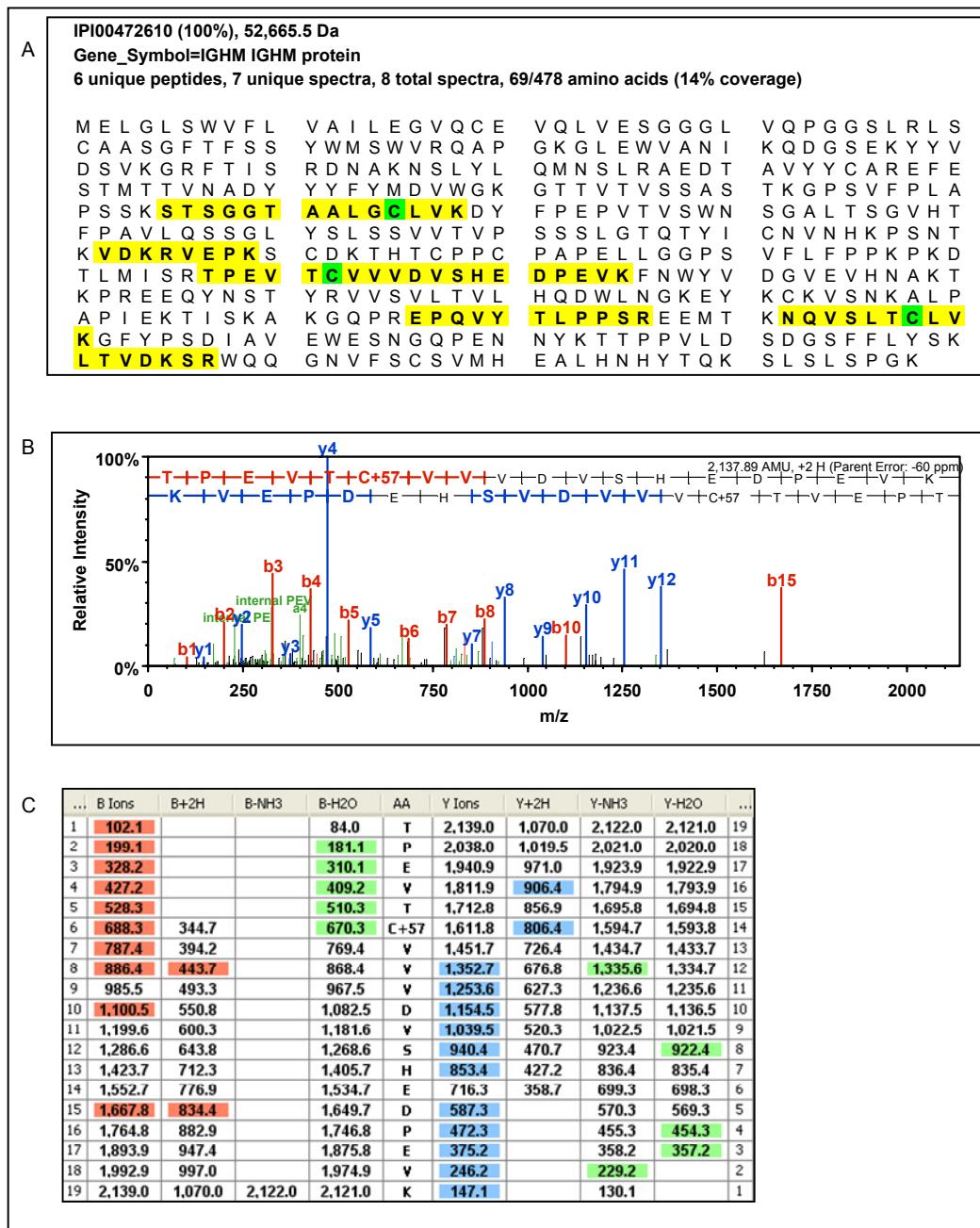
h = gcf;
saveas(h,[plot_path 'eps\' num2str(pg(i)) '_bre.eps'])

saveas(h,[plot_path 'fig\' num2str(pg(i)) '_bre.fig'])
close(h);
end
```

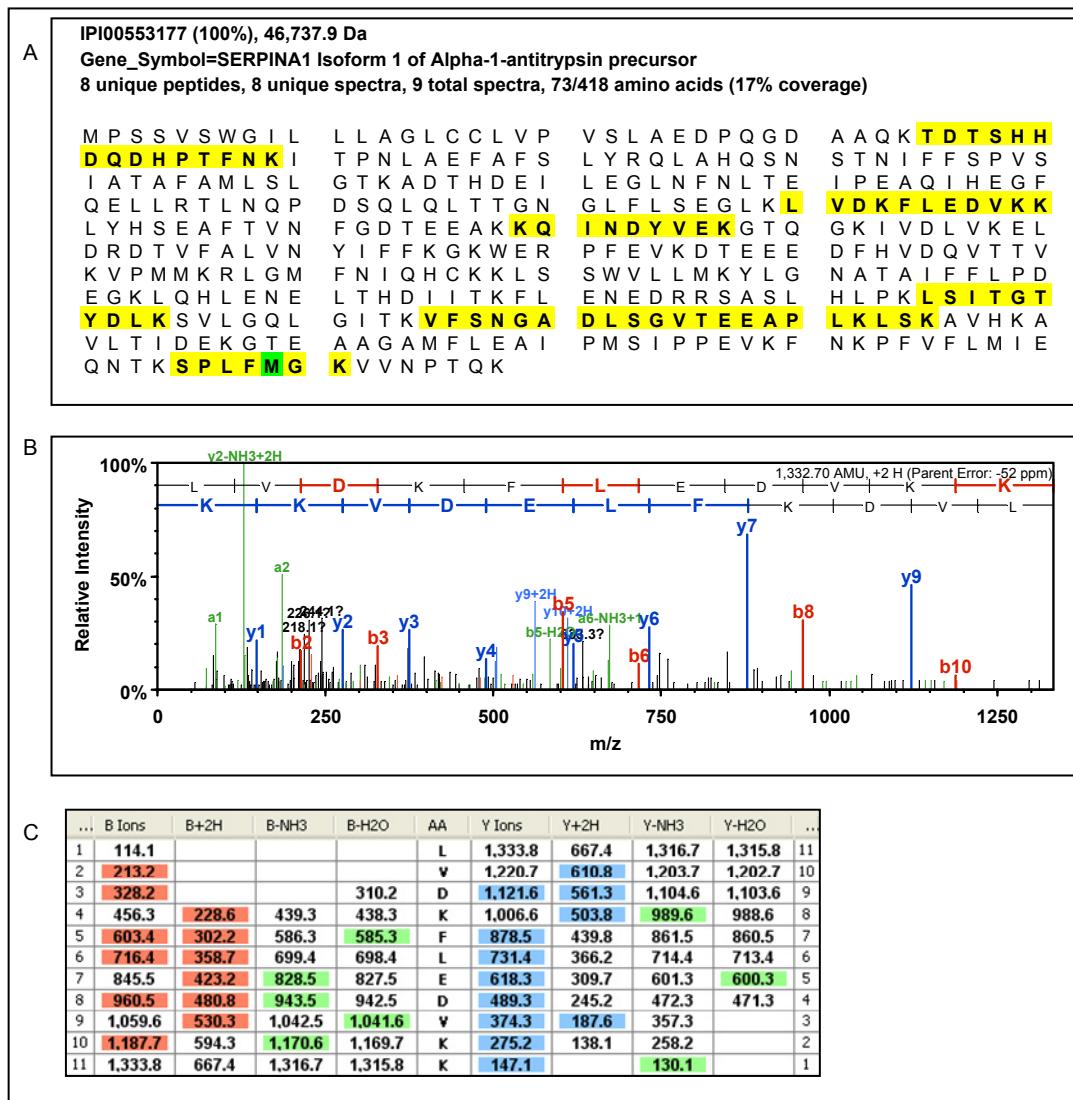


**Differently expressed protein feature identified by LC-MS/MS.** A) HP protein identified by 3 unique peptides (highlighted in yellow in the protein sequence). B) An MS/MS spectrum and C) table indicating the masses of identified fragment ions.

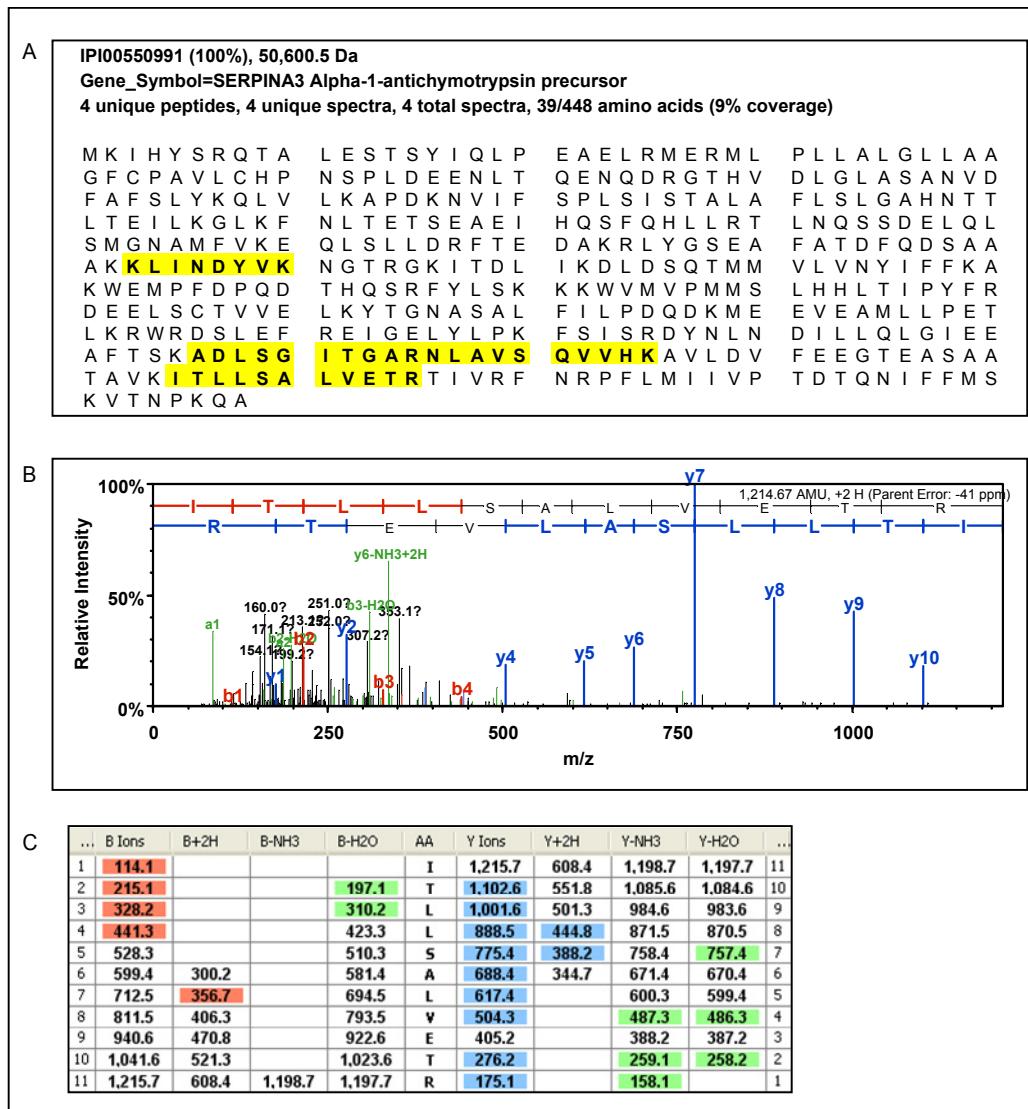




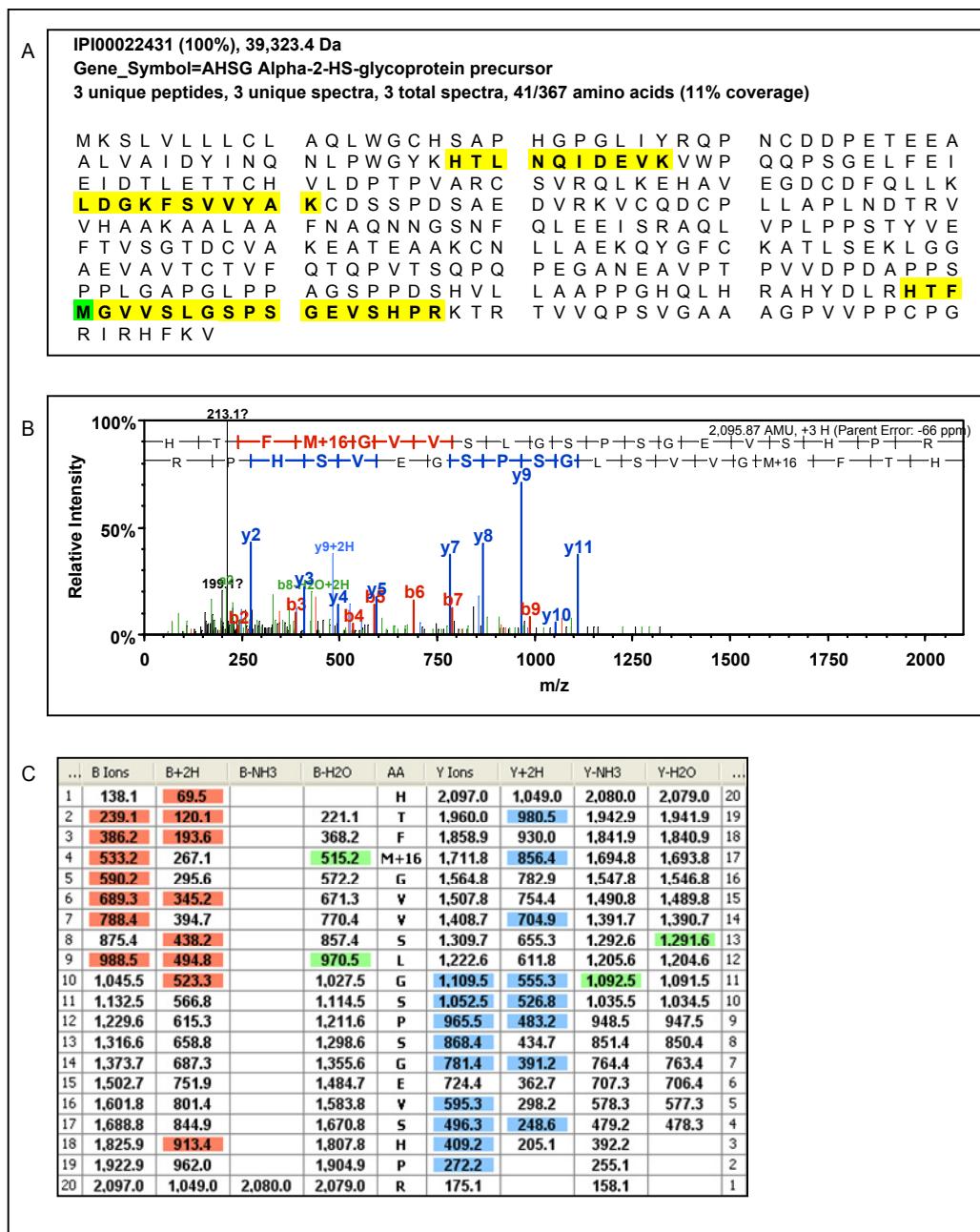
**Differently expressed protein feature identified by LC-MS/MS.** A) IGHM protein identified by 8 unique peptides (highlighted in yellow in the protein sequence). B) An MS/MS spectrum and C) table indicating the masses of identified fragment ions.



