# Error Metric for Indoor 3D Point Cloud Registration

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**Abstract**

An increase in commercial availability of 3D scanning technology has led to an increase of 3D perception for a variety of applications. High quality scanners require to be stationary and so multiple scans are required and subsequently need to be registered. A new error metric for registration based on the deviation of registered planar surfaces is introduced here and compared with a commonly used metric: mean square point-to-point distance. Four different sets of features are used to register six scans, the point-to-point errors are compared to the new error metric, planar surface deviation, and a disparity is observed for certain sets of features. The two metrics agree as to which sets of features gave the best registration but disagree as to which set produced the worst registration. It is concluded that further analysis and evaluation is required to determine which metric is more meaningful as a representative measure of registration accuracy and to also investigate other error metrics.

**Keywords:** Point Cloud Registration, 3D Laser Scanning, LIDAR, Feature Recognition, Principal Component Analysis

## 1 Introduction

LIDAR is a remote sensing technology that measures direction and range, similar to RADAR, except that it uses a laser. The laser beam from the LIDAR illuminates a surface; the surface may scatter some of the light back to the LIDAR from which the distance is determined using either phase-shift or time information. Stationary LiDARs perform a sweeping scan of their environment creating a point in 3D space for each range measurement; such a collection of points is referred to as a point cloud. For a dense, high resolution and accurate point cloud at relatively long ranges, LIDAR is type of technology typically used though there are other options available. The increase in commercial availability of such technologies means that 3D perception continually gains importance in applications such as 3D mapping and navigation, architecture, augmented reality, robotics and gaming.

A LiDAR scanner is used here to collect point cloud data due to its cost, accuracy and availability. Like many other similar technologies it is a stationary unit and so multiple scans are required from multiple vantage points to attempt to reduce of impact of occlusions and capture a complete or near-complete point cloud. The multiple scans lead to the common problem in computer vision of registration. The task of registration is to place the individual point clouds in the same spatial reference frame by estimating rigid body transformations between the datasets. The problem is difficult because the correspondences of the datasets and the precise location of the scanner are unknown a priori; the difficulty in obtaining this information accurately means that it is problematic to evaluate meaningful and truly representative registration errors.

The purpose of finding such transformations is to acquire a more complete dataset which increases its usability and reliability which is important for many applications. Due to the relatively high accuracy of 3D laser scanning technology (typically ±2 mm at 25 m), the importance of accurate registration becomes of greater significance since the range accuracy is a key limiting factor of registration accuracy. The required registration accuracy is ultimately specified by the client and the application. The point cloud data may be used to provide an approximate representation of the scanned environment for visualisation applications or it may be used for some other application where metrology is of greater importance such as BIM (Building Information Modelling). BIM is one of the most significant drivers for 3D scanning technology and 3D imaging [1], and in the UK, government mandate states that by 2016, public sector centrally procured construction projects will be delivered using level 2 BIM [2].

Scanning processes in BIM have a required minimum accuracy, however, the ‘Client Guide to Scanning and Data Capture’ published by the BIM Task Group [3] advocate a functional performance approach rather than a prescriptive approach to establishing this number. This essentially means that considering the technology used for data capture, construction tolerances, budgetary restrictions and other constraints the best achievable accuracy should be sought.

In the next section, we discuss point cloud registration error metrics associated with the most popular registration methods such as ICP (Iterative Closest Point) [4]. ICP often requires good initial alignment typically achieved by feature-based registration. We also introduce our new error metric which measures the deviation of planar or near-planar surfaces in registered scans. We address the problem of registration error metrics of point clouds in scenarios where the true value is not observable. In real-world applications, an accurately and precisely measured true value is too difficult to obtain so we resort to measuring quantities about objects from the scene from which we can infer the degree of registration accuracy. Typically this may be corresponding points or nearby points and planes, however, since we work with indoor 3D scans in which there is typically an abundance of planar features, we use these to assess the degree of registration accuracy.

Real point clouds with planar regions have some surface deviation arising from range noise (ranging accuracy), surface profile and poor registration. In the ideal case, truly planar surfaces produce point clouds restricted to two dimensions such that there is no surface deviation; furthermore, perfectly registered ideal point clouds would also return no surface deviation. If we can account for range noise and surface profile in our error metric then planar surface as an error metric should provide representative registration errors.

