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M-ESTIMATOR SAMPLE CONSENSUS PLANAR EXTRACTION FROM IMAGE-BASED 3D POINT CLOUD FOR BUILDING INFORMATION MODELLING

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ABSTRACT: Building Information Models (BIMs) are used as an official standard to manage information in the construction industry. Creating a BIM model is still a laborious process, especially in existing buildings, where digital CAD models are often not available. The current process of creation of a BIM model for existing structures generally involves the generation of a geometric model from a 3D point cloud, commonly created by a laser scan, which can be time consuming and expensive. However, image-based 3D modeling techniques are more economical and efficient. In this paper, a 3D point cloud from images and laser scan were used to detect planes using plane detection algorithms based on the M-estimator Sample Consensus (MSAC). The accuracy of 3D point clouds of both techniques was compared using the Iterative Closest Point algorithm. The sample data used in the study was obtained from a laboratory, which contains 3D points from many visible planes, such as walls and floors. The MSAC algorithm was applied to detect planes in the 3D point clouds from the image-based and laser scanning techniques. The parameters derived from the plane detection algorithms were subsequently used to create BIM models through the eXtensible Building Information Modeling (xBIM). The proposed plane detection algorithm shows promising results with a low mean square error. These results demonstrate that a BIM model can be created from an image-based 3D point cloud, which is more convenient and easy to use than the point cloud from a laser scanner.

Keywords: Laser Scan, Building Information Modelling, Plane Detection, Image-based 3D Photogrammetry, RANSAC

1. INTRODUCTION

According to a smart market report by McGraw-Hill (2014) [16], the percentage of construction projects using BIMs has increased quickly in the recent few years. BIMs are used in the construction industry in more than 10 countries around the world. Building Information Modelling (BIM) is a new technique that has becomes an official standard in the construction industry. The National Building Information Model Standard Project Committee defines BIMs as “A BIM is a digital representation of physical and functional characteristics of a facility as such it serves as a shared knowledge resource for information about a facility forming a reliable basis for decisions during its lifecycle from inception onward.” The BIM method can help to clarify the construction progress by simulating 3D models combined with one standard format called “Industry Foundation Classes (IFC)” [3]. IFC is an intermediary for various computer programs that run many construction processes in the BIM systems. Laser scanning technique has emerged as a tool for data collection for BIM professionals to help in to create BIM models. They can provide a dense point cloud with accurate and detailed information of a building for the BIM process [14]. The raw point cloud data produced by a laser scan can be used as a reference to simulate a 3D model as shown Figure. 1. Normally, a point cloud is created by a laser scanner and then transformed into a geometric form by hand drawing or by automatic algorithms. The automatic algorithms can be created by tools such as PCL (Point Cloud Library). PLC is a popular tool for automatic processing of point cloud. This tool helps to manage and improve the quality of 3D point clouds, which can be used as a preprocessor. The drawback of this library is that it is not capable to create an automatic algorithm for creating the geometric BIM model [12].

There are a number of challenging tasks that need to be addressed when creating as-is BIM models. These include (1) how to effectively collect and document complete information about a building with minimum cost, labor effort, and time, (2) how to check if registration of each building component with its corresponding building information is correct, and (3) how to identify unseen building elements that are occluded, such as pipes behind decoration layers. From previous research, researchers have been trying to find automatic economical solutions for the construction of BIM although, up until now, no solutions have prevailed.

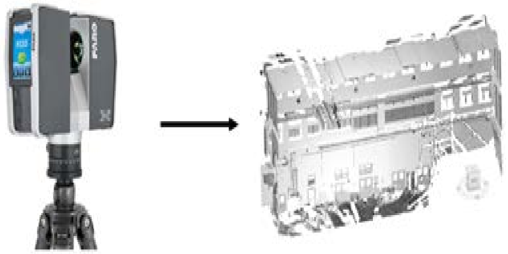

Fig.1 A raw point cloud obtained from a laser scanner.

The use of laser scans for data collection in Building Information Modelling (BIM) is expensive and can be difficult to setup and operate, and often experienced operators are required [5]. However, the image-based 3D modeling technology can offer the same quality 3D point cloud as laser scanners with cheaper costs, which provides a promising path to address some of the challenges associated with BIMs. The image-based point cloud may not be as accurate as of the laser scanning, but the SFM is cheaper and easier to use [2,4]. In addition, the manual methods of creating a 3D geometry model still take a considerable amount of time to construct such a complex 3D model from the point cloud. To overcome this problem, it is essential to design an automated workflow for the generation of BIM data from 3D point clouds (Thomson and Boehm, 2015). The automatic simulation of 3D models from a laser scanner point cloud using commercial software, such as Imagine, is still not accurate in case of sizing, which can lead to inaccuracy in forming 3D models. Table 1 provides a summary of problems found in creating 3D BIM models from laser scanners.

