# A Semi-Automatic Image-based Object Recognition System for Constructing As-is IFC BIM Objects based on Fuzzy-MAUT

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**Abstract**

Building Information Modelling (BIM) could support different activities throughout the life cycle of a building and has been widely applied in design and construction phases nowadays. However, BIM has not been widely implemented in the operation and maintenance (O&M) phase. As-is information for the majority of existing buildings is not complete and even outdated or incorrect. Lack of accurate and complete as-is information is still one of the key reasons leading to the low-level efficiency in O&M. BIM performs as an intelligent platform and a database that stores, links, extracts and exchanges information in construction projects. It has shown promising opportunities and advantages in BIM applications for the improvement in O&M. Hence, an effective and convenient approach to record as-is conditions of the existing buildings and create as-is BIM objects would be the essential step for improving efficiency and effectiveness of O&M, and furthermore possibly refurbishment of the building. Many researchers have paid attention to different systems and approaches for automated and real-time object recognition in past decades. This paper summarizes state-of-the-art statistical matching-based object recognition methods and then presents the image-based Industry Foundation Classes (IFC) BIM object creation application, which extracts object information by simply conducting point-and-click operations. Furthermore, the object recognition research system is introduced, including recognizing structure object types and their corresponding materials. This paper combines the Multi-Attribute Utility Theory (MAUT) with the fuzzy set theory to be Fuzzy-MAUT, since the MAUT allows complex and powerful combinations of various criteria and fuzzy set theory assists improving the performance of this system. With the goal of creating an effective method for as-is IFC BIM objects construction, this image-based object recognition system and its recognition process are further validated and tested. Key challenges and promising opportunities are also addressed.

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## 1 Introduction

In real projects, the majority of owners and stakeholders pay attention to the initial design and construction phases as the primary areas of BIM implementation. However, the subsequent operation and maintenance (O&M) are the longest and costly phases over the life cycle of a building. According to National Research Council (1998) and Teicholz (2004), over 85% of the total costs in ownership and 30-50 years of a building lifecycle spend on O&M. In Hong Kong, it is expected that the total number of buildings will increase to 58,000 in 2050. Existing buildings in 5 to 35 years old have contributed nearly 75% of the total buildings. In particular, there are more than 2000 buildings over 50 years old in Hung Hom area. There have been tragic building collapse accidents in Hong Kong including the one happened in the City University of Hong Kong on May 21. 2016 (Daily News 2016). Moreover, on January 29, 2010, building collapse accident suddenly happened in Ma Tau Wai road. An old six-story walkup building suddenly crumbled at about 1.30pm. Four people died and two were injured (People.cn 2010). Reasons for those accidents were often related to inefficient operations and maintenance of existing buildings and lack of effective information support.

Many activities in O&M are information-related activities. However, information, especially stored in hard-copy documents, is usually outdated and unreliable. Furthermore, most existing buildings today even do not have completed or accurate as-is information documents. Accurate and real-time information in O&M is critical to making correct decisions. The inaccurate and poor information would lead to inefficient maintenance and delay or even wrong decisions. Managing information through effective methods in O&M is extremely important to provide the best services to the building occupants (Lee and Akin 2009).

As an intelligent and parametric digital platform, Building Information Model (BIM) supports various activities throughout the life cycle of a building. One of the significant concepts of BIM is "BIM is a database that stores, links, extracts and exchanges information" (Eastman et al. 2008). Smith and Tardif (2009) stated that applying BIM in O&M would minimize information loss remarkably, especially when information transferring from the construction phase to the O&M phase. During the past decades, BIM has shown promising possibilities and great opportunities to improve the low-level efficiency of building management in O&M phase (Forns-Samso 2011). For instance, the Shanghai Centre in China also developed a comprehensive platform in O&M, which integrated disparate BIM, CMMS, and BAS (Lu et al. 2017).

However, most existing buildings today do not have meaningful BIM models. Furthermore, constructing as-is BIM for existing buildings is considered to be a time-consuming and complex process, because great effort, high cost and skilled workers are all necessary. In order to implement as-is BIM and further improve efficiency and effectiveness of O&M, this paper presents the possibilities to have a high-efficient and low-cost image-based semi-automatic object recognition system to assist constructing as-is Industry Foundation Classes (IFC) BIM objects. In general, this paper first extensively introduces computer vision systems. Then, multi-criteria decision-making approaches and fuzzy theory are described in detail. An image-based object recognition system for IFC BIM object generation method is presented for this study. A series of evaluation tests is conducted to verify the functional performance and demonstrate the effectiveness and efficiency of the innovative approach proposed in this paper. This study is based on the authors' conference paper on 2016 CIB w78 conference (Lu and Lee 2016).

## 2 Literature Review

Considering the unreliable and inefficient storage method in the O&M phases (e.g., hard-copy documents shown as Fig.1), proposition of a high-efficient and convenient system to assist in constructing as-is IFC BIM is raised due to research attempts and industry trends. This literature review firstly discusses the computer vision based systems in civil engineering. Multi-criteria decision-making algorithms can thus be studies through the review of current literature discussing advantages related to object recognition in the AEC/FM sector. This section aims at providing a well-grounded foundation for further completed system development.

**Figure 1** Existing documents for O&M management (photos taken by authors)

### 2.1 Overview of Computer Vision Systems in Civil Engineering

Although the majority of as-is BIM creation methods are developed based on laser scanners, computer vision methods have irreplaceable advantages comparing to methods using laser scanners, referring to the Fig.2. For instance, besides the high price of laser scanners, point clouds would contain noisy and miss data, and further it is considered to be a time-consuming and tedious process (Fathi et al. 2015). Computer vision systems have been introduced to the construction field recently (Azar 2015, Lu and Lee 2017). They implement and combine various techniques and theories (e.g., artificial systems, physics-based and probabilistic models) to extract and analyse data from images, and reconstruct properties of each object (e.g. shape, illumination, and colour distributions). The images can be in different forms, including video, images via multiple cameras, or multi-dimensional data from Google tango. In the early stage of computer vision, researchers usually used image processing technologies to pre-process the image for further analysis (Szeliski 2010). Fig.2 presents current processing and recognition methods according to their appearing years. Image processing implements different algorithms on images and outputs data or parameters related to the target images. Input images can be digital images or analogy images. Typical image processing operations mainly include fundamental image processing & registration methods, image registration, image differencing and morphing, image recognition, and image segmentation. Although extra efforts in processing and applications needed to be developed using computer vision methods, image-driven methods have shown promising effective and economical possibilities through comparison research with laser scanners (Bosché et al. 2015; Dimitrov and Golparvar-Fard 2014; Lu et al. 2018).