# 2 Registration Error Metrics

A method which is often used for registration of two point clouds is ICP (Iterative Closest Point); in this algorithm, one point cloud, the reference or the target is kept constant, while the other one is transformed to minimise the distance of the closest points between the reference and target. The rigid body transformation is iteratively evaluated for the revised closest points. ICP is very popular due to its simplicity, however, it only works very well in ideal cases, subsequently there are a very large number of ICP variants (around 400 papers in the past 20 years with ICP in the title or abstract) [5] which enable it to be more robust or faster but the basic principal remains the same which is that the distance between iteratively revised closest points are minimised.

A paper by Rusinkiewicz and Levoy [6] reviews some of the efficient variants of ICP and classifies these as affecting one of the 6 stages of the algorithm: selection, matching, weighting, rejecting, assigning an error metric and minimising the error metric. Most of the variants aim to add speed and robustness to the algorithm, but here we are concerned with the accuracy of registration which is ultimately determined by the error metric. The metric specified in the original ICP paper [4] is the sum of squared point-to-point distances, other metrics include a combination of point-to-point and difference in colour [7], point-to-plane [8] and point-to-line [9] distances. Certain metrics may behave better than others in certain cases in terms of converging to the ground truth but their limitations are intrinsic to ICP. Whether the ICP variant uses points, planes, lines or anything else, the limitation lies in the fact that corresponding references are chosen by proximity. After numerous iterations the error may converge, but it may or may not converge to the true value; in either case, this cannot be known from summing squares distances between points which are not truly corresponding.

Another limitation of ICP is that it converges monotonically to local minima and the final result is very dependent on the initial conditions, for this reason, most ICP variants require a good initial estimate to increase the likelihood of converging to a global minimum. The initial estimate is typically evaluated using methods which are more robust to range noise such as feature-based registration. Feature-based registration algorithms attempt to identify truly corresponding points and to minimise the sum of these squared point-to-point distances. They are limited in accuracy due to range noise and on the premise that corresponding points are only truly corresponding within a certain tolerance. Nonetheless, they are a popular tool in determining coarse registration which is typically followed by fine registration performed by ICP.

Even with a good initial estimate, ICP is very susceptible to range noise which is something which is typical of real data; Low and Lastra [10] have shown that rate of convergence and likelihood of convergence to a global minimum can be improved by supressing noise through smoothing of smoothly varying surfaces. In our collected data, as mentioned previously, the data is relatively low in noise though there are many points which are perturbed by noise (44 million points per scan), the accuracy of range measurements is accurate within a standard deviation of 2 mm at 25 m. This level of noise and number of points may prove to inhibit ICPs likelihood of converging to the global minimum [11].

Recently there has been a re-emergence and increased interest in registration of point clouds represented as Gaussian mixture models [12]–[14], these models do not require pair-wise correspondences in the same way as ICP or feature based registration algorithms but instead use a probabilistic approach to reduce correspondence mismatch errors. Due to the simplicity and popularity of ICP, here we compare our metric with point-to-point/plane only and analysis on the mixture model registration errors is reserved for future work.

# 3 Planar Surface Deviation (PSD)

There are a number of advantages to using planar surfaces for an error metric. Particularly in our application of indoor 3D scanning, planar surfaces such as walls, ceilings and furnishings are typically found in abundance. Also, planar regions are identified by many points, at least hundreds if not thousands within a 25 cm radius depending on the distance of the scanner to the surface. Such a large number of points can be utilised to supress noise (by averaging or plane-fitting, for example) without deforming the structure by smoothing or other pre-processing. Lastly, unlike feature points, planes are localised in one dimension; relatively small variations in the other two dimensions do not alter the distance normal to corresponding registered planes and subsequently do not significantly affect the error metric. As a result, errors on planar surfaces should be calculated on multiple orthogonally orientated samples.