This paper proposed an automatic plane detection algorithm from an image-based 3D point cloud using the M-estimator Sample Consensus (MSAC) algorithm. (Torr and Zisserman, 2000). The algorithm was applied to detect planes from the point clouds from the image-based and laser scanning techniques data for comparison. The output from the algorithm is plane parameters, [6] which will be used in the eXtensible Building Information (xBIM), which is a toolkit to create the Industry Foundation Classes (IFC) to create a geometric model in BIM modeling. The toolkit provides the ability to read, write and view IFC files compliant with the IFC4 standard and is written in C# [18]. The contribution of this work is to demonstrate the application of an image-based point cloud for creating a geometric model for BIM using an automatic algorithm.

Table 1 The summary of problems found when creating a 3D BIM model by laser scanners

3D modeling stage	Problem
Acquisition of point cloud	Expensive equipment, required expertise to operate equipment
Automatic Geometric modeling from Commercial software	Size does not match the actual building size
manual geometric Modelling	take time to create models and can be difficult to create a complex model

The rest of the paper is organized as follows, Section 2 is the Literature Review, which summarizes previous work on the automatic creation of 3D geometry model for BIM. The methodology of the proposed algorithm is explained in Section 3. Section 4 presents experiments and results followed by a conclusion in Section 5.

2. RELATED WORK

2.1 3D Modelling in BIM

Point cloud data captured by a laser scanner are normally used as a reference for the construction of as-is BIMs [5]. Gao et. al., proposed multiple laser scan for constructing as-is BIMs to capture the geometric information by performing multiple laser scans of a facility (research lab) during the renovation process at different phases. The laser scan data can be used to generate the geometric model of the facility. Multiple visible components such as ceilings, wall and floors, and non-visible components such as water pipes hidden behind the finished surfaces and air ducts were created with geometric models. Viorica et. al., [17] proposed a general framework in creating as-built models. The author discussed various research works from different communities that are recently being used and have the capability to be used in the future for solving the challenging tasks associated with as-built BIM generation for infrastructure. The authors emphasized on the importance of how to accurately generate geometric models. The author proposed that current techniques should be incorporated with object detection techniques for accurate as-built BIMs generation. [15] Thomson et. al., proposed automatic geometry generation from the point cloud data for BIM.

The authors proposed to automatically reconstruct basic Industry Foundation Classes (IFC) geometry from points clouds data and also, to create point cloud data from an IFC geometry. They used the PCL implementation of the RANSAC algorithm to detect the horizontal and vertical planes for IFC geometry. Additionally, the geometric models were also used to create points of cloud data from IFC components for verification.

2.2 Automatic Planar Extraction from Point Cloud

As stated in, [17] a point cloud is normally acquired by a laser scanner, and extracting planes from the point cloud still requires considerable effort to create planes manually. Thomson et. al. [15]. used the RANSAC algorithm implemented in PCL to detect horizontal planes such as floors and ceilings and vertical planes (e.g. walls) from a laser scan point cloud. Pang et. al. [10] created an algorithm to segment point cloud into different components of rooms such as floors, planes and pipes by applying classification algorithms. The authors used Support Vector Machine (SVM) with Fast Point Feature Histogram (FPFH) to classify each area of a sampled point cloud data. This method still has problems with noise in the sampled point cloud, although the authors were able to demonstrate the ability to classify planes, pipes and building components for 3D modeling for BIM. Xu et. al. [19] used the voxel and graph-based segmentation (VGS) to improve geometric primitive recognition from point cloud to classify planes and cylinders from a point cloud. From previous research, it is cleared that plane segmentation from a point cloud data is important for automatic generation of BIM models from the point cloud. Therefore, this research project demonstrated the use of an image-based 3D point cloud for the plane segmentation task in the BIM modeling. The image-based method to acquire a point cloud is a much cheaper option than a laser scanner.

3. METHODOLOGY

The methodology of the proposed method is described in Figure. 2. The automatic plane detection algorithm is by the Matlab implementation. The images and the laser scanned point cloud used in this research was taken from a civil engineering laboratory. The point cloud data was used for the automatic detection of planes to obtain plane parameters.