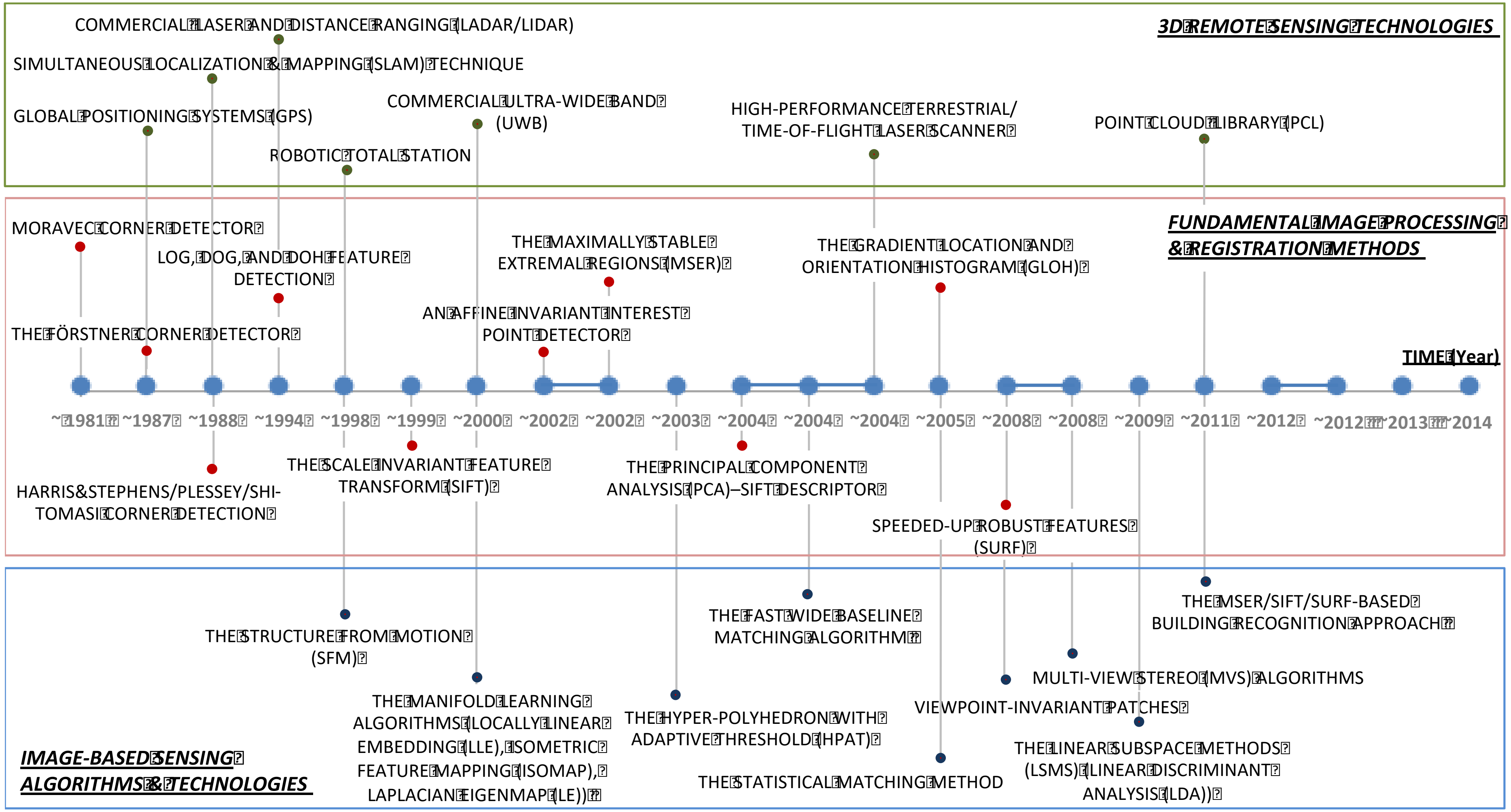



**Figure 2** Brief summary of image-based methods and different types of image-based configurations

## 2.2 Overview of Multi-Criteria Decision-Making Algorithms

Multi-criteria decision-making (MCDM) provides a systematic and comprehensive decision-making method, which can integrate different inputs with benefit information and views from decision-makers (Kabir 2012; Sadiq and Tesfamariam 2009). MCDM can identify and quantify various considerations of decision-makers, and compare different factors at the same time. Through summarizing various researchers' works, MCDM can be categorized into multi-objective decision-making (MODM) and multi-attribute decision-making (MADM). The target of MODM is optimizing multiple objective functions and gets the final decision. Meanwhile, MADM focuses on ranking and selecting among various decision alternatives described by multiple criteria according to the decision-makers' knowledge and experience (Karami 2011). In this paper, multi-attribute utility theory (MAUT) and the fuzzy set theory are used. MAUT is one kind of MADM and used for evaluating different items taking multiple computing attributes into consideration (Wang et al 2010; Pachauri et al 2014). The basic model is expressed as following.

$$U(A_i) = \sum_k^K w_k u_k(x_{ik}) \qquad (1)$$

where $U(A_i)$ performs the utility of alternative i, $w_k$ is the weight of the attribute/criterion k, and $u_k(x_{ik})$ presents the utility of attribute/criterion k of alternative i, $x_{ik}$ provided that the value of attribute/criterion k of alternative i is $x_{ik}$.

The fuzzy set theory is a class of objects, with a continuum of membership grades. In this paper, both certain membership function and fuzzy membership function are used (Fig.3). A fuzzy set A of a universal set X is defined by a membership function f [A(x)]. Each element x in X is mapped to a membership grade between 0 and 1 in y axial (Erol et al 2011).

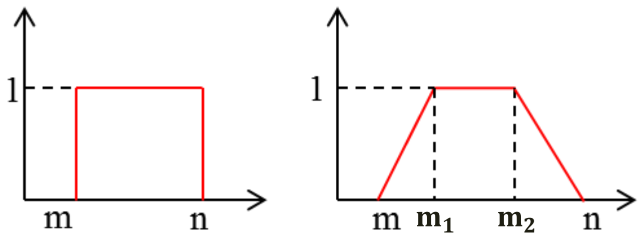



**Figure 3** Certain membership function (left) and fuzzy membership function (right) (revised from Lu and Lee 2016)

The trapezoid membership (ranging from m to n) can be expressed as $u_M(x)$ as shown in equation (2):

$$u_M(x) = \begin{cases} \frac{1}{k_m}x - \frac{m_1 - k_m}{k_m} & (x < m_1) \\ 1 & (m_1 \le x \le m_2) \\ -\frac{1}{k_m}x + \frac{m_2 + k_m}{k_m} & (x > m_2) \end{cases} \qquad (2)$$

where $k_m$ is the reciprocal of the hypotenuse.

In order to take into account possibilities of information shortage and inaccuracy in the data in the forms of images and drawings, the fuzzy logic algorithms are investigated, which can reason with imprecise information. From the preliminary studies on the algorithms (see Table 1), fuzzy logic systems can make decisions even with incomplete or uncertain information. However, as individual fuzzy logic algorithms cannot automatically acquire the rules used to make those decisions and have its own limitations, this research adopts an intelligent hybrid system (i.e., a fuzzy-MAUT system), which combines fuzzy algorithms with MAUT in order to overcome the limitations of individual algorithms. Through combining each individual evaluation, MAUT would obtain overall utility values and express various preferences in the form of a utility function. Interpretability and accuracy, which are main strengths of the MAUT method, are the key criteria for choosing algorithms.