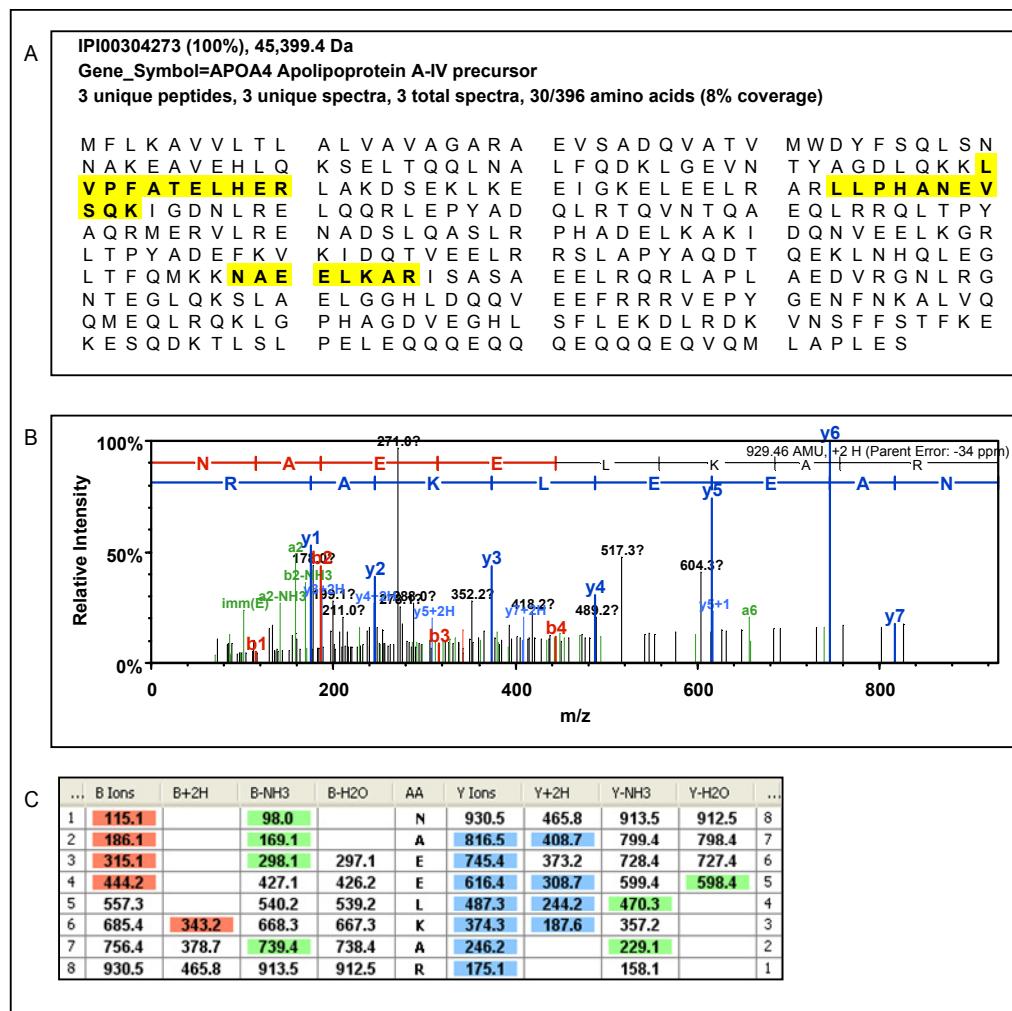
**Differently expressed protein feature identified by LC-MS/MS.** A) SERPINA1 protein identified by 8 unique peptides (highlighted in yellow in the protein sequence). B) An MS/MS spectrum and C) table indicating the masses of identified fragment ions.



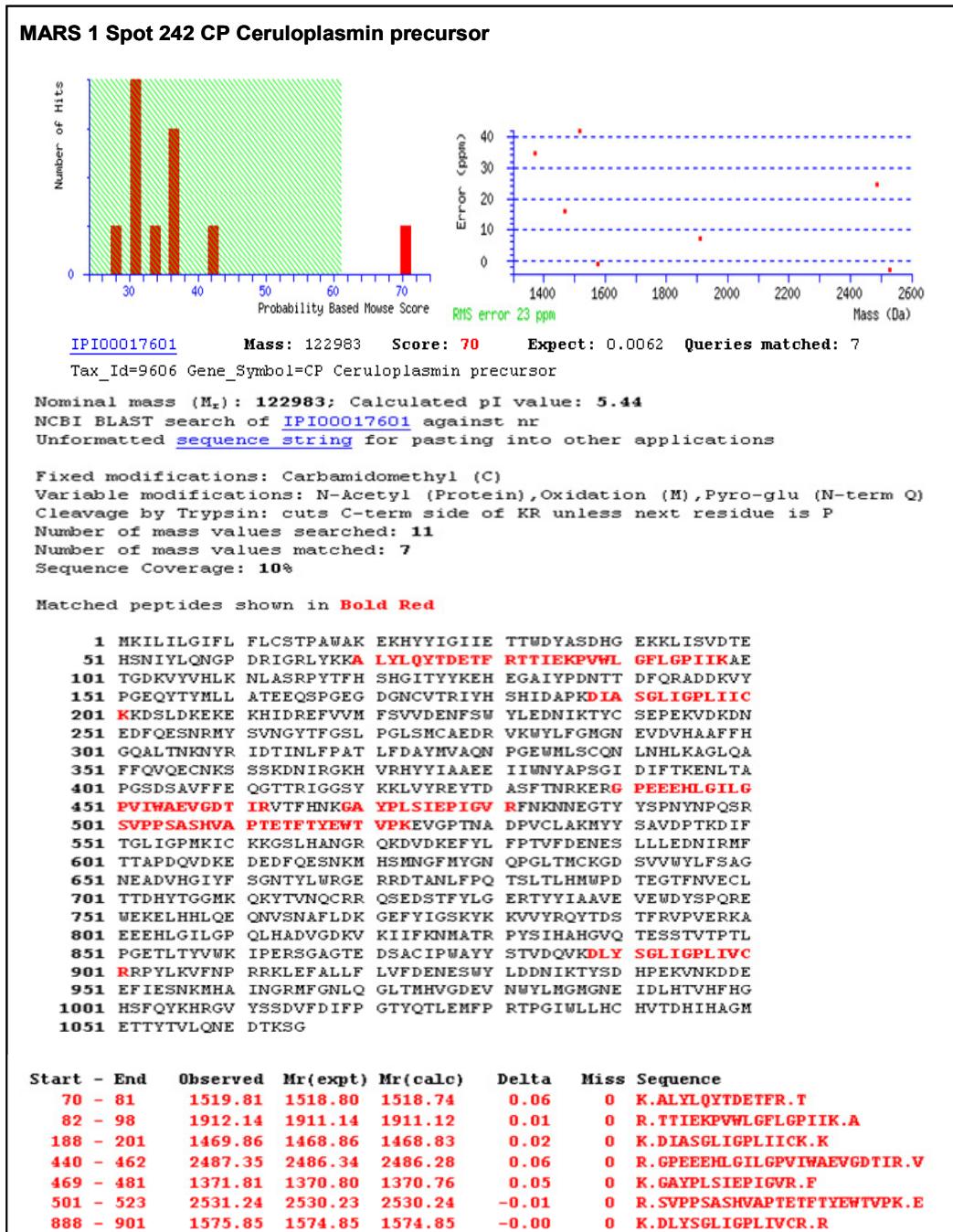
**Differently expressed protein feature identified by LC-MS/MS.** A) SERPINA3 protein identified by 4 unique peptides (highlighted in yellow in the protein sequence). B) An MS/MS spectrum and C) table indicating the masses of identified fragment ions.



