Development of a Semi-Automatic Image-based Object Recognition System for Reconstructing As-is BIM Objects based on Fuzzy Multi-Attribute Utility Theory

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Abstract
Building Information Modeling (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 As-is information for the majority of existing buildings is not complete and even outdated or incorrect.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 our image-based building object recognition 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. In this paper, we combine 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 as-is BIM objects equipped with the semi-automatic object recognition system, our image-based object recognition system and its recognition process are validated and tested. Key challenges and promising opportunities are also addressed.

Keywords: Fuzzy-MAUT, fuzzy set theory, as-is BIM object, image-based object recognition

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 (http://news.mingpao.com/pns/dailynews/web_tc/article/20160521/s00001/1463767114593). 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 (Figure 1). 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 & Akin 2009).

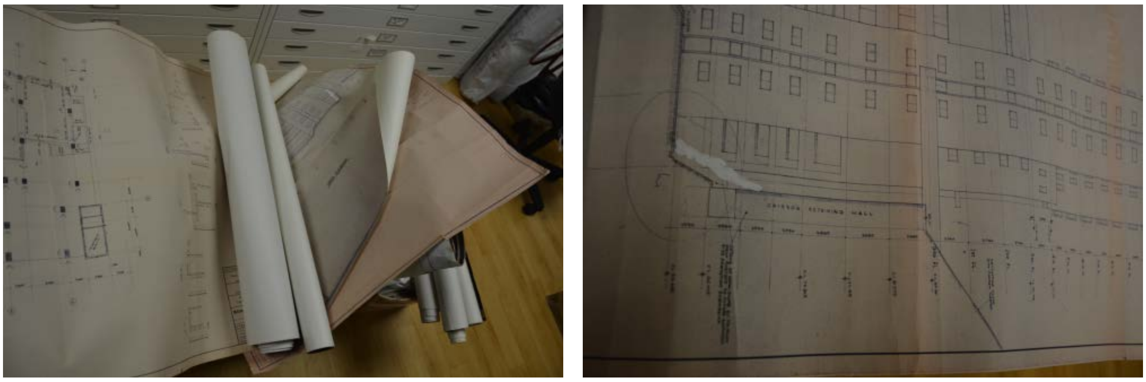


Figure 1 Existing Documents for O&M (photos taken by author in 2016)

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).

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 BIM objects. In general, this paper will first extensively introduce computer vision systems. An image-based computational system and the object recognition system developed for this study are presented. 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.

2 Literature Review

2.1 Overview of Computer Vision Systems in Civil Engineering

Computer vision systems have been introduced to the construction field recently (Azar 2015). They implement and combine various techniques and theories (e.g., artificial systems, physics-based and probabilistic models) to extract and analyze data from images, and reconstruct properties of each object (e.g. shape, illumination, and color 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 preprocess the image for further analysis (Szeliski 2010). Figure 2 presents image-based processing 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 analog images. Typical image processing operations mainly include image registration, image differencing and morphing, image recognition, and image segmentation.