Every single intelligent technique has its specific computational properties, which could be suitable for certain types of problems. Combining different techniques can overcome each individual limitation. The Fuzzy-MAUT is a hybrid system, in which the fuzzy set theory offers range definitions under cognitive uncertainty, while MAUT provides a comprehensive calculation of adaptation, parallelism and generalization. With the ultimate goal of developing an easy, accurate and efficient as-is BIM construction system, this study developed an as-is IFC BIM objects construction system based on Fuzzy-MAUT.

**Table 1** Summary about algorithms related to object recognition

| **Based Method** | **Brief Introduction** | **Extended Method Statements** | **Advantages** | **Limitations** | **Literatures** |
|---|---|---|---|---|---|
| Ant Colony Optimization (ACO) | This algorithm is a multi-agent system and relies on feedback and heuristic information to get close to the optimal solution. | ACO based image feature selection method / image processing | Comparing to traditional ACO algorithm, this improved one uses the directed graph with O(2n) arcs instead of O($n^2$);<br>The feature set of this algorithm focuses on small size and with high classification accuracy. | Research is experimental rather than theoretical;<br>Changes of probability distribution depends on iteration;<br>The time of convergence is not certain. | Chen et. al (2013);<br>Tian et. al (2008);<br>Dorigo and Socha (2006); |
| | | ACO based image detection method | This method can reduce the computational load. | The accuracy mostly relies on the character of the image. | |
| Genetic Algorithms (GA) | This algorithm is a 'population-based' method and based on probabilistic search concept, which mainly depends on natural selection and biological genetics. | An improved GA with a K-nearest neighbor algorithm (GA+Knn[1]) | Improve the work efficiency by applying 0-10 weightings instead of 0-1 weightings;<br>The whole process could finish in a reasonable amount of time. | The scale of genetic algorithm cannot be controlled well (especially applying in house or engine);<br>Complexity. | Tam et. al (2007);<br>Crispin et.al (2007);<br>Punch et.al (1993); |
| | | A genetic algorithm template-matching approach (using in PCB[2]) | This approach can achieve multiple-object recognition;<br>It based on a generalized grey-model template[3] for positions and angles of components. | In a real project, it takes large amounts of time to complete fitness function evaluations; The speed of convergence is not efficient enough. | |
| The Fuzzy Logic Theory (FL) | The Fuzzy logic theory is mainly based on an 'approximate' form with many-valued logic types rather than only one fixed or exact meaning. Further, fuzzy relies on the concept of partial truth and more related to natural languages. | A combined fuzzy pixel-based and object-based approach[4] | The object-based fuzzy logic approach and pixel-based one can be complementary in the information providing aspect;<br>The accuracy improved. | Time-consuming is a key point. | Sumer and Turker (2013);<br>Jiang (2011);<br>Kim et. al (2009);<br>Shackelford et. al (2003);<br>Chen and Pham (2000); |
| | | An adaptive fuzzy-genetic algorithm approach | This approach combined fuzzy logic with genetic algorithms. It improves the accuracy; More efficient comparing to the conventional GA approach. | There is no assurance to get global optimal solution; | |
| | | The hybrid neuro-fuzzy system | This system is combined fuzzy logic with neuro-computing system[5];<br>This system achieves much more robust, energy-efficient object recognition than before;<br>This system improves adaptability and performance. | It requires to be careful about parameters choosing and computing time. | |

1. The K-nearest neighbor algorithm (Knn) is a non-parametric method, which used for classification and regression;
2. The PCB is the printed circuit board in industry;
3. The generalized grey-model template is a template-matching method and it is used for multiple components to be located and recognized;
4. The object-based fuzzy logic approach is using the objects classification and can provide object feature information, such as shape and neighbourhood;
5. The neurocomputing system or neural network is considered to be simplified mathematical models of 'brain' systems and they can function automatically to adjust their behaviour.

## 3 Research Approach

Based on a comprehensive literature review, this study consists of two stages: system development and system validation (as shown in Fig.4). In the first stage, alternative object characteristics for recognition are defined (including object and material recognition). Preliminary experiments based on image-based technologies were performed to confirm characteristics for object and material recognition among the alternatives identified. Then, the novel semiautomatic image-based system was proposed to construct as-is IFC BIM objects in IFCs based the fuzzy-MAUT framework. The new fuzzy-MAUT framework developed in this study includes functions designed for building object recognition and material recognition. In the second stage, the system was validated. Its performances were verified using photos collected by digital cameras. The results based on this experimental investigation were used to evaluate for accuracy to further improve the system.

Considering this study was based on the authors' conference paper on 2016 CIB w78 conference (Lu and Lee 2016), the main improvement and difference between these two studies are as following:

a). From the objective aspect: the objective of this study is focusing on presenting a completed and well-designed process of constructing an as-is IFC BIM object from images. While, the previous conference was only focusing on object recognition from images.

b). From the improved content aspect: first, the literature review was enriched to prove the idea of this study. Moreover, an IFC generation application and framework would be provided to integrate the information from object recognition part and material recognition part and then construct the completed as-is IFC object.