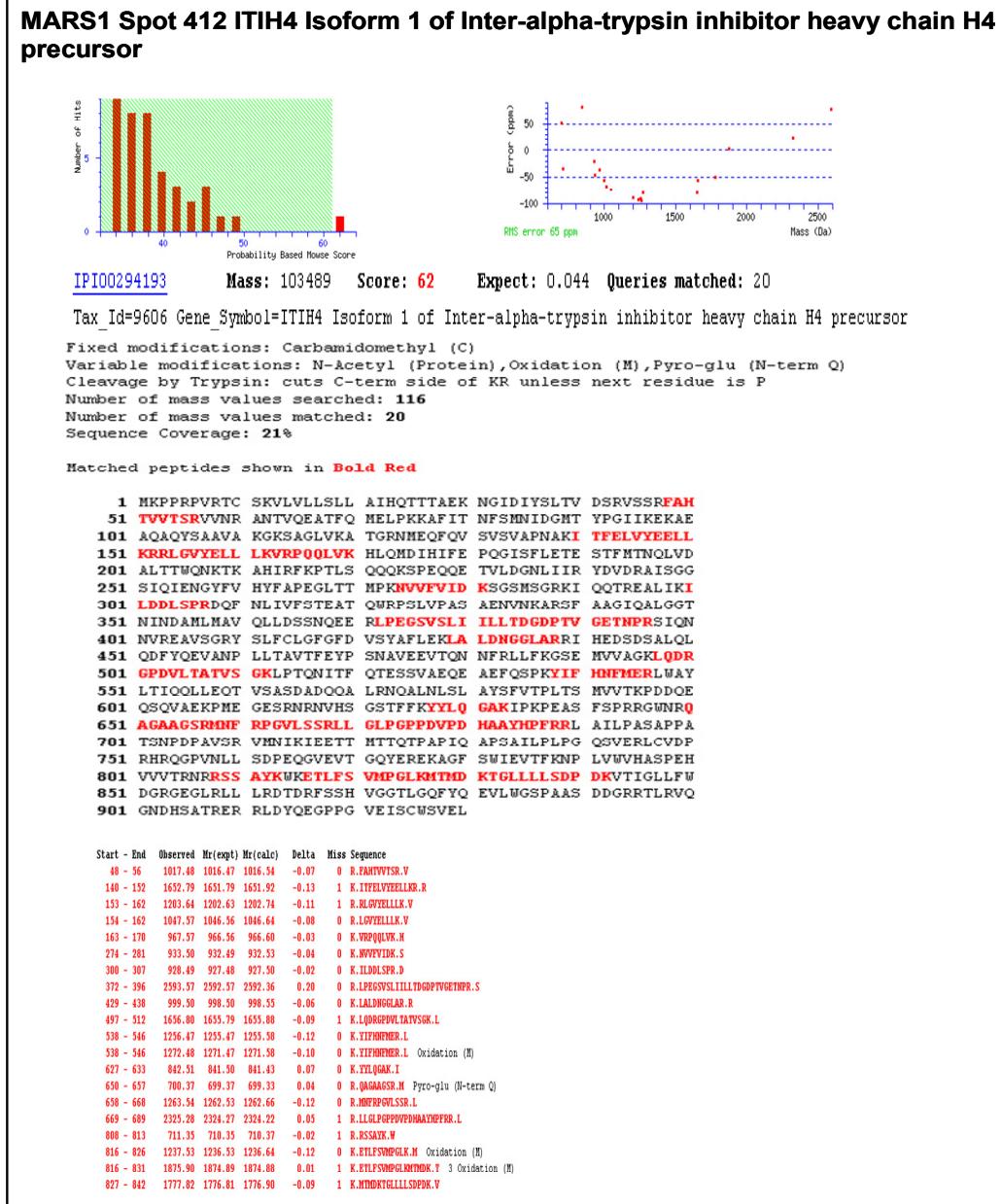
**Differently expressed protein feature identified by LC-MS/MS.** A) AHSG protein identified by 3 unique peptides (highlighted in yellow in the protein sequence). B) An MS/MS spectrum and C) table indicating the masses of identified fragment ions.



**Differently expressed protein feature identified by LC-MS/MS.** A) APOA4 protein identified by 3 unique peptides (highlighted in yellow in the protein sequence). B) An MS/MS spectrum and C) table indicating the masses of identified fragment ions.



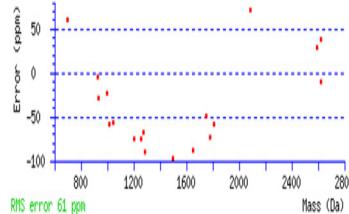
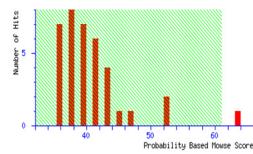
**MALDI-TOF PMF protein identification.** Prominent peaks in the mass range 700-4000 from the MALDI-TOF spectrum were used to generate a peptide mass fingerprint which was searched against the IPI-Human database using the Mascot search engine. A) Probability based Mowse score, B) RMS based error scores for the peptide mass in the PMF and C) details of the identified protein's score, sequence including matched peptides are shown.



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**MARS1 Spot 472 ITIH4 Isoform 2 of Inter-alpha-trypsin inhibitor heavy chain H4 precursor****Probability Based Mowse Score**

Ions score is  $-10^4 \log(P)$ , where P is the probability that the observed match is a random event.  
Protein scores greater than 61 are significant ( $p < 0.05$ ).



1. [IPI00218192](#) Mass: 101488 Score: 64 Expect: 0.031 Queries matched: 19  
Tax\_Id=9606 Gene\_Symbol=ITIH4 Isoform 2 of Inter-alpha-trypsin inhibitor heavy chain H4 precursor

Match to: IPI00218192 Score: 64 Expect: 0.031  
Tax\_Id=9606 Gene\_Symbol=ITIH4 Isoform 2 of Inter-alpha-trypsin inhibitor heavy chain H4 precursor  
Found in search of F:\Musarat\2008\Musarat\27022008\IPI00218192\27022008\_18.txt

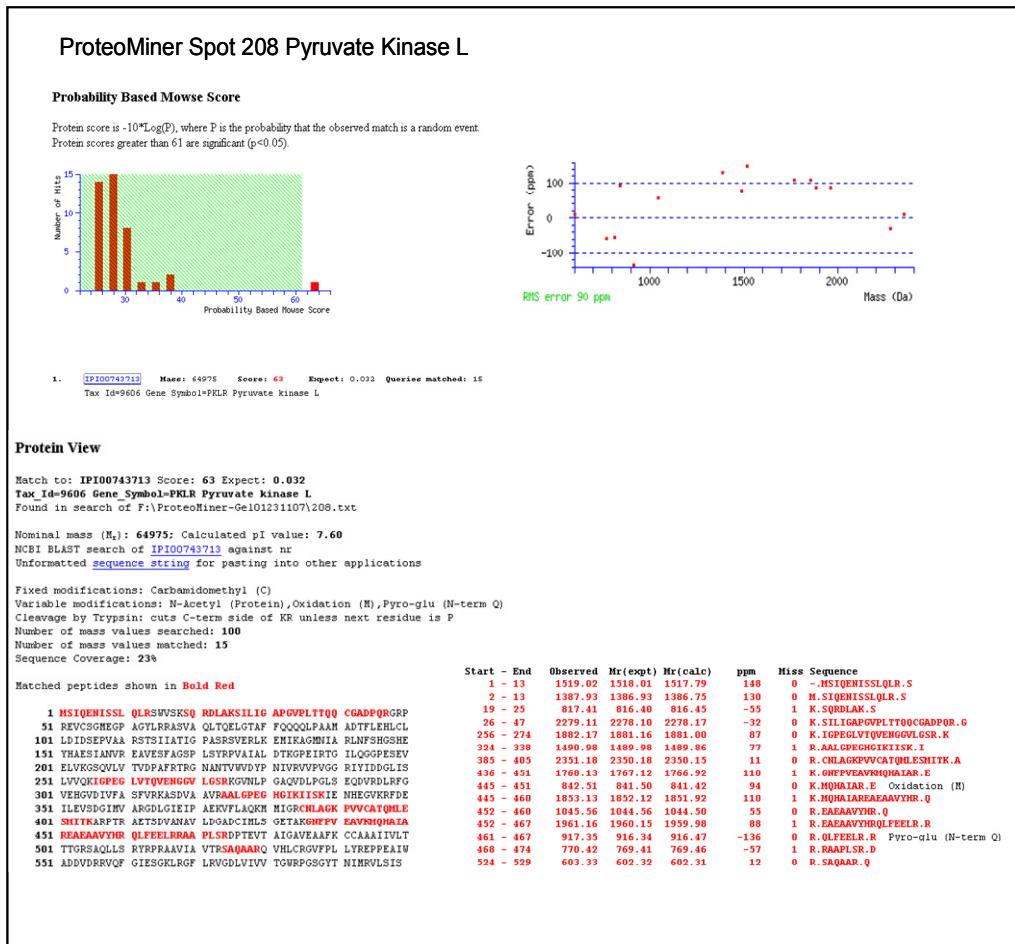
Nominal mass ( $M_z$ ): 101488; Calculated pI value: 6.21  
NCBI BLAST search of [IPI00218192](#) against nr  
Unformatted [sequence string](#) for pasting into other applications

Fixed modifications: Carbamidomethyl (C)  
Variable modifications: N-Acetyl (Protein), Oxidation (M), Pyro-glu (N-term Q)  
Cleavage by Trypsin: cuts C-term side of KR unless next residue is P  
Number of mass values searched: 100  
Number of mass values matched: 19  
Sequence Coverage: 22%

Matched peptides shown in **Bold Red**

	Start - End	Observed Mr(expt)	Mr(calc)	Delta	Miss	Sequence
51	<b>TVIVISRUVN</b> ANTVQEA <del>T</del> Q MELPKKAFIT NFSMNIDGHT YPGIIKEKAE	1017.49	1016.48	10.54	-0.06	0 R.JANTVIVIS.R.V
101	AQAQYSAAVA KCKSACLVKA TGR <b>MEQPFQV</b> SVSVAPNMAKI <b>TEFLVYEELL</b>	1748.78	1747.77	17.86	-0.09	0 R.MEQPFQVSVAPNMAKI.I