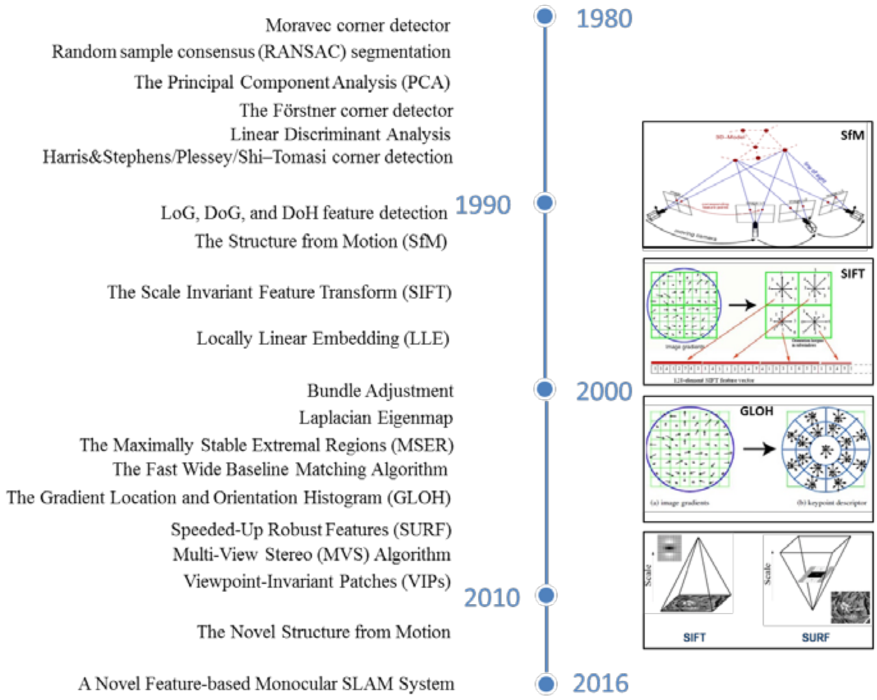


Figure 2 Brief summary of image-based methods and different types of image-based configurations (Partial plot information: http://www.myexception.cn/software/404734.html)

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 & 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.

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

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 (Figure 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).

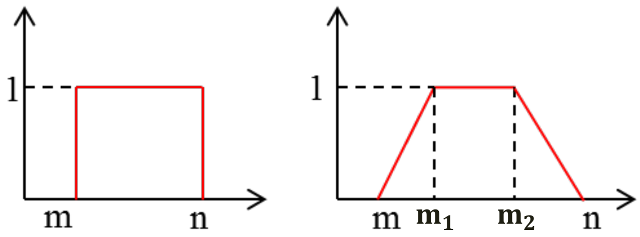


Figure 3 Certain membership function (left) and fuzzy membership function (right)

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

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

where k_m is the reciprocal of the hypotenuse.

The object recognition approach used in this paper combines MAUT and fuzzy set theory. This theory has two important characters: 1) Fuzzy systems are suitable for uncertain or approximate reasoning. It also allows decision making with estimated values under incomplete or uncertain information. 2) Through combining each individual evaluation, MAUT would obtain overall utility values and express various preferences in the form of a utility function.

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.

3 The Image-based Semi-Automatic Object Recognition System

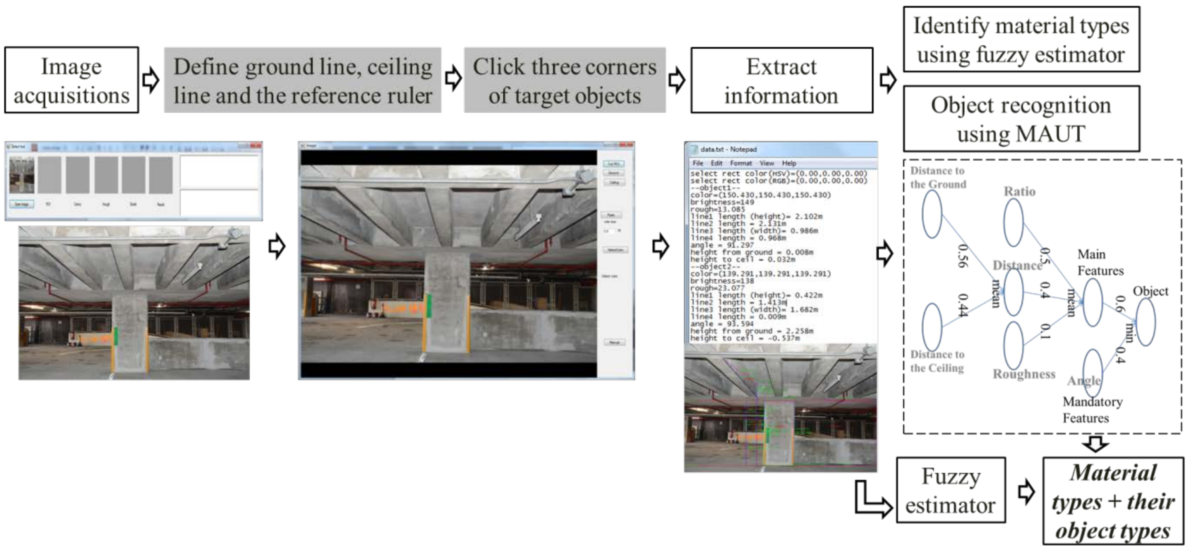


Figure 4 The overall process of this image-based semi-automatic object recognition system (including building objects and their corresponding materials)

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 Figure 4.