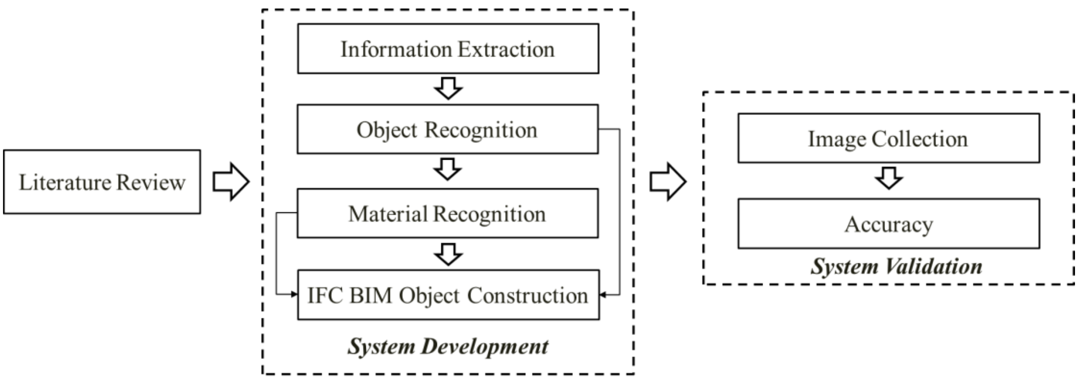



**Figure 4** Research approach

# 4 The Image-based Semi-Automatic Object Recognition System

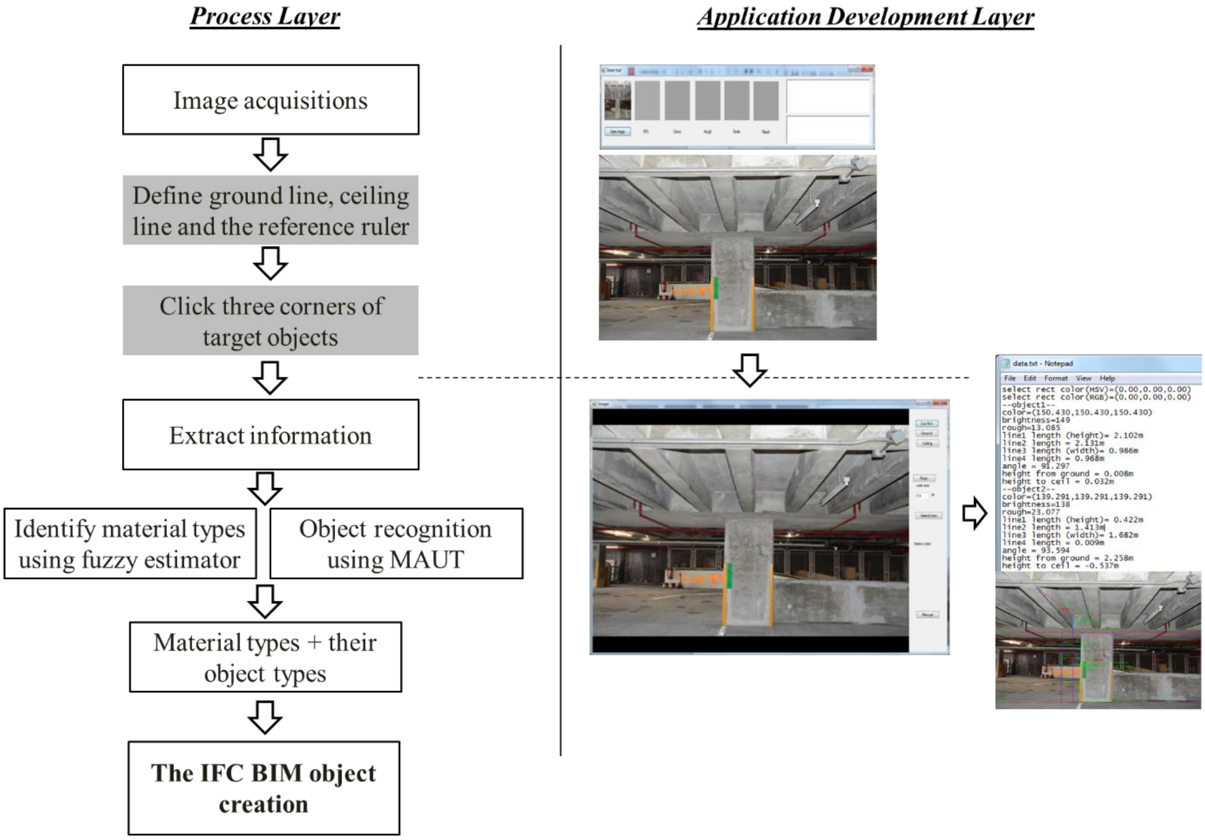



**Figure 5** The overall process of this image-based semi-automatic object recognition system (including building objects and their corresponding materials)

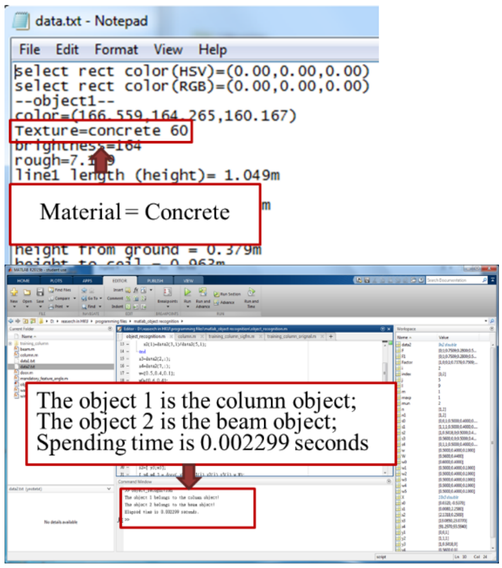



**Figure 6** Data output from the image-base application and the results using fuzzy-MAUT system

The image-based semi-automatic object recognition system, including the types of building objects and materials, consists of identifying material types using the fuzzy estimator and recognizing building components using MAUT. The overall process is presented in Fig.5. Moreover, the output results extracted from the photo is presented in Fig.6.

### 4.1 Image-based Information Extraction Application

In our surroundings, the majority of buildings (e.g., interiors) would be decorated at a certain degree (e.g., the same colour and texture) (Fig.7, left part). Under this complex environment with fewer features or no obvious characters, edges, points or lines might not be detected accurately (Fig.7, right part). For instance, because of the complex man-made environment and sundries, using Hough transformation will detect a large number of lines, some of which are not related to target components (Duda and Hart 1972). This image-based information extraction application uses the semi-automatic method and aims at effectively detecting information under man-made environments.

Furthermore, this image-based information extraction application has some basic requirements towards image acquisitions and camera configuration.

a) A good balance between distance and distortion is required for the application. If the camera position is an undefined variable, the same field of view can be produced by different combinations of the focal length or the distances to the camera. However, the difference is that if the camera is close to the target object, the effect of perspective will increase. Distortions will also appear when the camera is close to the target object using a wide-angle lens. In order to improve the image quality and reduce blur, one should control the distance between the camera and the target object.

b) Choosing a longer focal length of the digital camera. According to the equation (3), a longer focal length results in a smaller axial magnification, while a smaller focal length will lead to a larger axial magnification. In order to control the transformation, one should choose a longer focal length of a camera.

$$M_{ax} = \left|\frac{d}{d(s_o)}\frac{s_i}{s_o}\right| = \left|\frac{d}{d(s_o)}\frac{f}{(s_o - f)}\right| = \left|\frac{-f}{(s_o - f)^2}\right| = \frac{M^2}{f} \tag{3}$$

where the axial magnification of an object is $M_{ax}$ and f is the focal length. $s_o$ is the distance between the lens and the object, while the $s_i$ is the distance between the lens and the image in the digital camera.


**Figure 7** Structural components in a typical building (photos taken by author (left part); Image processing and information extraction using Hough Transformation (right part) (revised from Lu and Lee 2016)

In general, basic requirements for this image-based information extraction application are reducing blur and distortion in the collected images. In the application, only point-and-click operation is needed in order to reduce the processing time and simplify the process (Norman 2005). The prototype application is programed in C# language. The framework is presented in Fig.5. Seven features are extracted through this application, including ratio (height/width), the vertical distance between the top point of line 1 to the ceiling line, the vertical distance between the bottom point of line 1 to the ground line and the roughness of the selected surface, the angle between the line 1 and the ground, RGB value and percentage of noisy points for the selected objects. Line 1 is defined as the first line clicked by users (Fig. 8).