151	<b>KRRLGVYELL</b> LKVRPQQPLVK HLQNDIHIFFE PQQGISFLETE STFHTNQLVD	1496.68	1495.67	1495.02	-0.14	0 K.IITFLVTEELL.R
201	ALTTWQNKTK AHIRFKEPLTS QQQ <b>KSPPEQKE</b> <b>TULDGNHLIIR</b> YDVDRRAISGG	1652.78	1651.77	1651.92	-0.15	1 K.IITFLVTEELL.R
251	SIQQIENGVYFT HYFAPEGLTQ MPK <b>WVFVID</b> KSGSMSGRKI QTREALIKI	1203.66	1202.65	1202.74	-0.09	1 R.RLGVTEELL.V
301	<b>LDLISPRDQF</b> NLIIVFSTEAT QURPSLUPAS AEVNWKARSF AAGIQALGGT	1047.59	1046.58	1046.64	-0.06	0 R.LDQVTEELL.V
351	NNDANLMAV QLLDSSNQEE <b>RLPEGSVSLI</b> <b>ILLYTDGDPTV</b> GETHPRSI	1811.84	1810.84	1810.94	-0.10	0 K.SPEIQQETVQAGLIL.R.Y
401	NVREAVASGRY SLFCLCGFGD VSYAFLE <b>KLA</b> <b>LDNGGLARRI</b> HEDSDSALQL	933.51	932.51	932.53	-0.03	0 K.NWVIVDK.S
451	QDFYQEAVNP LLATVTFEYQ SNAVEEVTON NFRLLFKGSE MVVAGKLQDR	697.34	696.33	696.29	0.04	0 K.SGNSR.R. Oxidation (M)
501	GPDLVTATPS GKLPTQNIIT QTESSVAEQE AEFQSPK <b>YIF</b> <b>HDTQHMER</b> WAY	928.51	927.50	927.50	-0.00	0 K.ILDQVSP.R
551	LTIQQLLEQT VSASDADQQA LRNQALNLSL ATSFVTPILTS HVVTKPDDQE	2593.45	2592.44	2591.36	0.08	0 R.LPFGSVSLIILLYTDGDPTVGETHPR.S
601	QSQVAEKPM EGESPNRNWHS AGAAGSRMNF RPGVLSSRLL GLPGPPDWPD	999.53	998.53	998.55	-0.02	0 K.IALQNGLAR.R
651	HAAYHFRRL AILPASAPPA TSNPDPAVSR VNNIK <b>IETT</b> <b>HTTQTPACPS</b>	1256.49	1255.49	1255.50	-0.09	0 K.IIPEPDR.R
701	<b>CSRSRAPAVP</b> APIQAPSAIL PLPGQSVREL CVDPRHRQGP VNLLSDPEQG	1272.50	1271.49	1271.58	-0.08	0 K.IIPEPDR.R. Oxidation (M)
751	VEVTGGQYER <b>KAGFWSIETV</b> FKNPLVWVHA SPERVWVTRR RRSAYAKWKE	2006.04	2005.03	2004.00	0.15	0 K.IEETMTMTQIPACPS.R.S Oxidation (M)
801	TLFSVMPGK <b>MHDKTLGLL</b> LSDPDKVITG LLFWDGREG LLLRLRDTDR	1284.55	1283.57	1283.63	-0.11	0 K.AGFWSIETV.P
851	FSSHVGGTLG QFYQEVWLGS PAASDDGRRT LRVQGNDHSA TRERRLDYQE	1777.78	1776.77	1776.90	-0.13	1 K.HDQHDTMTLLSOPK.V
901	GPPGVIEISWC SVEL					

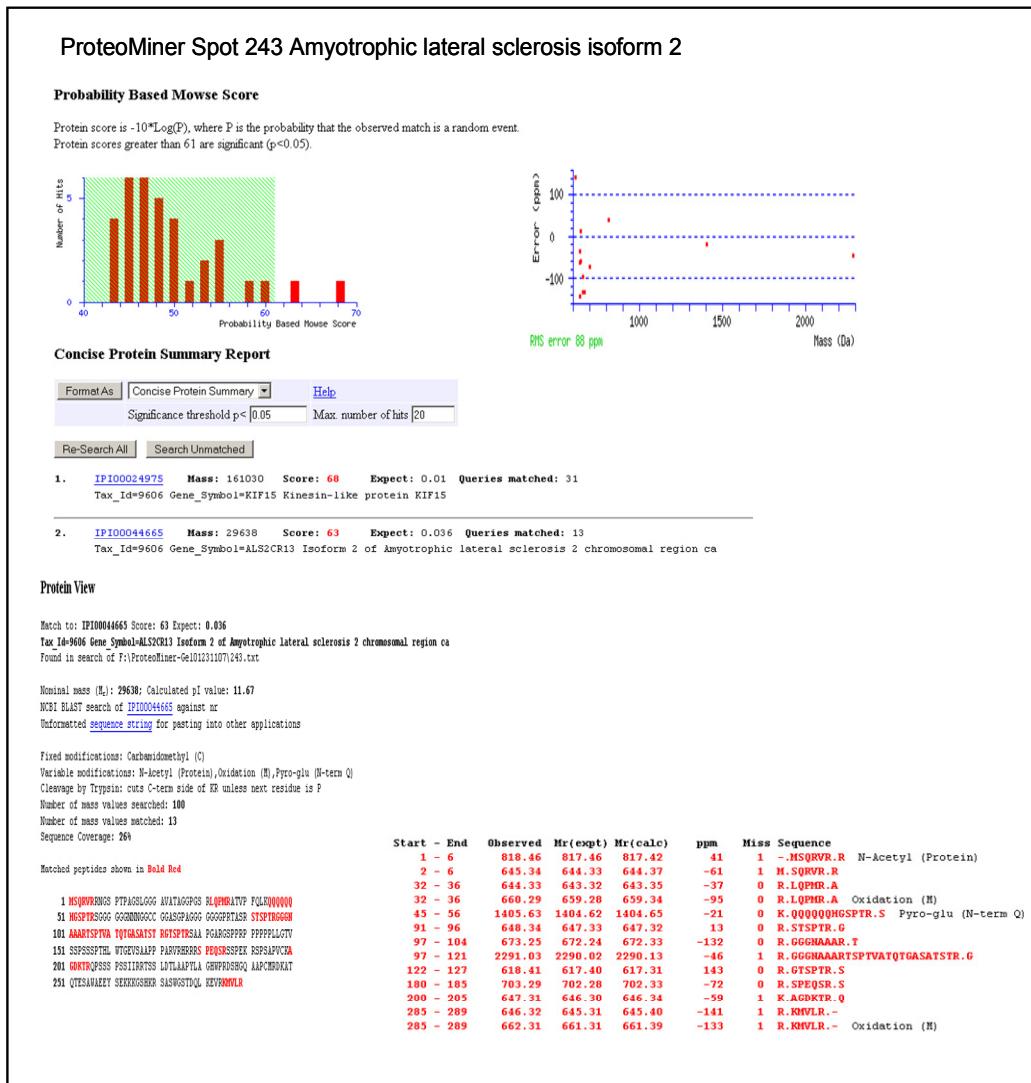
**MALDI-TOF PMF protein identification.** Prominent peaks in the mass range 700-4000 from the MALDI-TOF spectrum were used to generate a peptide mass fingerprint which was searched against the IPI-Human database using the Mascot search engine. A) Probability based Mowse score. B) RMS based error scores for the peptide mass in the PMF. C) Details of the identified protein's score, sequence including matched peptides are shown.



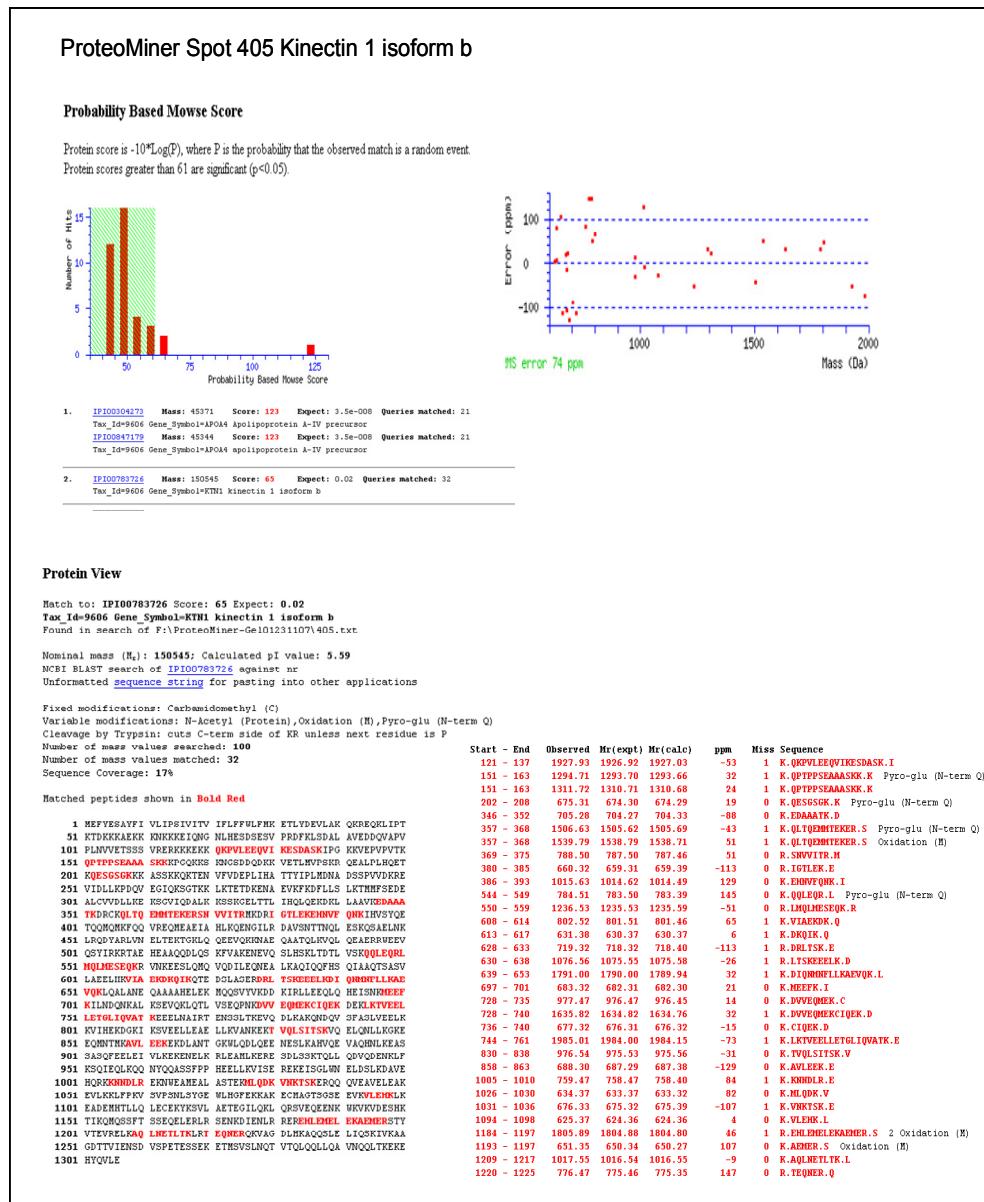
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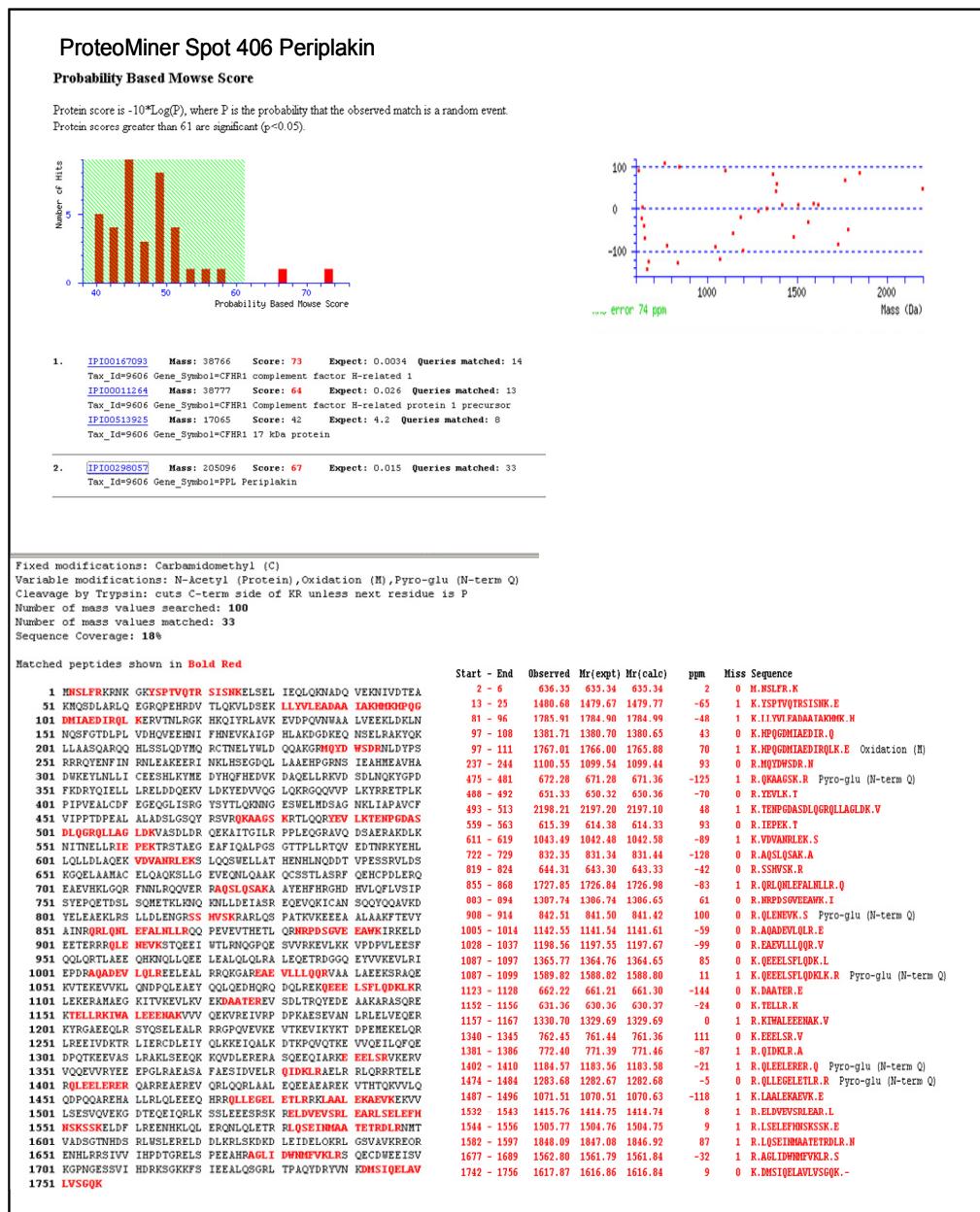
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## ProteoMiner Spot 435 Pericentrin

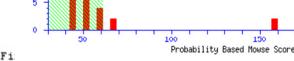
## Probability Based Mowse Score

Protein score is  $-10^4 \log(P)$ , where P is the probability that the observed match is a random match. Protein scores greater than 61 are significant ( $p < 0.05$ ).