To evaluate the surface deviation of planar regions in combined registered scans, knowledge of the surface normal is required first; the normal is the direction in which we determine the surface deviation. First we identify the query points, which are the points which lie at the centre of the regions of interest; such points can be identified using shape detection algorithms such as RANSAC [15] and Hough transforms [16], however, for simplicity and proof of concept we identify such points manually here.

Next we identify points in the neighbourhood of our query point and use these to calculate the normal. Surface normal estimation can be achieved in many different ways (see [17]), the simplest is based on first order 3D plane fitting outlined in [18], which is essentially a least-square plane fitting estimation problem. The surface estimation problem is reduced to an eigenvector and eigenvalue analysis (or principal component analysis) of a 3D covariance matrix created from the neighbourhood of points around the query point. The surface normal is then estimated by the eigenvector corresponding to the smallest eigenvalue which corresponds to the direction of smallest variance [19]; additionally, the square root of the eigenvalue determines the standard deviation along the corresponding eigenvector. By comparing the standard deviation of individual planar regions to the registered and combined region, we obtain our planar surface deviation metric.

PSD is well suited to our application of indoor 3D scanning due to the typical abundance of planar surfaces in many buildings, however, scenes that lack plentiful planar surfaces would deem this metric far less useful. Since most new scanning applications are concerned with buildings and large structures, it is fair to say that PSD would be suited for many applications. Additionally, it should be noted that this is metric, currently, does not identify corresponding planes but only evaluates errors for nearby planes which are assumed to be corresponding; this means that the usefulness of the metric is determined by reasonably well registered scans which will depend on the search radius for neighbourhood points and the size of the plane itself. For example, if the registration returns planes which are not very close together then they may be excluded from the neighbourhood around your query point and provide an overly optimistic registration error. Another limitation of PSD depends upon the surfaces themselves, the surface may have a certain profile which cannot easily be known from the scan data, such a profile would manifest as surface deviation. Additionally the surface profile will be measured differently depending on the position of the scanner relative to the surface normal; this would cause misinterpretation of the true position of the surface.

# 4 Method

We scanned the nanotechnology laboratory in the Department of Electronic and Electrical Engineering at UCL from 6 vantage points (see Figure 1). The main types of features used for registration here are checkerboard targets which are strategically placed on walls and planar surfaces which are also used for registration. The first step of registration is to identify the features, 3 sets of features are extracted from the scans (automatically identified checkerboards (AI CHB), manually identified checkerboards (MI CHB) and automatically identified planes (AI Planes)) and a 4th set is acquired by using total station surveying instruments (total station identified checkerboards (TSI CHB)). To register two scans, the correspondences are identified between features from sets A and B. These correspondences are then used to determine the transformation required to minimise the distance between the corresponding features. Following this, the correspondences are then used to perform fine registration to minimise the distances further. We then compared the mean correspondence distance (also referred to as CD or point-to-point distance) after fine registration with the planar surface deviation (PSD) of a number of planar regions. Since the laboratory is rectangular, we take the mean PSD of five regions (typically containing many thousands of points) from the long walls, short walls and the ceiling, respectively labelled X, Y and Z. The errors, in both cases, are evaluated for the final registration of the 6 scans.

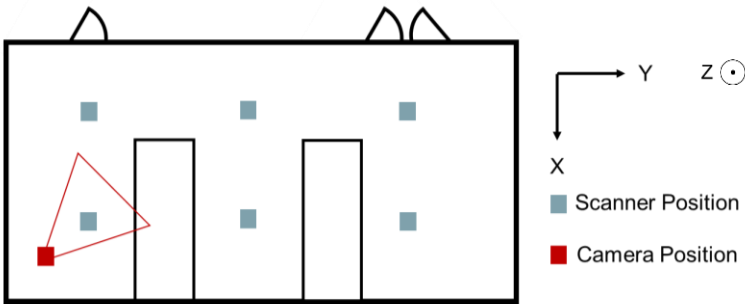


*Figure 1 – Laboratory layout indicating workbenches, scanner position and camera angle for Figure 2.*

| Method | Feature Set A | Feature Set B |
|---|---|---|
| Manual CHB | MI CHBs | MI CHBs |
| Automatic CHB | AI CHBs | AI CHBs |
| Total Station CHB | AI CHBs | TSI CHBs |
| Automatic Planes | AI Planes | AI Planes |