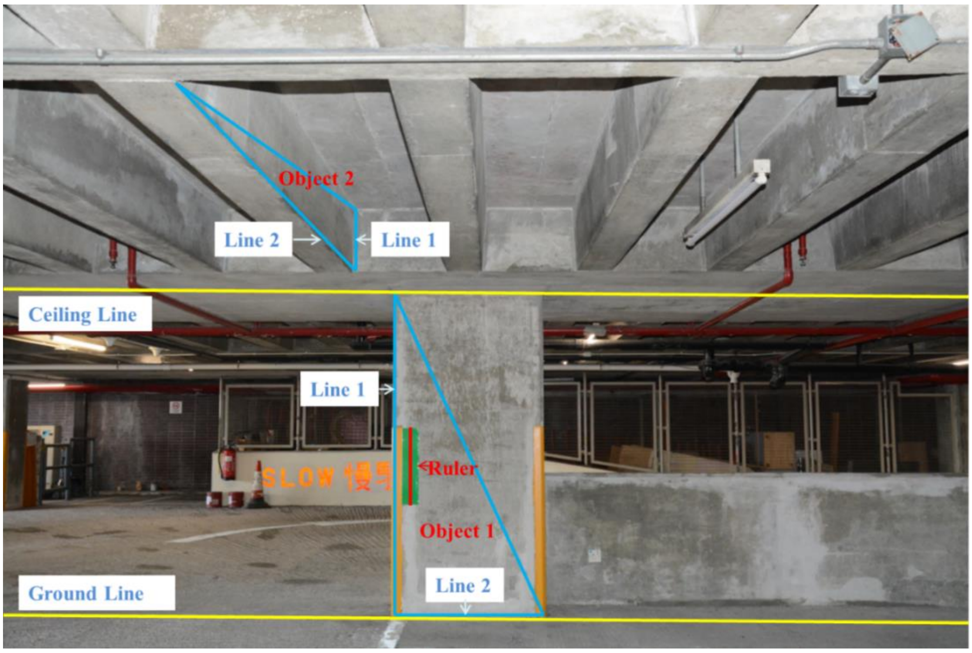



**Figure 8** Indicated plot of this image-based information extraction application

### 4.2 Introduction of the Fuzzy-MAUT based Object Recognition Framework

The overall recognition decision tree (material and object) using Fuzzy-MAUT is shown in Fig.9. The object recognition profile follows the blue part and material is red part.

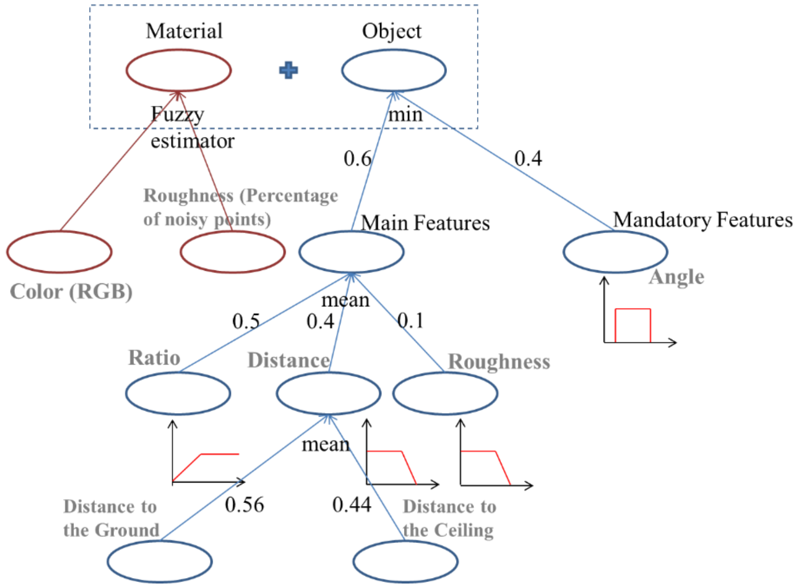



**Figure 9** Profile and framework for object and material recognition

#### 3.2.1 Object recognition part

The calculation in the whole process will follow the weighted scoring rule (Schmitt 2002). Let $W = (w_1, \dots, w_n)$ be the element representing the arguments' weights as $w_1 \geq w_2 \geq \dots \geq w_n$, and $X = (x_1, \dots, x_n)$ are the corresponding input elements. Define that f is an unweighted scoring rule. Then the weighted scoring rule F based on f can be defined by the following formula:

$$F(X) = (w_1 - w_2) \times f(x_1) + 2 \times (w_2 - w_3) \times f(x_1, x_2) + \dots + n \times (w_2) \times f(x_1, x_2, \dots, x_n) \quad (4)$$

The unweighted scoring rule f can be Min, Max or Mean functions to analyse the results. According to different targets and layers in this process, different f is defined in the framework (referring to Fig.9).

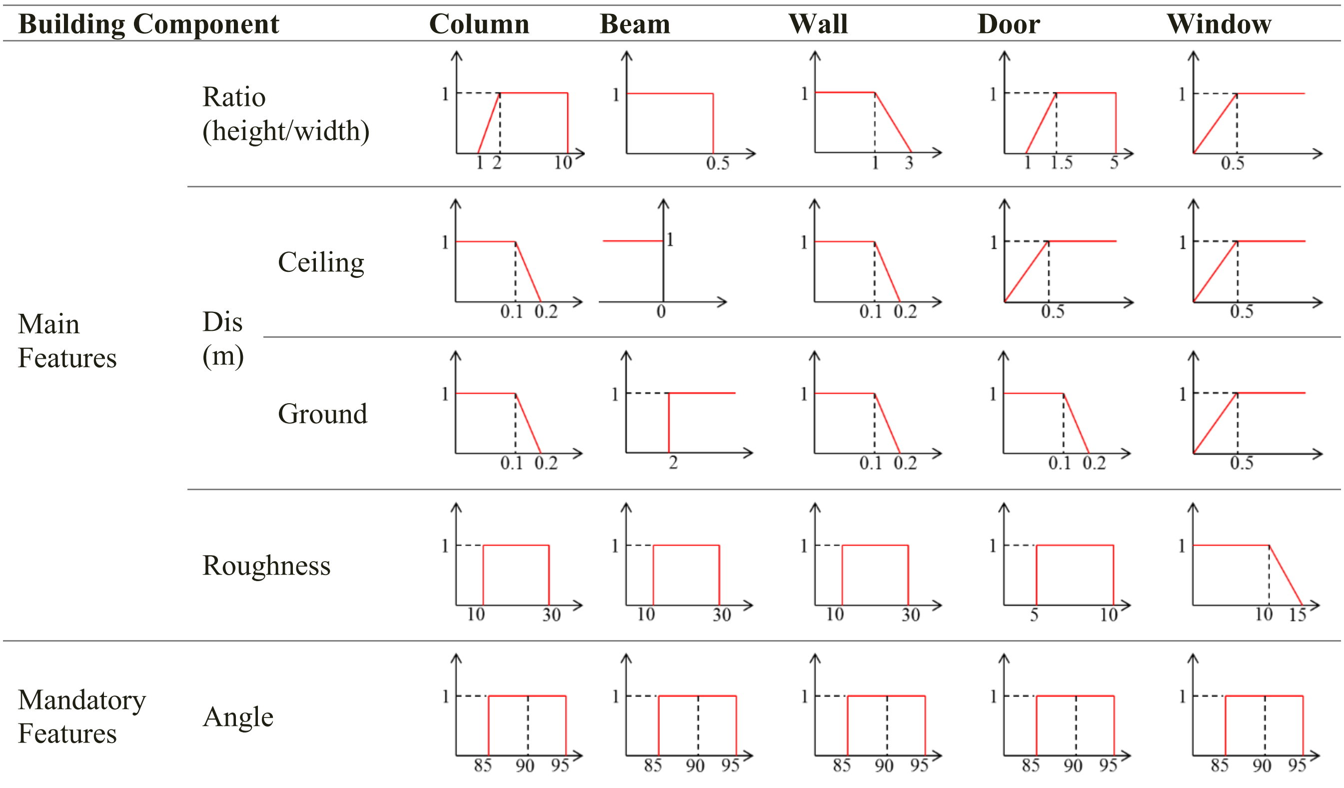
This paper tries to distinguish and recognize five different types of building components: beam, column, wall, door and window. Four main features, including ratio, the vertical distance between the top endpoint of line 1 to the ceiling line, the vertical distance between the bottom endpoint of line 1 to the ground line and the roughness of the selected surface, are used. One mandatory feature, which is the angle between the line 1 and the ground, is chosen. Table 2 shows the range of each feature for different building components, while table 3 defines membership functions of each feature for different building components based on the literature review and preliminary studies based on collected data.