1. [TP100847179](#) Mass: 45344 Score: 158 Expect: 1.1e-011 Queries matched: 26 Tax\_Id=9606 Gene\_Symbol=APOA4 apolipoprotein A-IV precursor

2. [TP100304273](#) Mass: 45371 Score: 158 Expect: 1.1e-011 Queries matched: 26 Tax\_Id=9606 Gene\_Symbol=APOA4 apolipoprotein A-IV precursor

3. [TP100479143](#) Mass: 38644 Score: 68 Expect: 0.01 Queries matched: 49 Tax\_Id=9606 Gene\_Symbol=PGNT Pericentrin



Fig

Variable modifications: N-Acetyl (Protein), Oxidation (M), Pyro-glu (N-term Q)

Cleavage by Trypsin: cuts C-term side of KR unless next residue is P

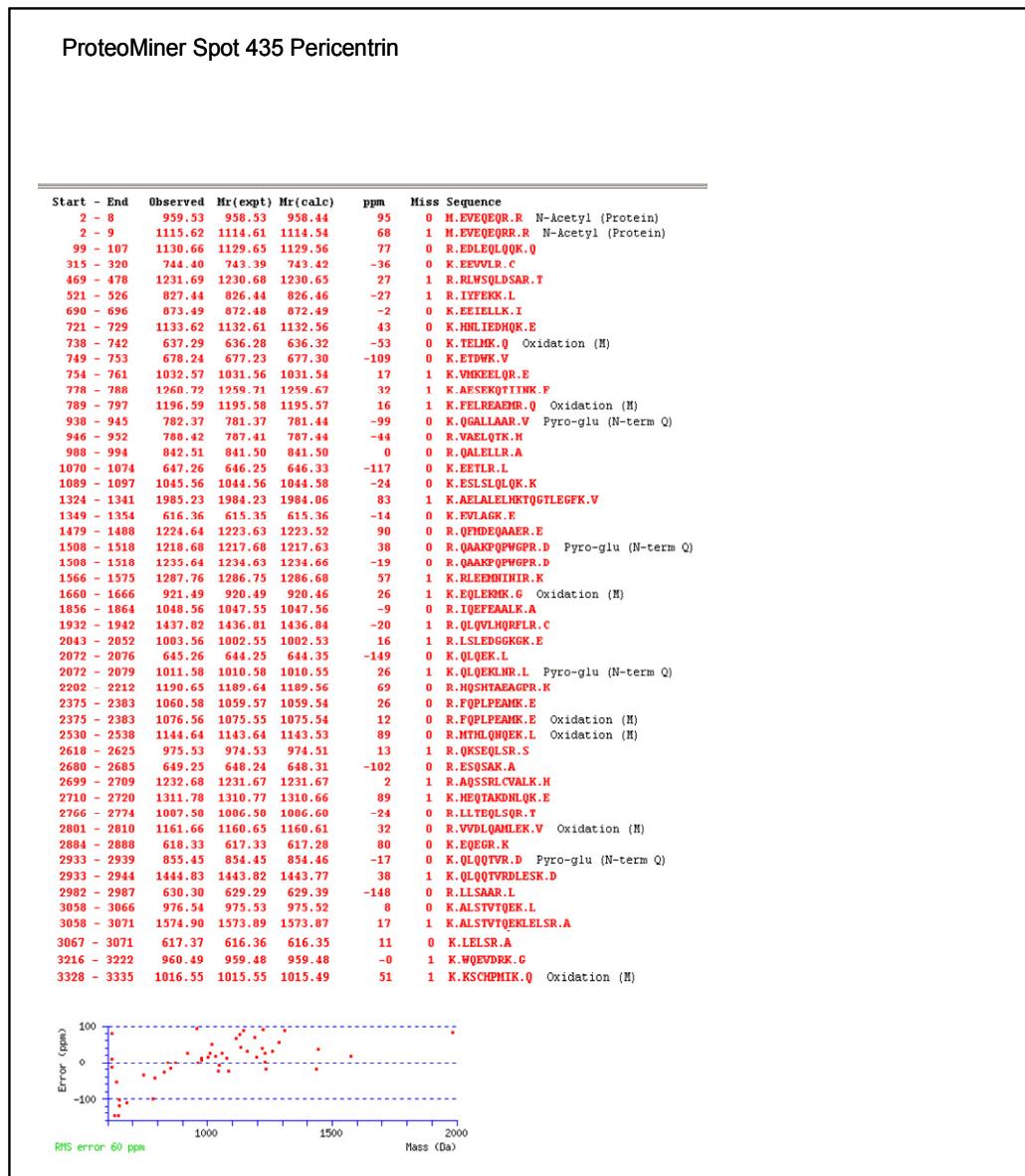
Number of mass values searched: 100

Number of mass values matched: 49

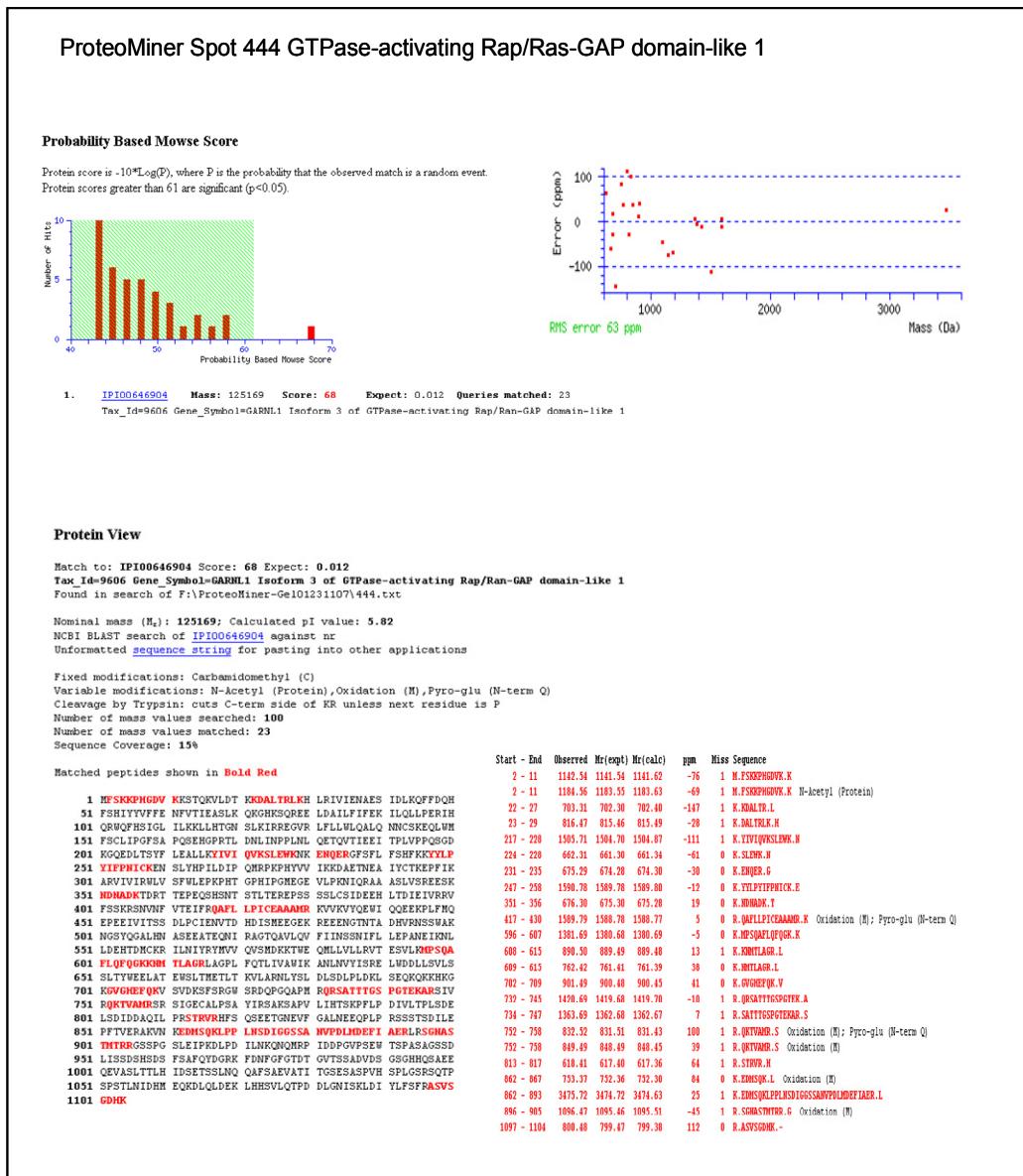
Sequence Coverage: 10%

Matched peptides shown in **Bold Red**

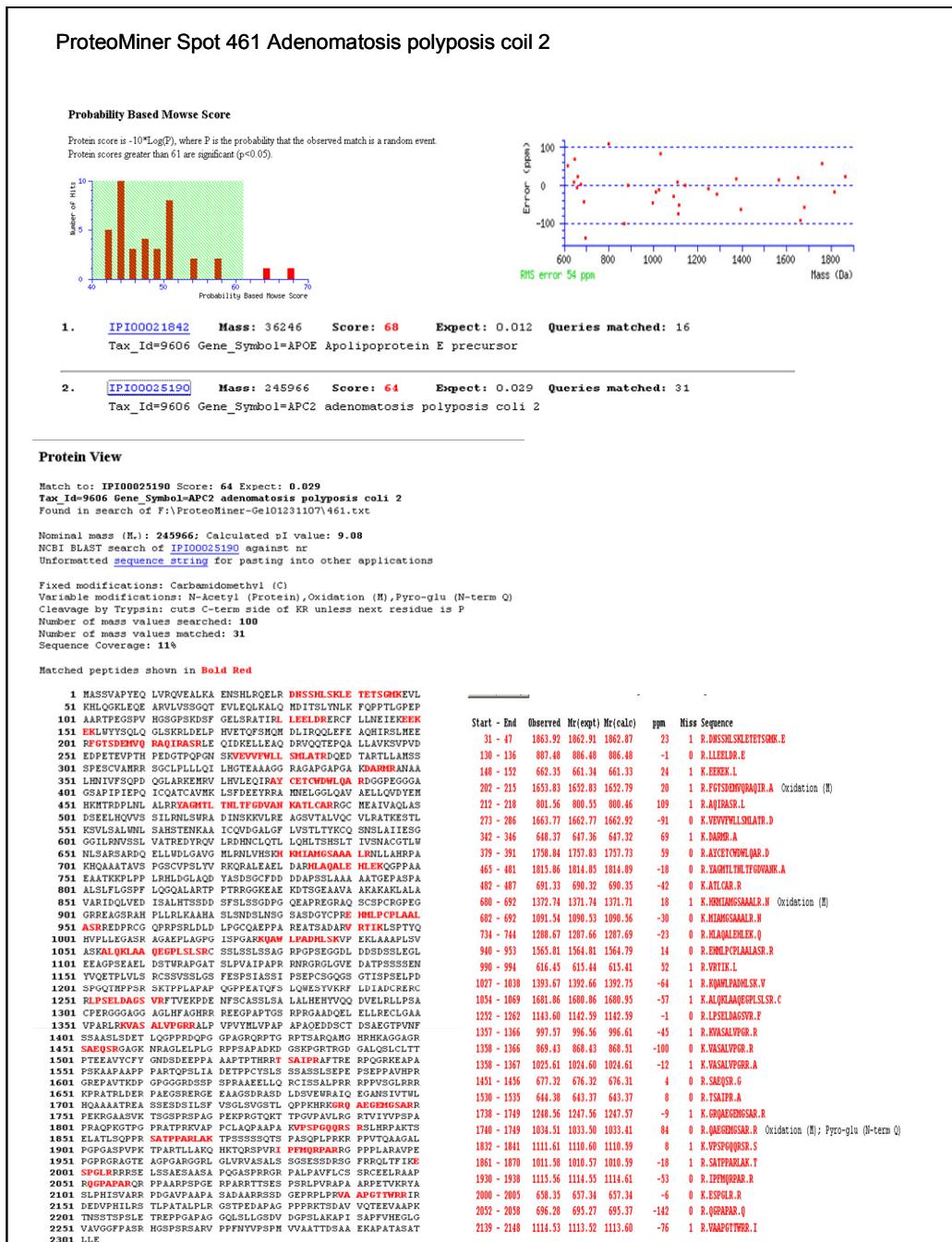
1. **MEVEQEQR** RVEAGRTKLA HFVQRKTKGD SSHSEKKTTAK RKGSAVDASV  
 51 QEESPVTKED SALCGGGDTC KSTSCDCTPD GAGGAAFAQGP EDCDGEKRED  
 101 **LFQIQQK** QWN DHFPEQQGHE TVSDHPEPEQH GMFTVGDHPF EQRMQFTVSD  
 201 HPEPQHGMFT VSDHPEQHPE MFTISDHQPE QRGMFTVSDH TPEQRMQFTI  
 201 SDHQAERQH FTKECEQECE LAITDLESGR EDEAGLHQSQ AVHGELEAL  
 251 RLSLSNHHATA QLELTQANLQ KERKETALTEL REHLLNSRQG ELALLOQSRRQ  
 301 HELELLREHQH AREK**EIVVLR** CGQAAEELKE KLGSEMEHNA QIVKVTLKEWD  
 351 ESEKDULCLEN LRKESAKHR SEMEDLQNQF QKELAEGRAE LKIFQDNRQ  
 401 AERALRNLES HNQAAIIEKLRL EDLQSEHORC LEDLEFKFKE SEKEKQLELE  
 451 NLQASYEDLQK AQSQEETR**W**SQLDARTS FQELSEHHEQ LLARTSRVED  
 501 LEQLQKREKET QHSESLERQLR **IY**TFEKKLDDA KETYQEDDLT LQQLRQGARE  
 551 DALIDSVEVQ LSCVQLEKKE ERKGKDHVDE LEPERHKESL PRFOAELLEES  
 601 HRHFOALEKS PLCIOHGEHVY SDRCVCVETSA LGHEWRLEPS EGHSOELPVW  
 651 HLQGQVQDGD L EADTERAARH LQLETHHVVQ LSLLOTELEL **EIELLK**IENR  
 701 NLVYKELQHET RLKDEELKVK **H**OLLEDEHOKR LNNARAKRTEL **H**KQEFQFREET  
 751 **DWKH**QKRE**E**LF PEAKEKLTLM LLELREKAE **E**FRQTLHMKP **L**RAEADHQLQ  
 801 DQQAQAIQLDL ERSLTEQQD LQLQLEQDILS DDALHCSQCQ REPPTAQDGE  
 851 LAALHVKEDC AQLQMLAERSR FLEERKEITE KFSAEQQAFL QEAQFQHARE  
 901 LLOLQERHQO QLLSVTAELR ARHQAALGEL TASLESQGA **L**AAARVAEI**Q**  
 951 **TK**HAADLQAL ETRHLSLSSLDs LESCYSLEFQ TIREEHHQ**QAL** **E**LLRADFEEQ  
 1001 LNUKQSLHQT ITLQELEKLUK RHEHEGELQSW RDHHLTEAEST ELACTVHAEI  
 1051 QGVHQGERTGS EKTRALHE**E** ET**IL**QLSQASQA QPFIHQEE**RES** **L**SLQIQLQKHH  
 1101 QUQQLKDQVL SLSHEIRECR SELEVLQQRQ ERENKEGANL LSHLRAWDNL  
 1151 SHSERGALQD ABLRRLLQFLG ETLAAVTLR SRIGERVGLC DDDAGAGLAL  
 1201 STAPALEETW SDVALPELDL TLSCECAEMSS VAEISHMRH SFLHSPESVR  
 1251 ECEQPIRRVEF QSLSLSLAVDQG MEMALDSSRQ HEEARQHNSR KEFEKSFNNE  
 1301 ETACQVVRKHO ELLECLKEA AAK**E**LAEL**E**LF **H**KTQGTLE**G** KVE~~T~~ADLKE**V**  
 1351 **LAG**DESDERH LVELEKRSQ LQAAQAAQFQA ALREECTTRLW SRGEATADTA  
 1401 EAREAALEKE VEDLTKEQSQS TRQKAEDRS ALLSQMRLA SELEEQLSQH  
 1451 RGCACAAQAEV TALEQVQASD DHLRNRQ**QF** **H**DE**Q**AAE**REH** EREEFQFQEIQ  
 1501 RLEQQLR**QAA** **KP**WPGRD**S** QQAFLGEVDE LLQQLRKEI DEFNFELA**IQK**  
 1551 ESDARQVLM**E** EEE**IK**Q**LEEM** **H**IN**IK**R**CV**Q**A** LQEV**E**KE**Q**DR**E**  
 1601 VLKKQOMNSL LLLASTLQG**DL** DAGRCPEPPS PSPEPGEI**Q** LEV**T**Q**R**ALLR  
 1651 RES**E**VELD**LR** **E**LE**IK**Q**DL**E SKNE**E**EL**IL**LN LKLDQNQS**T** AVSL**R**LEEE  
 1701 NTSLKVIVTR SS**E**II**E**EL**KL**AT INNLQENQ**NR** LQ**E**KE**A**E**E** Q**L**HEV**E**IE**Q**  
 1751 HELSLHGQVFT HEVHSQAGQ LQ**E**LLCSQ**A** GGPGRQ**AL**Q**L**G E**L**EA**A**LF**A**RE  
 1801 ALSRLLAQ**P** PRISQALEAL Q**R**QLOGAAE**A** E**E**LO**A**EL**E**ER **N**VAL**R**EE**A**  
 1851 DMASR**I**Q**EF****F** **A**ALK**A**KE**A**TI AERNL**E**LE**I**DA**L** NQ**R**KA**A**SAE**A** LEAV**L**L**A**  
 1901 IRRALFOCPL AAGAAPP**E**LLQ**W**RA**Q**AC**RL**W D**W**LA**Q**AC**RL**W **R**KS**D**Q**G**PF**G**  
 1951 QAPPA**T**AT**HT**W VPG**A**HP**Q**DP**Q** D**Q**G**A**K**Q**Q**T**Q D**V**E**A**SH**A**AL **V**PU**V**PP**D**Q**G**  
 2001 LQPVLT**W**EDL APL**C**Q**E**GV**G** SV**L**T**V**Q**Q**RL Q**S**ELL**L**V**N**NT**R** **M**R**L**SL**D**GG**K**  