*Table 1 – Table identifying the features used in each registration method. MI – Manually Identified, AI – Automatically Identified, TSI – Total Station Identified and CHB – Checkerboard.*

## 5 3D Scans and Results

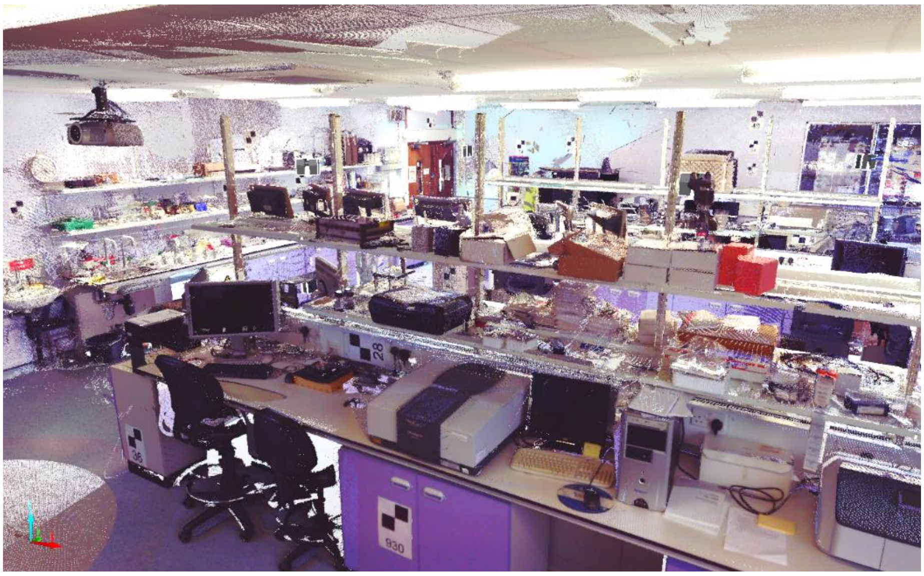

*Figure 2 - Screenshot of the six registered scans of the laboratory. Top right-hand corner of the room opposite the single door.*

| | | Manual CHB | Automatic CHB | TSI CHB | Automatic Planes |
|---|---|---|---|---|---|
| | **Correspondences** | 38 | 218 | 33 | 100 |
| | | | | | |
| **CD** | **Mean (mm)** | 0.8 | 0.6 | 2.7 | 6.7 |
| | **Deviation (mm)** | 0.4 | 0.7 | 1.8 | 6.9 |
| | | | | | |
| **PSD** | **X (mm)** | 0.8 | 0.8 | 16.3 | 1.3 |
| | **Y (mm)** | 0.9 | 1.2 | 10.0 | 3.2 |
| | **Z (mm)** | 10.2 | 10.1 | 4.0 | 6.2 |

*Table 2 - Table of alignment errors measured by CD (correspondence distance or point-to-point distances of corresponding points) and PSD (planar surface deviation) for the 4 methods. Mean and deviation of all correspondences are determined for CD. PSD is evaluated for a set of 3 orthogonal surfaces.*

## 6 Conclusion

It can be seen from Table 2 that CD and PSD agree that Manual and Automatic CHBs provide good alignment. CD states that Automatic planes produce the worst alignment while PSD states that Total Station CHBs produce the worst alignment. Though both alignment error measures agree as to which sets of features produce the best alignment, they disagree as to which produce the worst alignment. Further testing and evaluation is required to determine which method is the more meaningful measure of error. The CD error method hides variations in error in X, Y and Z so multiple checkerboards on the walls reduce the misalignment error in X and Y while hiding the much larger misalignment error in Z.

This work attempts to assess the accuracy of registration in a novel way by using the spatial deviation in the direction of the surface normal of overlapping planar regions from different scans. Planar features are found in abundance indoors, and using additional information from these planar regions gives for a more detailed analysis of the final registration. In the future, we intend to include more information in PSD, to also extend the method to better account for the type of surface in question and to analyse a wider range of metrics.

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