3.1 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 color and texture) (Figure 5, left part). Under this complex environment with fewer features or no obvious characters, edges, points or lines might not be detected accurately (Figure 5, 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 & 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.

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

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

Figure 5 Structural components in a typical building (photos taken by author in 2016) (left part); Image processing and information extraction using Hough Transformation (right part)

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 Figure 4. 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. 6).

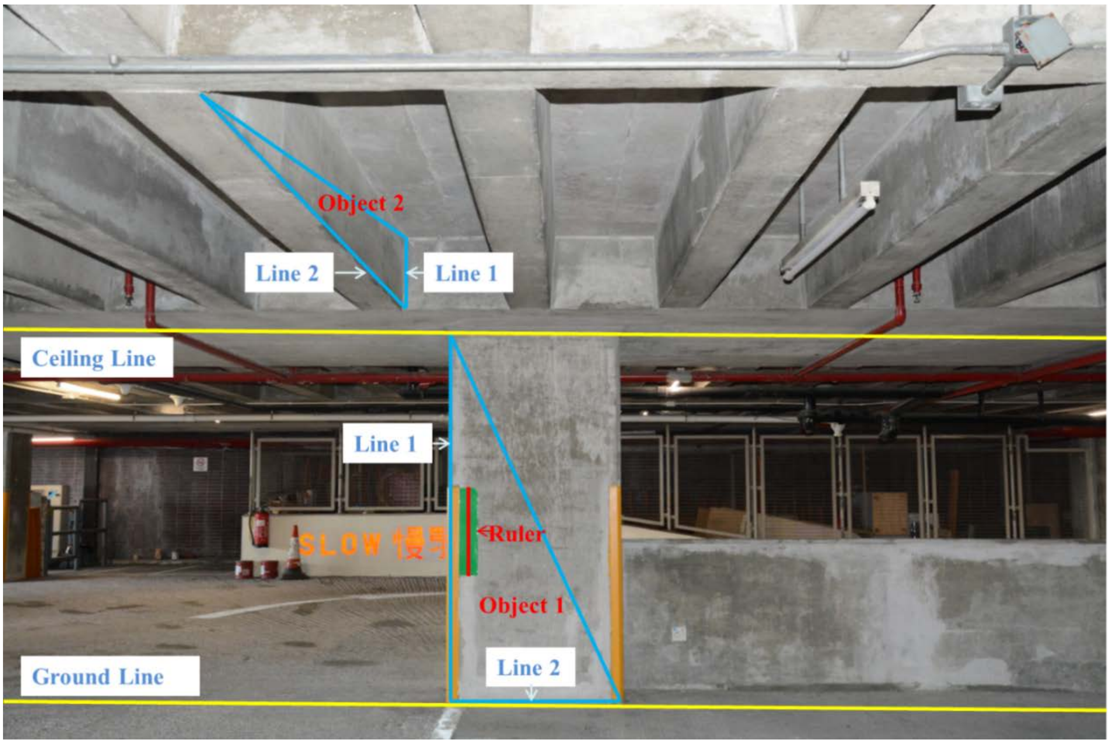


Figure 6 Indicated plot of this image-based information extraction application

3.2 Introduction of the Fuzzy-MAUT based Object Recognition Framework

The overall recognition decision tree (material and object) using Fuzzy-MAUT is shown in Fig. 7, left. The object recognition profile follows the blue part and material is red part. The output results extracted from the photo is presented in Fig. 7, right.