 2051 **GK**KEV**L**EP**C**Q**V** L**P**KV**D**LV**Q**AV**G** **R**Q**L**Q**E**KL**MR** L**Y**SH**T**Q**V**ND**D** A**D**TS**L**W**M**  
 2101 ASAHLESS**S** SDDSCD**Q**E**E**EP D**S**PH**H**IT**D**CD A**N**HT**T**Q**G**TD V**I**R**N**Q**A**IDA**C**  
 2151 DANTTPG**G**UT D**V**TKH**N**DS**L** PDE**M**P**D**ST**O** F**E**K**E**CD**M**SL S**S**PT**S**V**L**G**S**  
 2201 **F**Q**Q**SH**T**Q**E****A**D**U** **P**R**K**SP**V**G**H**D L**S**W**S**SP**E**VL F**K**D**W**TL**E**FW**P** S**L**P**V**TP**H**SG**A**  
 2251 LSLCSAD**T**SL G**D**RA**D**TS**L**P**Q** T**G**P**G**LL**C**SP G**V**U**S**AA**L**AL**Q** W**A**ES**P**ADD**H**  
 2301 H**V**ORTAV**E** T**V**ED**F**IT**T**SP**D** S**Q**ET**L**S**P**PPP G**L**E**G**KA**R**SSR **K**SD**G**SP**G**  
 2351 L**S**P**G**GG**P**PE**A** T**Q**AG**P**UT**V**TAS **I**S**G**P**F**Q**P**LE **A**MK**E**KE**V**RP**K** H**V**ALL**C**Q**M**  
 2401 D**E**SHQ**I**LL**Q**PS **E**GL**A**PP**S**GP**E** P**H**PR**P**KE**D**E**E** D**I**SL**H**GG**T**TQ E**V**PT**A**CP**D**MR  
 2451 G**L**LL**Q**U**V**Q**A** **E**LP**O**RL**Q**SG**D** L**G**H**S**LL**Q**LE**R** L**E**K**I**TR**E**Q**D**  
 2501 L**Q**E**K**SL**E**LL**H** L**P**DR**R**SS**L**LS**I** L**Q**AL**R**Q**L****M** **T****H****Q**0**H**Q**E**KL**Q** L**H**LT**A**LT**S**  
 2551 A**R**GS**Q**SL**A**RR**A** **E**PRO**F**EL**Y** **V**E**F**CK**I**AG**D** L**O**KT**L**SE**F**OF **K**AN**S**W**Q**LLA  
 2601 A**E**QT**V**W**D**LK S**D**LC**E**SP**Q****S** **F**Q**U**S**R**SL**C**Y Q**O**Q**V**Q**L**RS**M** L**S**SK**N**FL**K**A  
 2651 A**L**Q**E**LE**G**EG**S** Q**E**GR**A**Q**Q**LE**E** E**E**QL**B**RL**Q****R****E** **S**Q**A**SK**A**LL**E** **R**AS**E**LT**E**Q**A**  
 2701 **S**SR**L**CV**A**LK**H** **E**QT**A**DK**H**Q**Q**K EL**R**TR**E**NS**C**E **A**LL**A**Q**E**ER**S**Q**L** SEL**Q**DK**L**A**E**  
 2751 **S**ER**T**EL**L**SEA **R**LR**H**EL**LT****Q****E**Q **L****S****Q**BT**O**Q**H** E**H**OD**T**Q**H**AL L**Q**LK**E**E**K**SR  
 2801 **V**VD**I**Q**A**H**E**K **V**Q**Q**AL**H**S**Q**Q **G**LA**E**AA**Q**H**C** E**E**AL**R**RE**E**EV**S** AT**L**KE**T**VE**A**  
 2851 HT**Q**KE**L**EL**S** L**E**RE**E**PK**P**AM **L**Q**A**E**E**LS**H** P**R****E**PF**E**GR**A** AR**P**SA**E**AR**Q**S  
 2901 PAA**A**Q**U**Q**R**W Q**R**Q**E**KL**R** EL**O**Q**R**Q**D**HK **I**Q**U**Q**T**Q**V**D **L**ES**K**EV**P**G**S**  
 2951 E**L**HL**G**SA**R**A **G**AS**D**HL**A**RS**E** Q**O**RE**E**LE**A**MP**O** R**L**LS**A**AB**S**LT **F**TS**T**Q**A**BD**T**  
 3001 VND**W**TS**S**NE**K** AV**U**MSL**H**LT E**L**KS**D**LS**P**T S**S**Q**K**MA**E**EL Q**O**Q**V**D**U**LL**K**  
 3051 D**N**V**S**LT**K**W**S** **T****V**T**Q**E**K**EL**S** R**A**V**S**KL**E**LL**K** K**H**HL**Q**KG**C**SP S**R**RS**E**AN**H**  
 3101 D**E**T**A**P**O**SS**L** R**P**D**P**GR**L**PP**A** AS**E**KA**F**TS**M**N K**H**KL**Y**LY**H** Y**R**E**S**FR**A**LI  
 3151 Y**Q**KY**L**LL**L**LI G**G**Q**D**Q**S**Q**E**GT**T** L**S**MA**I**HL**G**Q**F** P**S**KA**E**R**K**ITS R**P**T**E**FT**R**AV  
 3201 R**U**V**I**AI**L**LR**L** R**F**U**K**W**Q**EV**D** R**R**GA**L**Q**G**KA P**R**P**G**R**A**R**Q**P Q**S**P**R**T**R**ESP  
 3251 P**T**RO**V**PS**G**HT R**D**P**A**GR**R**LA **A**AS**P**HS**G**GR **A**TP**S**PS**N**RL E**R**SL**T**AS**Q**P  
 3301 H**S**L**T**E**V**HH**I** E**V**I**Q**GR**L**GG**V** L**P**D**S**T**K****I****C** **H**PH**I**K



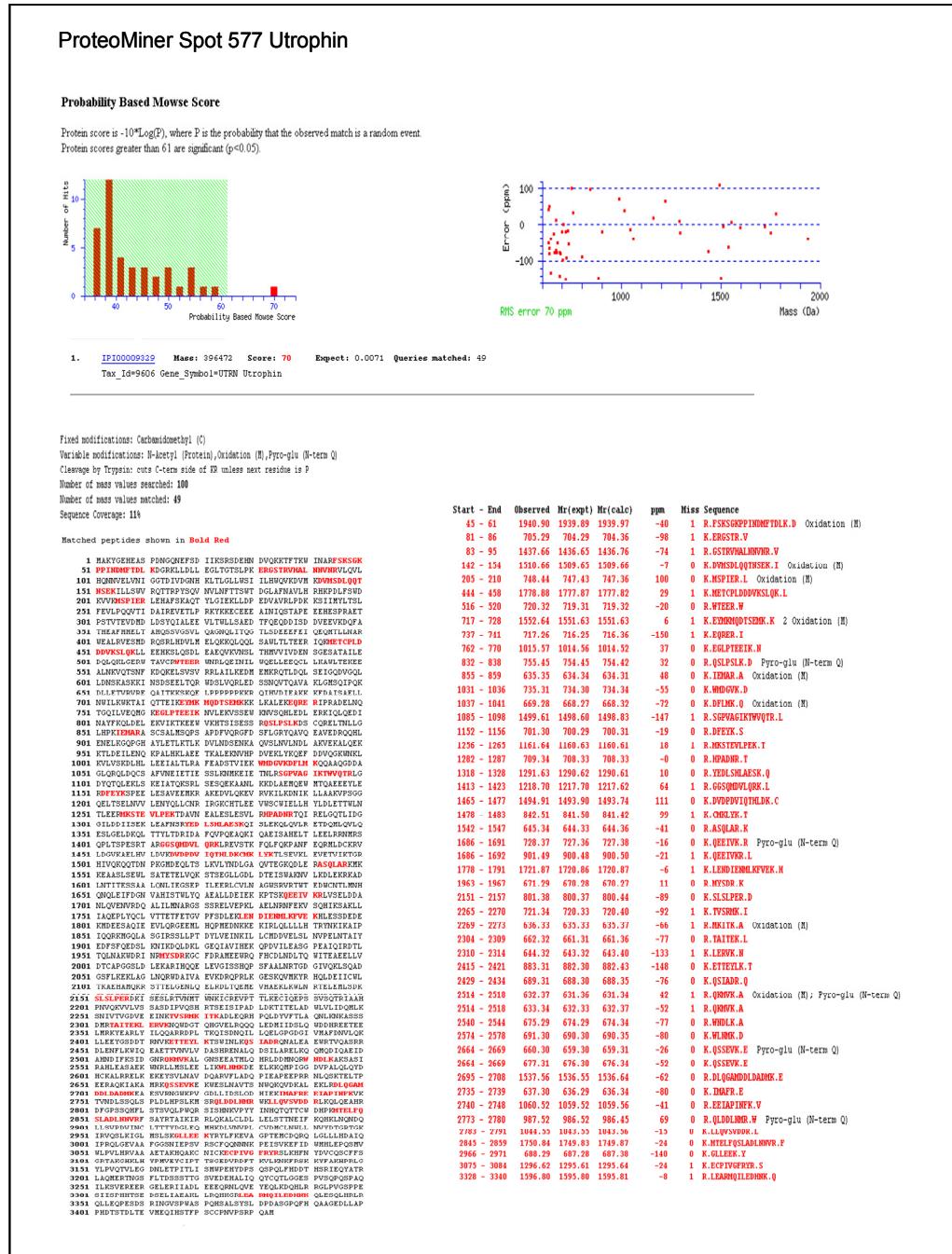
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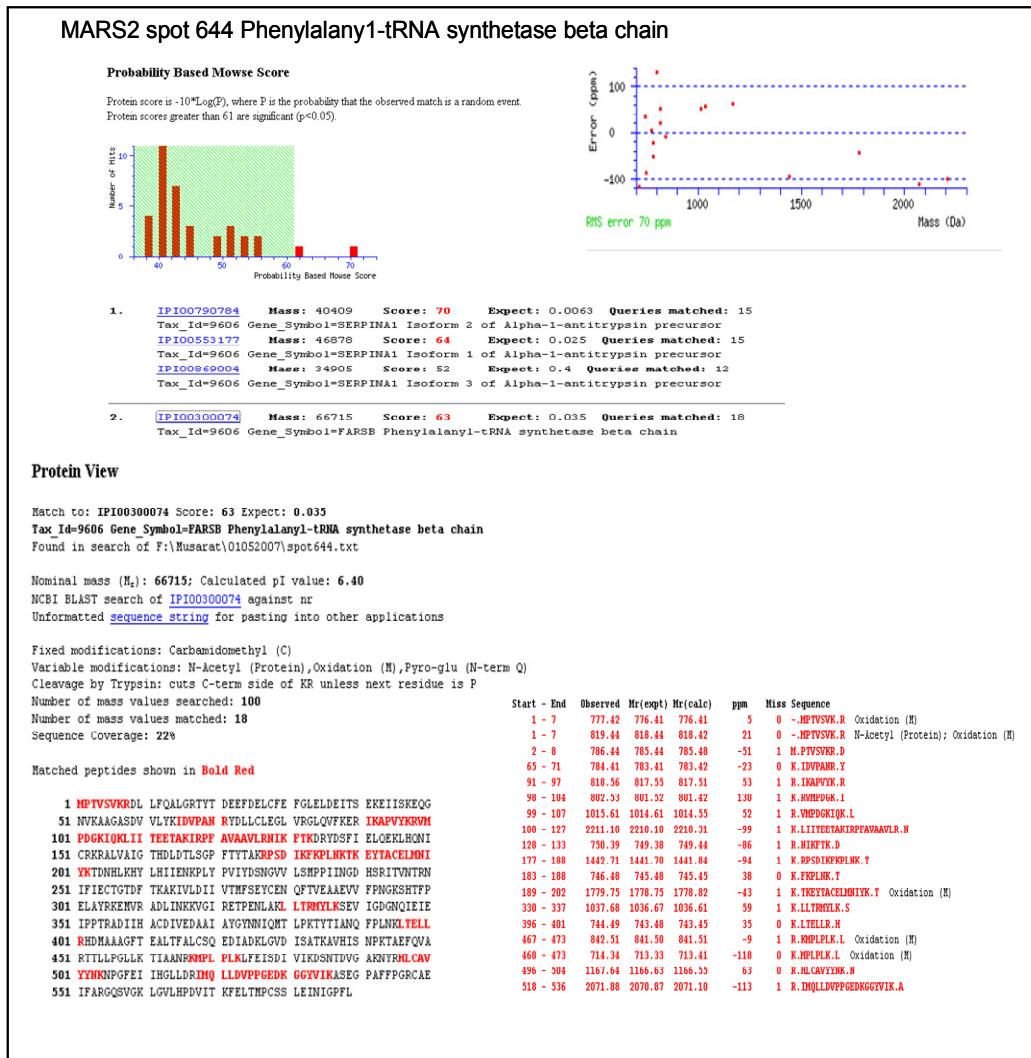
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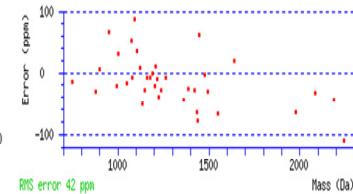
MARS2 spot 664 Protein DAPLE isoform 2

## Protein View

Match to: IPI00740019 Score: 82 Expect: 0.00046  
Tax\_Id=9606 Gene\_Symbol=CCDC88C Isoform 1 of Protein Daple  
Found in search of E:\Musarati\01052007\spot664.txt

Nominal mass ( $M_r$ ): 229215; Calculated pI value: 5.87  
NCBI BLAST search of [IPI00740019](#) against nr

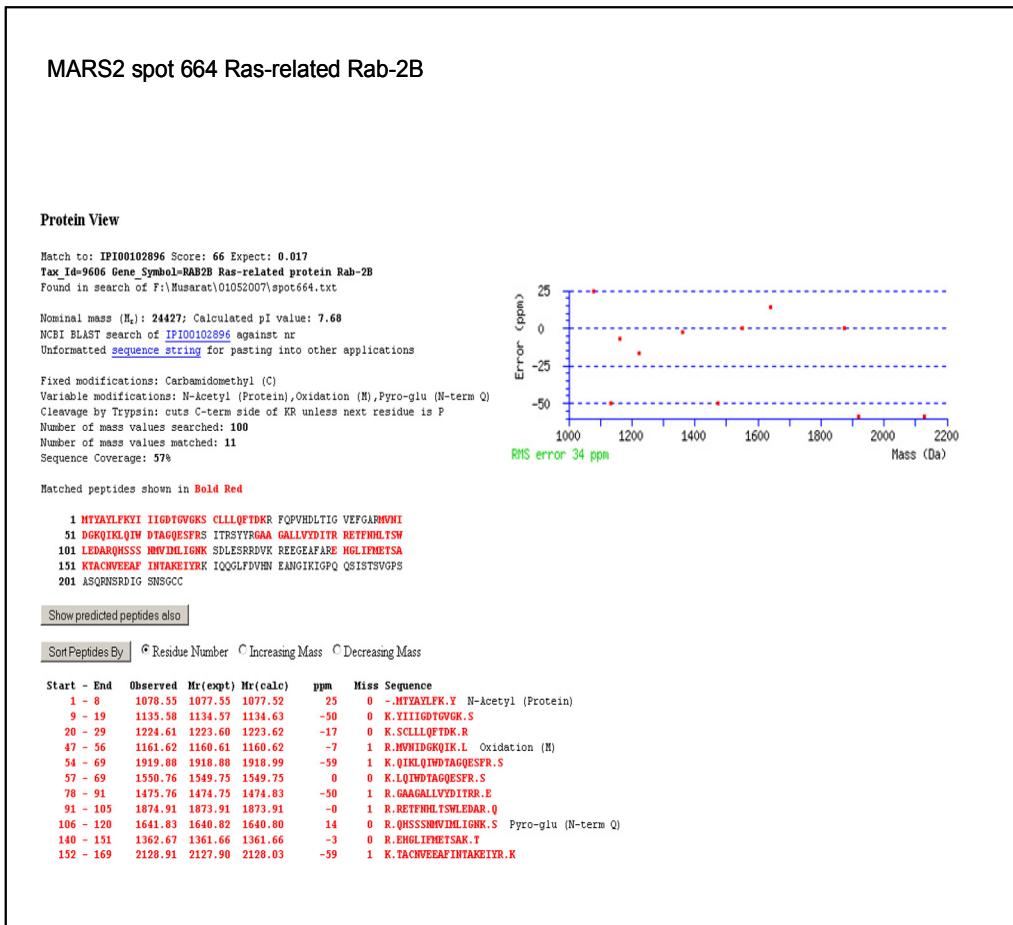
Fixed modifications: Carbamidomethyl (C)  