3.1 Planar Extraction by M-estimator Sample Consensus

A set of images were collected from a laboratory to create a 3D point cloud from images. The sample images of the data are shown in Figure. 3. The images were converted to the 3D point cloud model using the program called Agisoft [1] as shown in Figure 4(top). Another 3D point cloud was obtained from the same laboratory using a laser scan as shown in Figure 4(bottom).

The two models were then imported to CloudCompare so that the 3D point clouds are registered together via an Iterative Closest Point algorithm to have an identical reference world coordinate as shown in Figure 5 [13]. The point clouds were registered together so that the world coordinates of the two methods are identical and the comparison between the two methods can be compared.

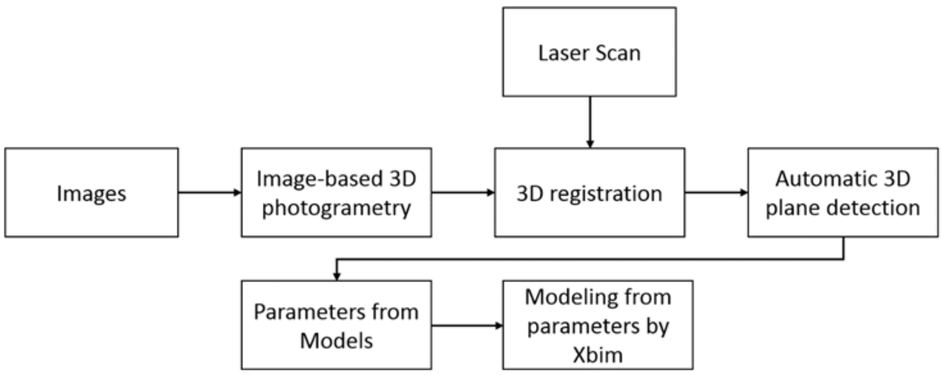

Fig.2 The outline of the proposed planar extraction algorithm using M-estimator Sample Consensus.

Fig.3 Sample images collected from a laboratory

Fig.4 (Top) the point cloud from image-based technique, (bottom) the point cloud from the laser scanner.

The planar extraction algorithm is summarized below in Algorithm As shown in Table 2, the following inputs are required, point cloud, maxDistance, maxAngularDistance, reference vector, inlier_to_stop and no_more_plane. The max distance is the distance between the inlier coordinates and a detected plane, which is as 0.02 meters. The maxAngularDistance is the distance between the normal vector and the reference orientation, which is set as 5 degrees. The reference vector is a reference orientation constraint, which is set as a horizontal vector perpendicular to a floor. The inlier_to_stop parameter the percentage of inliers point to allow the algorithm to terminate. This parameter must be configured appropriately in corresponding to the density of a point cloud. Finally, the no_more_plane parameter is set to zero or false to allow the algorithm to execute in the while loop.

Then, the algorithm starts the while loop by finding the set of inliers point cloud that may form a plane. The Region of Interest (ROI) is the region that can be specified for the constraint the search to only within this region. The default value is currently set to infinity. Then the Matlab function called pc_fit_plane is used to find fit the best plane to the region by a RANSAC algorithm. The output of this function is the set of inliers that form a detected plane. The selected inliers that may a possible plane are then given indices in the function called inliers_indices. If the percentage of inliers_indices is too low, then a plane is not detected and the algorithm continues to find a new plane and a new set of indices. A plane is found when the inliers_indices values are greater than inliers_to_stop, then inliers_indices will be set to as a found plane. The inliers_indices is used to fit a plane by a nonlinear least square method to find the best plane equation. The plane parameters are the output from the algorithm. When inliers are not enough to make a plane, then the value of no_more_plane is set to true and the while loop will terminate.

Table 2 The algorithm shows steps in the planar extraction algorithms

Algorithm: Planar Extraction

Input: The point cloud from images and the point cloud from a laser scanner, maxDistance, maxAngularDistance, reference vector, inlier_to_stop, no_more_plane.

Output: Plane parameters

```
while ~no_more_plane
      Set  Region_Of _Interest;
      Find_Points_In_Region_Of _Interest;
      pc_fit_plane;
      Set points to inlier_indices;
      if inlier_indices > inlier_to_stop Then
          Set_Inliers_Indices_to_Plane;
          Store_Plane;
     else
          no_more_plane = 1;
end
```

The planar extraction algorithm is based on M-estimator sample consensus method, which applies the cost function [16] in linear regression to estimate best approximate the sampled point cloud with the minimum least cost function values or mean square error values. The derived linear regression equation [7] for a sampled data can be defined as