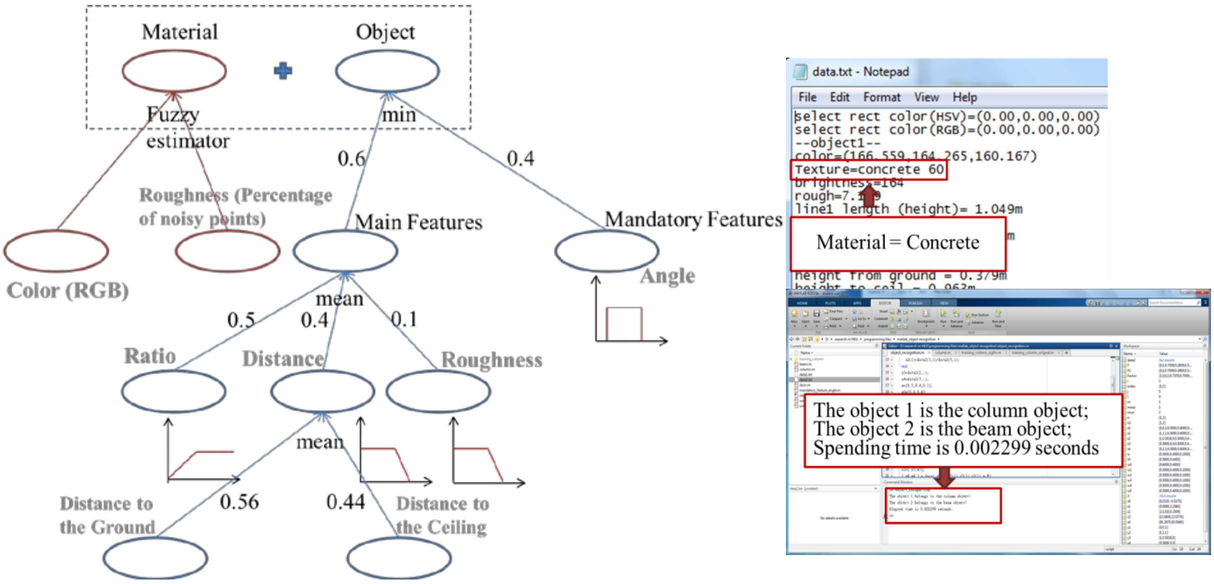


Figure 7 Profile and framework for object and material recognition (left part); Data output from the image-base application and the results using fuzzy MAUT algorithm (right part)

3.2.1 Object recognition part

The calculation in the whole process will follow the weighted scoring rule (Schmitt 2002).

Let $W = (w_1, \ldots, w_n)$ be the element representing the arguments' weights as $w_1 \geq w_2 \geq \cdots \geq w_n$, and $X = (x_1, \ldots, x_n)$ 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:

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

The unweighted scoring rule f can be Min, Max or Mean functions to analyze the results. According to different targets and layers in this process, different f is defined in the framework (referring to Fig. 7).

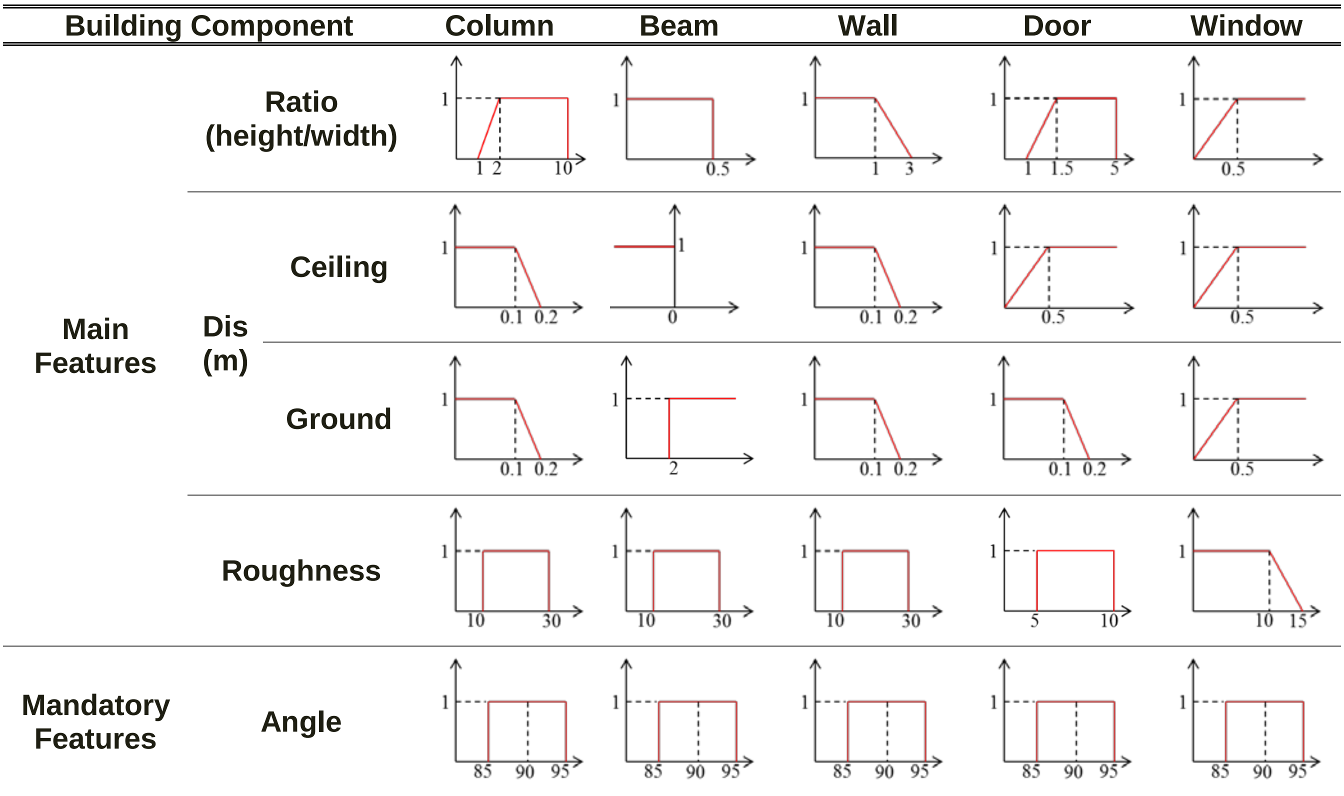
This paper tries to distinguish and recognize five different types of building components: beam, column, wall, door and window. Four main features, including ratio, the vertical distance between the top endpoint of line 1 to the ceiling line, the vertical distance between the bottom endpoint of line 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 1 shows the range of each feature for different building components, while table 2 defines membership functions of each feature for different building components based on the literature review and preliminary studies based on collected data.