Variable modifications: N-Acetyl (Protein), Oxidation (M), Pyro-glu (N-term Q)  
Cleavage by Trypsin: cuts C-term side of KR unless next residue is P  
Number of mass values searched: 100  
Number of mass values matched: 37  
Sequence Coverage: 18%



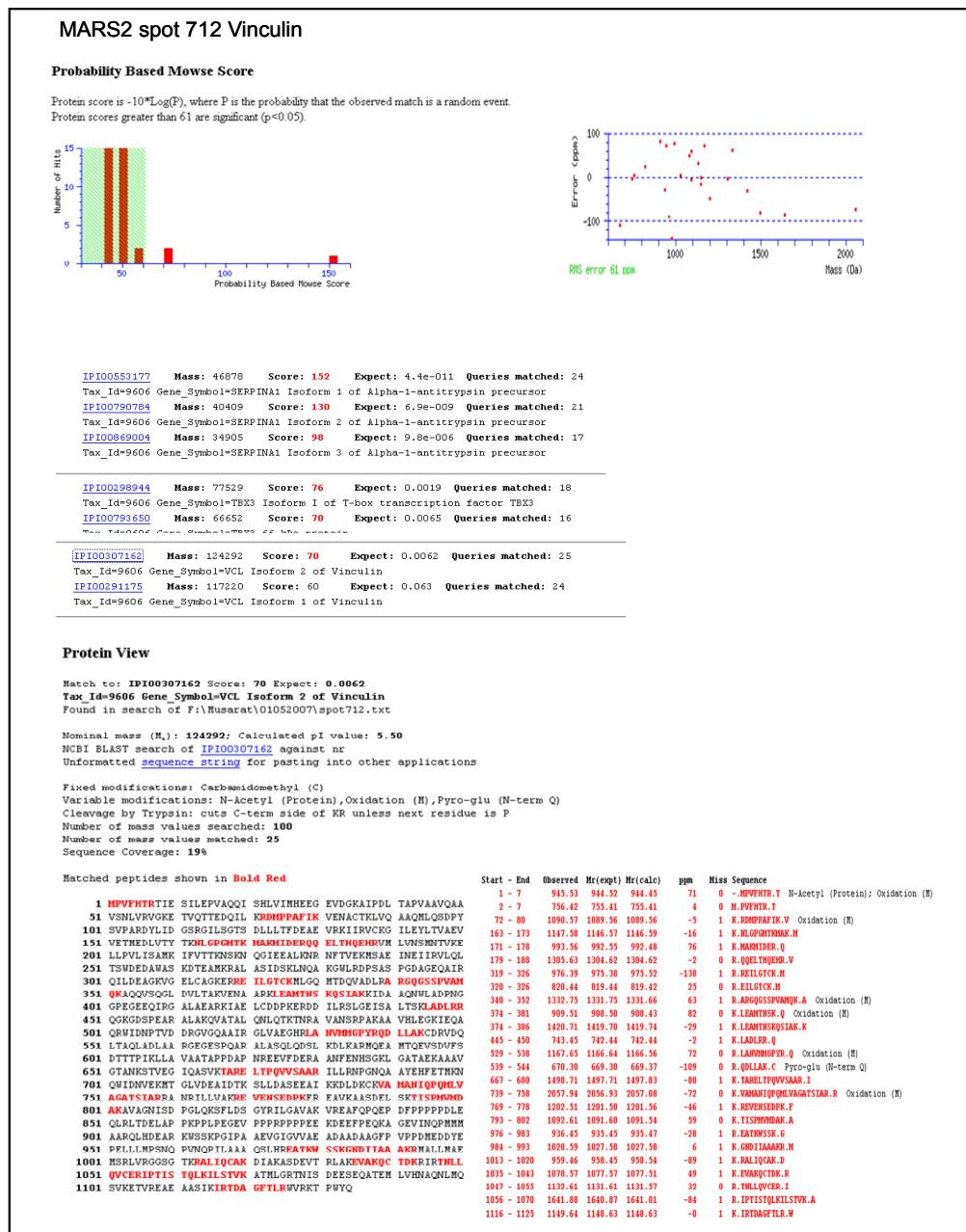
Matched peptides shown in **Bold Red**

		Start - End	Observed	Wavelength (nm)	Intens.	ppm	Miss Sequence				
1	MVTVTSSELL	LPLQSPPLVTV	VKTGPGFCGS	SGQNLTMTWD	LVDGICFLNQI	137 - 140	910.55	910.55	949.49	-1	K_RHIZIT,I
1	MLQDIPRFTN	QRINKEHNSV	VLNLQIQLT	VLWNKTTQY	EVQLQJIVNN	218 - 230	1405.73	1492.72	1429.77	-38	R_D,RPQGSPVPSIK
1	LPNWVQV	PLVWVKEE	PLVWVKEE	PLVWVKEE	PLVWVKEE	230 - 260	1221.43	1223.60	1223.45	-41	K_Q,HLQADLPA,T,K
1	QVQVQVAVH	QVQVQVAVH	QVQVQVAVH	QVQVQVAVH	QVQVQVAVH	230 - 262	1434.68	1433.67	1433.76	-65	K_Q,HLQADLPA,T,K
1	DQGDECTELI	QADQPPRQFV	SSXBBADPSS	TSSBLADPSS	TSSBLADPSS	313 - 321	1184.59	1180.58	1180.55	35	R_D,RLHLSLSE
1	MLAEVADLK	ATLRVRCQEL	TEFLQVLT	HEFVQDVLQ	LOKVKQENIQ	328 - 336	1161.62	1160.61	1160.62	-7	R_D,RLHLSLSE
1	LAADASARCA	LAADASARCA	KANVPERLE	ELTRLCRKEV	YDVFYDVEV	339 - 348	1154.62	1152.63	1152.64	-7	K_L,HLQDFTP,K,R
1	ELRENNILII	ETTAALELQF	TAARAKDRV	HELEKELNI	ESKLHLELD	348 - 364	1051.62	1049.62	1049.62	-3	K_A,HLQDFTP,K,R
1	RDTHWTRK	RDTHWTRK	RDTHWTRK	RDTHWTRK	RDTHWTRK	364 - 376	1474.76	1474.75	1474.76	-3	K_A,HLQDFTP,K,R
1	KGKFVFLNCC	KGKFVFLNCC	KGKFVFLNCC	KGKFVFLNCC	KGKFVFLNCC	424 - 441	2083.89	2084.88	2084.85	-33	K_Q,SGNSASR,PSLW,K,N
1	QDQGQDQD	QDQGQDQD	QDQGQDQD	QDQGQDQD	QDQGQDQD	442 - 451	1076.59	1075.58	1075.53	52	K_M,HLQASASR,K
1	DDAQNQED	DDAQNQED	DDAQNQED	DDAQNQED	DDAQNQED	454 - 463	1075.65	1075.65	1075.65	-4	R_D,ASQSLVQSLQKED,E
1	EAHQHLQSLK	PERQHLQSLK	EAHQKEKEA	ELKEKEQELR	QEGRNLARAK	464 - 501	1796.86	1795.85	1795.86	64	R_D,ASQSLVQSLQKED,E
1	WTSVLETATE	WTSVLETATE	WTSVLETATE	WTSVLETATE	WTSVLETATE	507 - 508	1170.57	1171.55	1171.55	7	R_Q,SYQSVN,D
1	QLDADANELR	ELWIRHMTQS	TLQAMEREN	QDQEKEELR	NRVNLKQLL	509 - 514	1044.60	1043.59	1043.59	-10	R_D,ASQSLVQSLQKED,E
1	75KRSERELLE	75KRSERELLE	75KRSERELLE	75KRSERELLE	75KRSERELLE	516 - 520	991.55	990.55	990.55	-20	R_D,ASQSLVQSLQKED,E
1	GEKSERELLE	GEKSERELLE	GEKSERELLE	GEKSERELLE	GEKSERELLE	520 - 524	1110.59	1110.59	1110.62	-21	K_Q,SLQSLER,Q
1	RELELLARLL	ALQEGAKELR	KALQFQVQAL	EDKEKEKE	AKRQLWQALR	525 - 530	1066.57	1065.56	1065.65	11	R_D,ASQSLVQSLQKED,E
1	75KRSERELLE	75KRSERELLE	75KRSERELLE	75KRSERELLE	75KRSERELLE	531 - 535	1076.55	1077.55	1077.56	-8	R_Q,SYQSVN,D
1	75KRSERELLE	75KRSERELLE	75KRSERELLE	75KRSERELLE	75KRSERELLE	536 - 540	1077.55	1077.55	1077.56	-8	R_Q,SYQSVN,D
1	75KRSERELLE	75KRSERELLE	75KRSERELLE	75KRSERELLE	75KRSERELLE	541 - 545	1077.55	1077.55	1077.56	-8	R_Q,SYQSVN,D
1	75KRSERELLE	75KRSERELLE	75KRSERELLE	75KRSERELLE	75KRSERELLE	546 - 550	1077.55	1077.55	1077.56	-8	R_Q,SYQSVN,D
1	75KRSERELLE	75KRSERELLE	75KRSERELLE	75KRSERELLE	75KRSERELLE	551 - 555	1077.55	1077.55	1077.56	-8	R_Q,SYQSVN,D
1	SGEDTQXKIL	SGEDTQXKIL	SGEDTQXKIL	SGEDTQXKIL	SGEDTQXKIL	556 - 560	1077.55	1077.55	1077.56	-8	R_Q,SYQSVN,D
1	QHILKECETI	QHILKECETI	QHILKECETI	QHILKECETI	QHILKECETI	561 - 565	1077.55	1077.55	1077.56	-8	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	566 - 570	1077.55	1077.55	1077.56	-8	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	571 - 575	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	576 - 580	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	581 - 585	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	586 - 590	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	591 - 595	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	596 - 600	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	601 - 605	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	606 - 610	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	611 - 615	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	616 - 620	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	621 - 625	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	