**Table 2** The range value for each object types (revised from Lu and Lee 2016)

| Property | Column | Beam | Wall | Door | Window | Weights |
|---|---|---|---|---|---|---|
| Ratio (height/width) | 1~10 | [0, 0.5] | 0~3 | 1~5 | 0~+∞ | 0.5 |
| Distance (m) (To the ground) | 0~0.2 | [2,+∞] | 0~0.2 | 0~0.2 | 0~+∞ | 0.4 |
| Distance (m) (To the ceiling) | 0~0.2 | [−∞,0] | 0~0.2 | 0~+∞ | 0~+∞ | |
| Roughness | [10, 30] | [10, 30] | [10, 30] | [5, 15] | 0~15 | 0.1 |
| Angle | [85, 95] | [85, 95] | [85, 95] | [85, 95] | [85, 95] | |

*~ represents the range is a fuzzy range, while [] is a certain range.

**Table 3** Membership functions for each object types (revised from Lu and Lee 2016)



### 3.2.2 Material recognition part

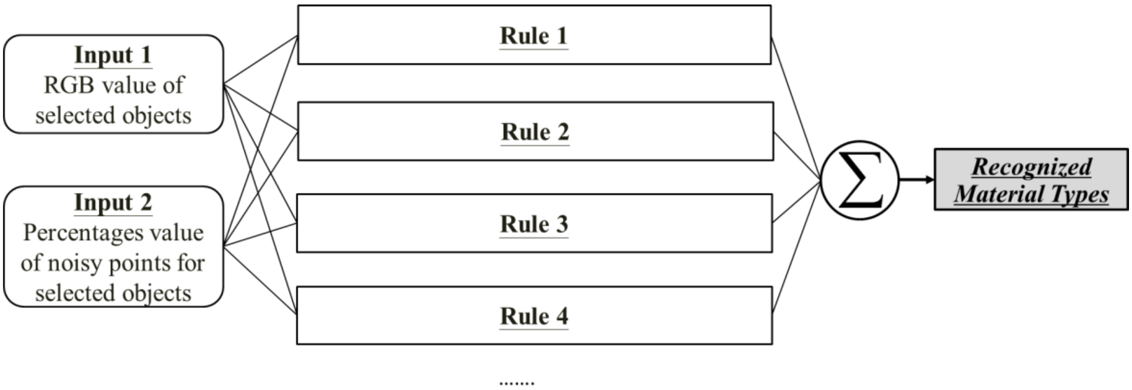



**Figure 10** Fuzzy rules and process of material recognition

The material recognition part implements the fuzzy estimator. This system is designed for maintaining and operating single existing building. Four kinds of materials commonly used in our university campus are selected as a case study. 50 photos for each material (i.e., concrete, white brick, red brick and white paint) are selected under different conditions (e.g., sunny weather and pool lighting condition). After training and learning using collected photos, the percentages of noisy points for four kinds of materials are summarized into membership functions as shown in Fig.11 (right part). Fuzzy rules and recognition process are presented in Fig.10. Samples of fuzzy rules are set as following:

Rule 1: If the surface of selected object is smooth and the colour is white, then material of this object is white paint.

Rule 2: If the surface of selected object is intermediate rough and the colour is not white, then material of this object is concrete.

Rule 3: If the surface of selected object is rough and the colour is not white, then material of this object is red brick.

Rule 4: If the surface of selected object is rough and the colour is white, then material of this object is white brick.

Framework and process of training parameters for the fuzzy estimator are expressed in detail as shown in Fig.11.

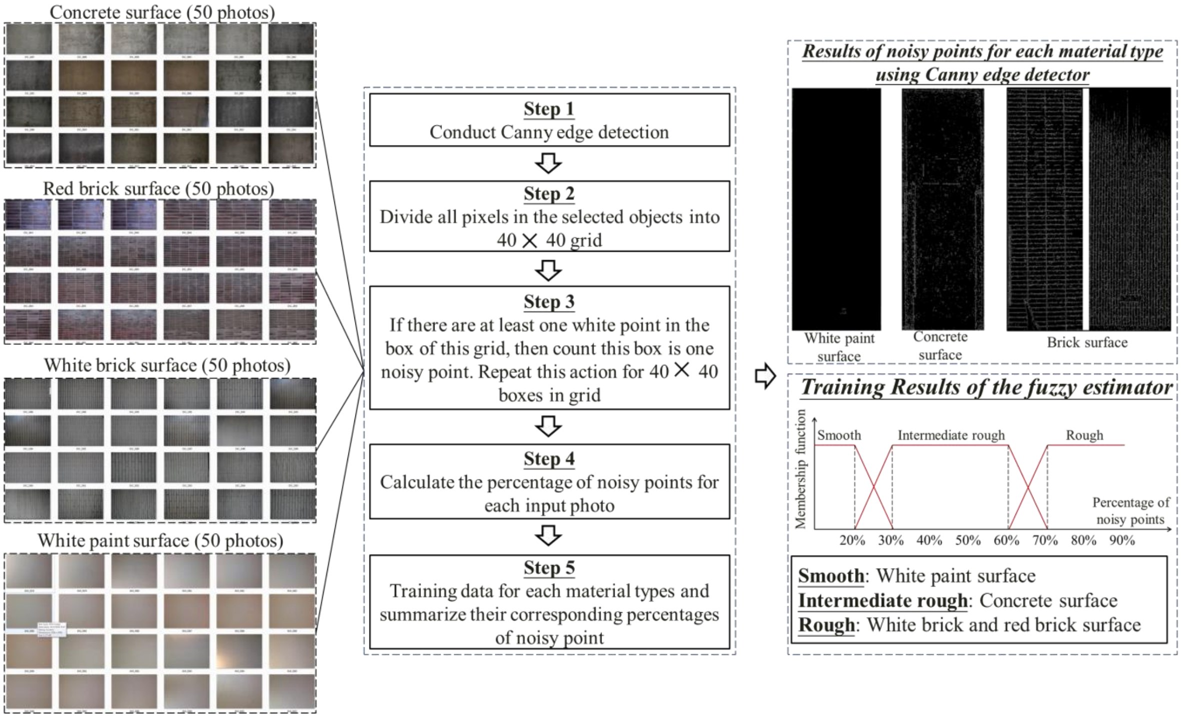



**Figure 11** Framework and process of training fuzzy estimator (revised from Lu and Lee 2016)

## 5 IFC BIM Object Generation

IFC is a widely used object-oriented open standard data schema for BIM and is an object oriented and semantical model, including components, attributes, properties and relationships of a building (Khalili and Chua 2013), initiated by buildingSMART in 1994. It has now been widely used and become a formally registered international standard as ISO/PAS 16739. IFC could support geometric representations and rich semantic information.