Table 1 the range value for each object types

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 2 membership functions for each object types



3.2.2 Material recognition part

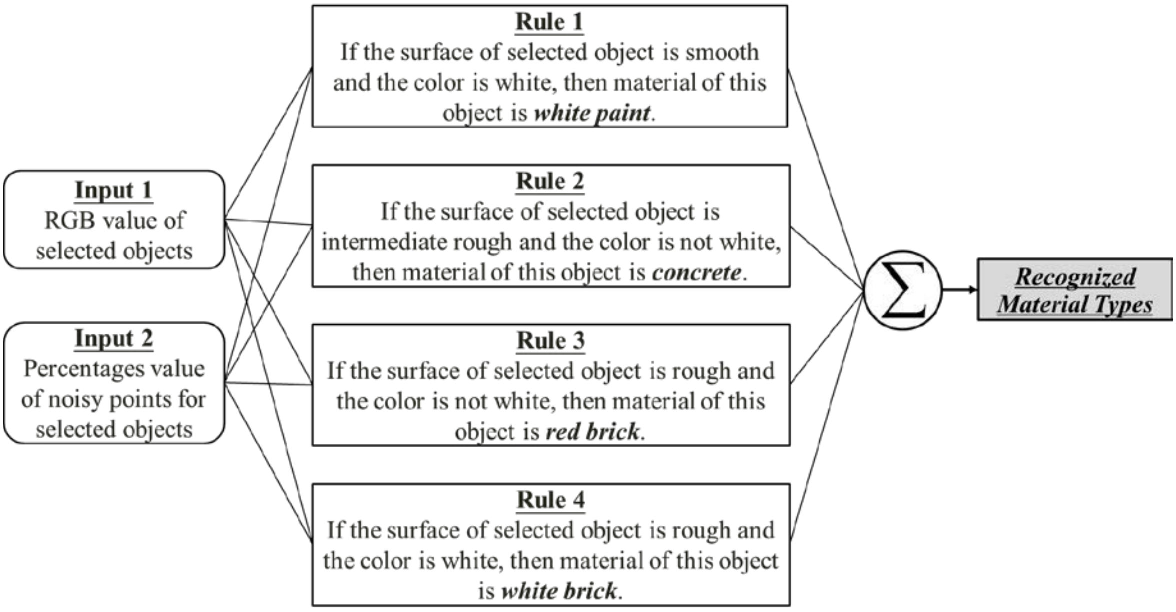


Figure 8 Fuzzy rules and process of material recognition

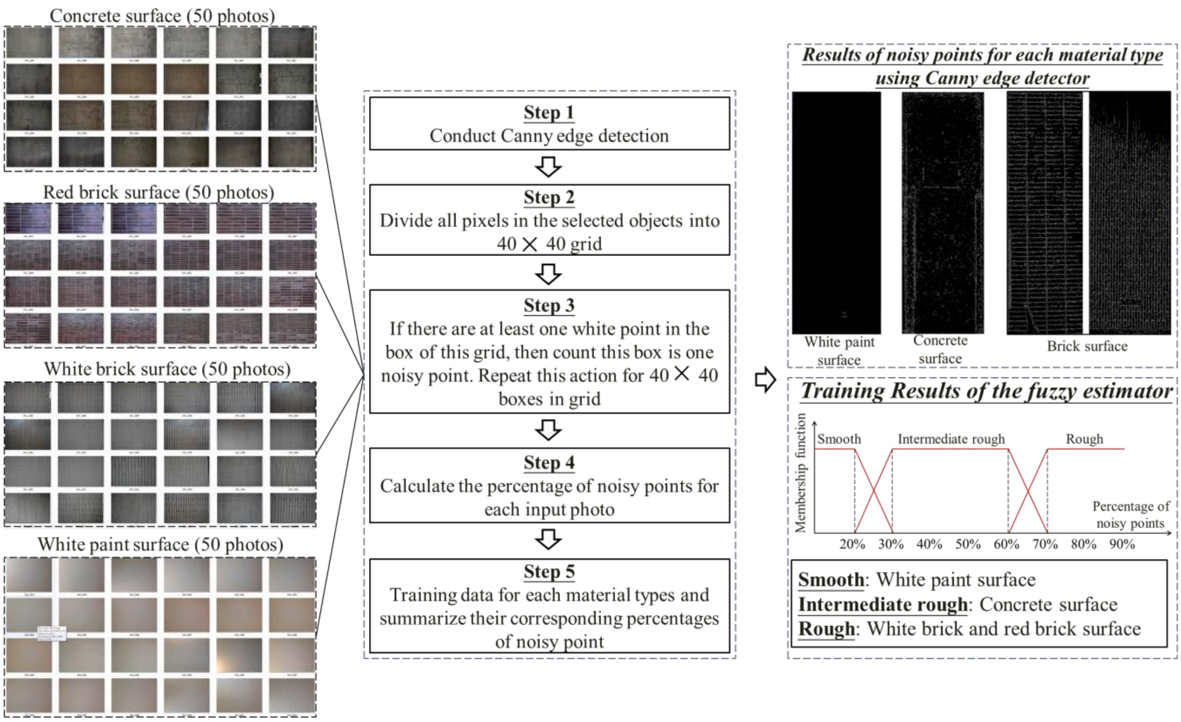


Figure 9 Framework and process of training fuzzy estimator

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. 9 (right part). Fuzzy rules and recognition process are presented in Fig. 8. Framework and process of training parameters for the fuzzy estimator are expressed in detail as shown in Fig. 9.

4 Evaluation and Discussions

The system presented in this paper aims at developing a semi-automatic image-based approach to extract information (i.e., object and material). It is expected that this system of constructing as-is 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 color.

Referring to Figure 10, this paper tested over 80 images. In these particular tests, all the objects in the images were recognized correctly and computing time were less than 0.01 second. In general, the recognition results are satisfied and accurate. This semi-automatic image-based system is proved to be an effective and convenient method in the early stage of constructing as-is BIM objects.

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 & 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. 10, this system describes the basic idea to collect all the essential data from existing data sources. The construction of an as-is BIM object should focus on surveying the geometry and surface of the target building as the first step, and improve this collected information into a primary semantically rich model and eventually achieving a BIM representation.

Figure 10 Object recognition procedures using the image-based semi-automatic object recognition system (i.e., the image-base application and Fuzzy-MAUT algorithm)

5 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, CAD drawings and possibly other data sources, this paper gave a brief introduction of computer vision technology and Multi-Criteria Decision Making Algorithms (MCDM). Then, we built a system of a semi-automatic image-based system (using Fuzzy-MAUT algorithm) as the first step to achieve the goal. The system consists of two parts: information (i.e., object and material) collection and object recognition. More than 80 images are tested in this system and it provides satisfied results. As future work, we will include non-geometric information into the data structure and develop complete BIM objects that fulfill requirements for O&M.

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