626 - 630	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	631 - 635	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	636 - 640	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	641 - 645	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	646 - 650	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	651 - 655	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	656 - 660	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	661 - 665	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	666 - 670	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	671 - 675	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	676 - 680	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	681 - 685	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	686 - 690	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	691 - 695	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	696 - 700	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	701 - 705	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	706 - 710	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	711 - 715	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	716 - 720	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	721 - 725	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	726 - 730	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	731 - 735	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	736 - 740	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	741 - 745	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	746 - 750	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	751 - 755	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	756 - 760	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	761 - 765	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	766 - 770	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	771 - 775	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	776 - 780	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	781 - 785	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	786 - 790	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	791 - 795	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	796 - 800	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	801 - 805	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	806 - 810	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	811 - 815	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	816 - 820	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	821 - 825	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	826 - 830	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	831 - 835	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	836 - 840	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	841 - 845	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	846 - 850	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	851 - 855	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	856 - 860	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	861 - 865	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	866 - 870	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	871 - 875	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	876 - 880	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	881 - 885	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	ELKEKEQELR	886 - 890	1078.39	1078.38	1078.37	-15	R_Q,SYQSVN,D
1	ELKEKEQELR	ELKEKEQELR	ELKE								

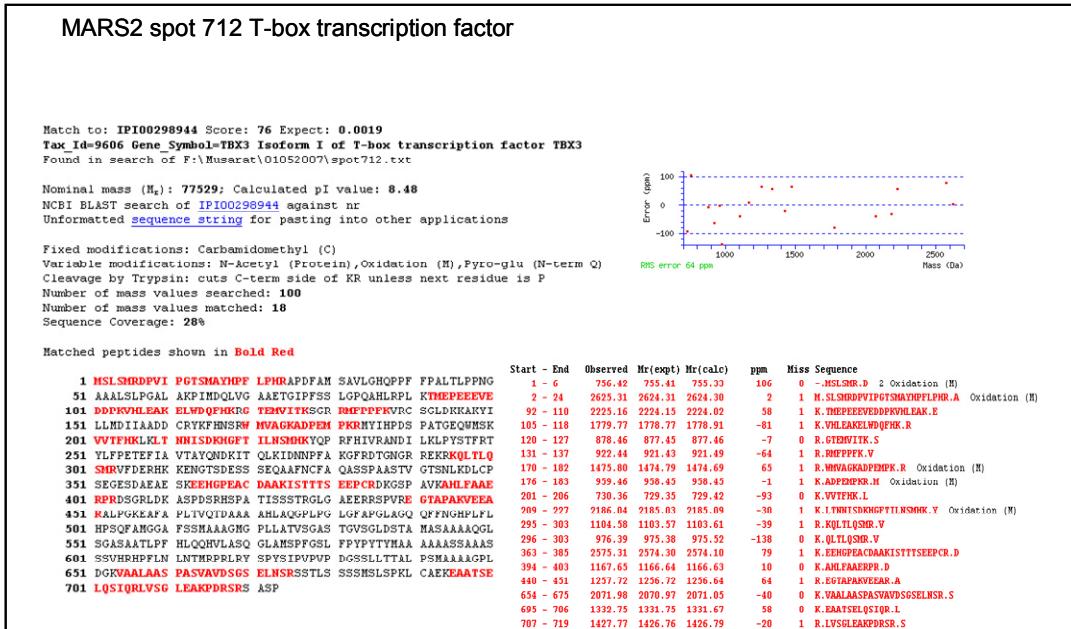
**MALDI-TOF PMF protein identification.** Prominent peaks in the mass range 700-4000 from the MALDI-TOF spectrum were used to generate a peptide mass fingerprint which was searched against the IPI-Human database using the Mascot search engine. A) Probability based Mowse score, B) RMS based error scores for the peptide mass in the PMF and C) details of the identified protein's score, sequence including matched peptides are shown.



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