This system creates IFC BIM objects automatically based on IFC schema. For example, the *IfcBeamStandardCase* in Fig.12 represents a beam entity of a BIM object in IFC. The related information about this wall, such as its location (*IfcLocalPlacement*), material (*IfcMaterialProfileSetUsage*), shape (*IfcProductDefinitionShape*), and other semantic information could also be parsed and included. Then, all created IFC BIM objects are further placed into the predefined local coordinate system, which is assumed as (0,0,0) in this study.

This IFC BIM Generation part is developed to create an IFC BIM object. The application of generating an IFC BIM object based on recognition results was developed based on ifcengine (http://www.ifcbrowser.com/) and using C# languages (Fig.13). Both IFC2×3 and IFC4 are chosen to be the basic schema standards of this application development. Moreover, Constructive Solid Geometry (CSG) representation is used to create the IFC BIM objects in this study and CSG presents a geometric representation based on the CSG model (Liebich 2009). A solid model represented by CSG is defined as combining a collection of primitive solids using certain operations (Fig.12). Advanced geometric representation can also be created using the CSG or with enhanced profile types (Fig.12). Based on the recognised object and its corresponding material, the resulting IFC file of the target building object would be created, as shown in Fig.14.

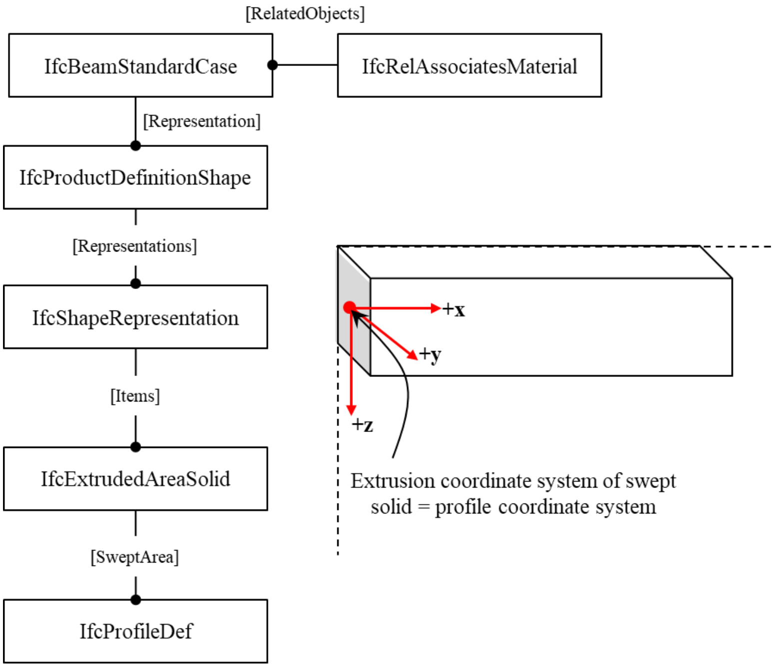



**Figure 12** The data structure of IfcBeamStandardCase

(see also IfcBeamStandardCase 2011 )

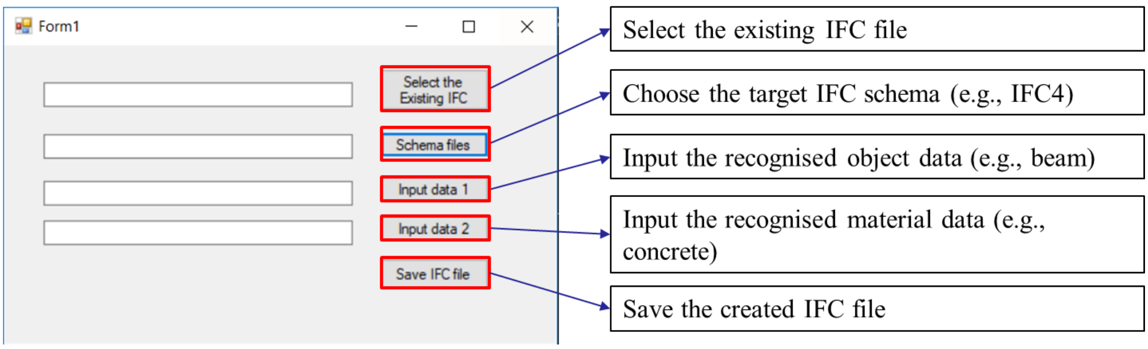



**Figure 13** The application of generating a IFC file based on recognition results

```
#71 = IFCRELASSOCIATESMATERIAL('1u8pJjDnfgbaBodVz1_qHi', #5, $, $, (#47), #72);
#72 = IFCMATERIALLAYERSETUSAGE(#73, .AXIS2., .POSITIVE., -488.5, $);
#73 = IFCMATERIALLAYERSET((#74), $, $);
#74 = IFCMATERIALLAYER(#75, 977., $, $, $, $, $);
#75 = IFCMATERIAL('concrete', $, $);
```

**Material Part**

```
#76 = IFCSHAPEREPRESENTATION($, $, $, $);
#77 = IFCSHAPEREPRESENTATION(#21, 'Body', 'SweptSolid', (#78));
#78 = IFCEXTRUDEDAREASOLID(#79, #86, #90, 2125.);
#79 = IFCARBITRARYCLOSEDPROFILEDEF(.AREA., $, #80);
#80 = IFCPOLYLINE((#81, #82, #83, #84, #85));
```

**Geometry Part**

**Figure 14** The selected parts of the output IFC file

## 6 System Evaluation and Discussions

With the goal of assisting in as-is IFC BIM objects construction, this image-based object recognition system and its recognition process are further validated and tested. Based on the previous studies (Brilakis et al. 2006; Caputo et al. 2010; Dimitrov and Golparvar-Fard 2014; Golparvar-Fard et al. 2014; Lu et al. 2018), it is a necessary and effective method to use photos collected by digital cameras or mobile phones to test the accuracy and robustness of developed system as the basis for the verification. Hence, referring to Fig.15, over 70 images are collected using digital cameras for further evaluation the accuracy of the developed system.

Information would be extracted from images based on the design of system firstly (referring to Chapter 4). Samples of extracted information are presented at Table 4. In these tests, 71 out of 74 objects in the images were recognized correctly and computing time were less than 0.01 second. In general, this semi-automatic image-based system is proved to be an effective and convenient method in the early stage of recognising building objects (i.e., column, wall, window, door and beam) and constructing as-is IFC BIM objects.

The system presented in this paper aims at developing a semi-automatic image-based approach to recognise object and material of building components. It is expected that this system of constructing as-is IFC BIM object has the following merits:

- Images collected by using common digital cameras can be used as an input data, which is at relatively low cost and convenient to collect.
- The image-based system (using Fuzzy-MAUT algorithm) is suitable to recognize building elements from images, especially taken from environments that require uncertain or approximate reasoning. For instance, this system can extract information (i.e., object and

material) of building elements and recognize corresponding structural objects, when columns and beams are painted in the same colour.

In the failure recognition samples, the proposed image-driven system cannot distinguish two different types of building objects in some certain situations. Since the recognition system used the ratio as a key feature, for instance, if the ratio of a column was low because of the shape of the column is quite flat, the column has high possibilities of recognizing as a wall object. Hence, more intelligent and effective feature will be selected and determined in the future works. Moreover, this material recognition part can only recognise limited types (i.e., four common materials). In the future works, this study will involve into wider types of materials.

However, during the O&M phase, various kind of information is needed from different sources including BIM, maintenance history and status, operation records and status, controlling and monitoring equipment information and status etc. (Becerik-Gerber et al 2011; Cavka et al 2015; Mayo and Issa 2015). The image-based application presented in this paper can be used for collecting geometric data as the first step of constructing building elements. As shown in Fig.15, this system describes collecting all the essential data from existing data sources, and constructing of an as-is BIM IFC object including geometry and material. Extending the IFC BIM objects into a semantically rich model and eventually achieving a BIM representation will be covered in the future works.

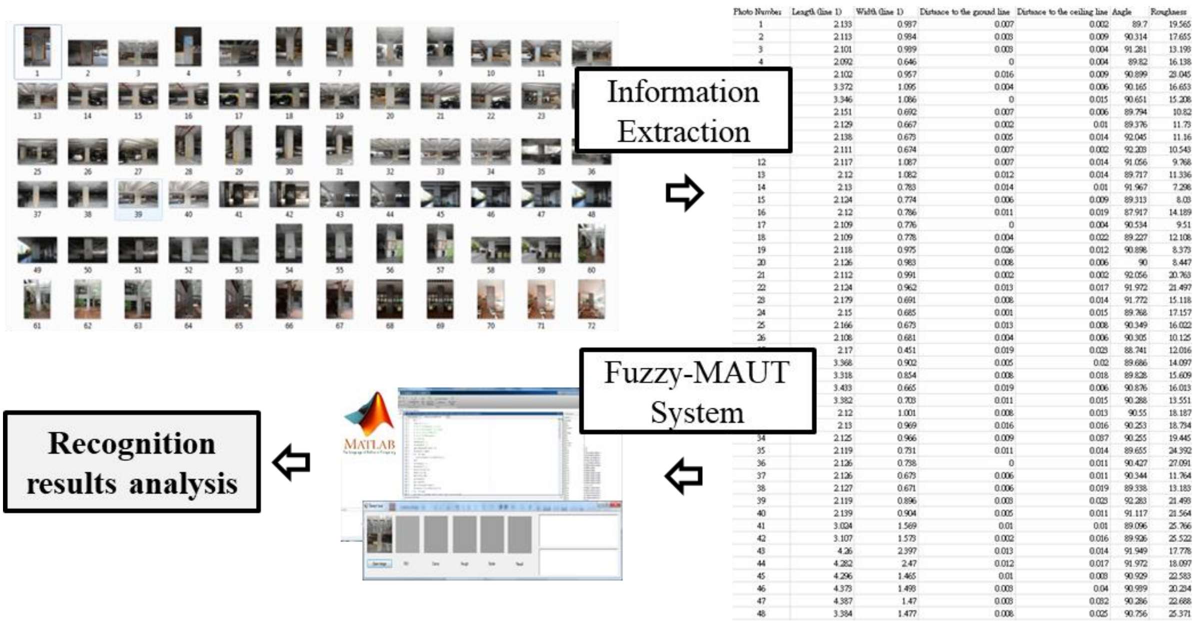



**Figure 15** Object recognition procedures using the image-based semi-automatic object recognition system (i.e., the image-base application and Fuzzy-MAUT algorithm)

**Table 4** Selected samples of extracted information from photos

| Photo Number | Length (line 1) | Width (line 2) | Dis to the ground line | Dis to the ceiling line | Angle | Roughness |
|---|---|---|---|---|---|---|
| 1 | 0.369 | 2.684 | 3.16 | -0.442 | 85.806 | 5.104 |
| 2 | 0.486 | 3.12 | 3.584 | -0.578 | 85.9 | 6.127 |
| 3 | 0.618 | 3.695 | 4.249 | -0.727 | 84.224 | 5.276 |
| 4 | 0.466 | 3.021 | 3.388 | -0.534 | 85 | 6.169 |
| 5 | 0.356 | 2.553 | 2.57 | -0.416 | 84.431 | 12 |
| 6 | 0.461 | 3.091 | 3.049 | -0.553 | 82.057 | 13 |
| 7 | 0.452 | 3.125 | 2.886 | -0.545 | 85.739 | 15 |
| 8 | 0.483 | 3.277 | 4.089 | -0.613 | 80.97 | 20 |
| 9 | 0.395 | 2.61 | 3.528 | -0.48 | 82.761 | 25 |
| 10 | 0.341 | 2.18 | 2.547 | -0.427 | 94.569 | 15.633 |

## 7 Conclusion

In order to achieve sustainable development throughout the lifecycle of a building, especially the O&M phase, it is urgent to adopt BIM in order to facilitate operations and maintenance of an existing building. Consequently, it is important and necessary to construct as-is BIM models for existing buildings as many of them do not have a proper BIM model. However, current methods and technologies of creating as-is BIM models mainly depend on extensive human effort and time. Although data may be collected automatically from diverse sources and methods (e.g., camera), managing useful data, existing methods to recognize building objects and construct geometric objects, and attach identified non-geometric information are all in manual or semi-automatic ways. In order to systematically automate the process of constructing as-is BIM models from images, and possibly other data sources, this paper gave a brief introduction of computer vision technology and Multi-Criteria Decision-Making Algorithms (MCDM) firstly. Then, a semi-automatic image-based system (using Fuzzy-MAUT algorithm) was built as the first step to achieve the goal. The system consists of two parts: object & material recognition and IFC BIM object generation. More than 70 images are tested in this system and it provides satisfied results. Furthermore, this system is proved to be a low cost and convenient system for IFC BIM objects generation.

As future work, some cross referencing and discussion of further implications to the actual findings will be included in this study. For example, the materials recognition as illustrated in Fig.9 the 'profile and framework for object and material recognition' will be used as the basis for having robust implications in this study. we will include non-geometric information into the data structure and develop complete BIM models that fulfill requirements for O&M.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