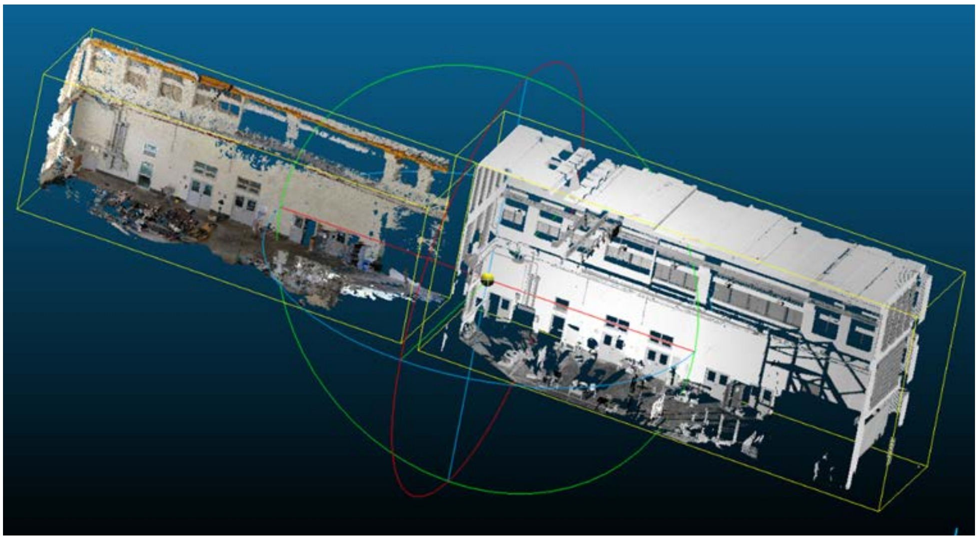

Fig.5 3D registration of the point clouds from the laser scanner and the image-based technique using CloudCompare

$$h_\theta(x) = \theta_0 + \theta_1 x \quad (1)$$

Where $h_\theta(x)$ is the hypothesis equation, θ_0 is the bias and θ_1 is slope and x represents the sampled data. The hypothesis equation (1) can be considered as a hypothesis of the sampled data. Assume that there is m data points, then the hypothesis equation of the first set of data is$h_\theta(x_1) = \theta_0+\theta_1 x,$ and then the sum of square error is divided by the number of training data m. The cost function is represented as C and can be described as [8]

$$C = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^i) - y^i)^2 \quad (2)$$

Where C is cost function, or mean square error, m is nuthe mber of training data, h_θ is hypa othesis equation, x is training data and y is real data.

The RANSAC algorithm has proven to be very successful for robust estimation [9], but one of the problems is that if the threshold T for inliers is set too high then the robust estimation is not efficient. The RANSAC algorithm finds the minimum cost function [11] for a set of inliers and can be represented as;

$$C = \sum_i p(e_i^2) \quad (3)$$

Where C is cost function or mean square error, e is error function and σ is standard deviation, and p is the robust error term which is defined as;

$$p(e^2) = \begin{cases} 0 & e^2 < T^2 \\ \text{constant} & e^2 \geq T^2 \end{cases} \quad (4)$$

Where T represents threshold. From equation (3) and (4) the inliers scores nothing while each outlier scores a constant penalty. As a result, higher T^2 is a solution with poorer estimation, hence higher C. In Torr and Zisserman [11] it was shown that this undesirable situation cannot be solved by the extra cost, but rather by minimizing C, which leads to a new cost function [11].

$$C_2 = \sum_i p_2(e_i^2) \quad (5)$$

Where C_2 is cost function or the mean square error, e is error function and σ is staa ndard deviation and the robust error term p_2 is represented as,

$$p_2(e^2) = \begin{cases} e^2 & e^2 < T^2 \\ T^2 & e^2 \geq T^2 \end{cases} \quad (6)$$

Where T is tthe hreshold. From equation (5) and (6), it can be seen that outliers are still given a fixed penalty but now inliers have scored on how they will fit the data. By keeping the value of $T = 1.96\sigma$, then the Gaussian inliers are incorrectly rejected five present of the time. By doing this, we are able to make the most accurate model by achieving lowthe est and optimal cost function for data estimation.

The M-estimator method was applied to find plane equation parameters for planar extraction. The method is implemented in the Matlab program and is able to detect multiple planes from the point cloud data, the plane equation [6] is defined as,

$$ax + by + cz + d = 0 \quad (7)$$

Where a, b, c are parameters of northe mal vector and d is distthe ance from the origin.

After deriving the plane parameters for both point clouds from a laser scan and image-based techniques, then the eXtensible Building Information Modeling (xBIM) toolkit is used to

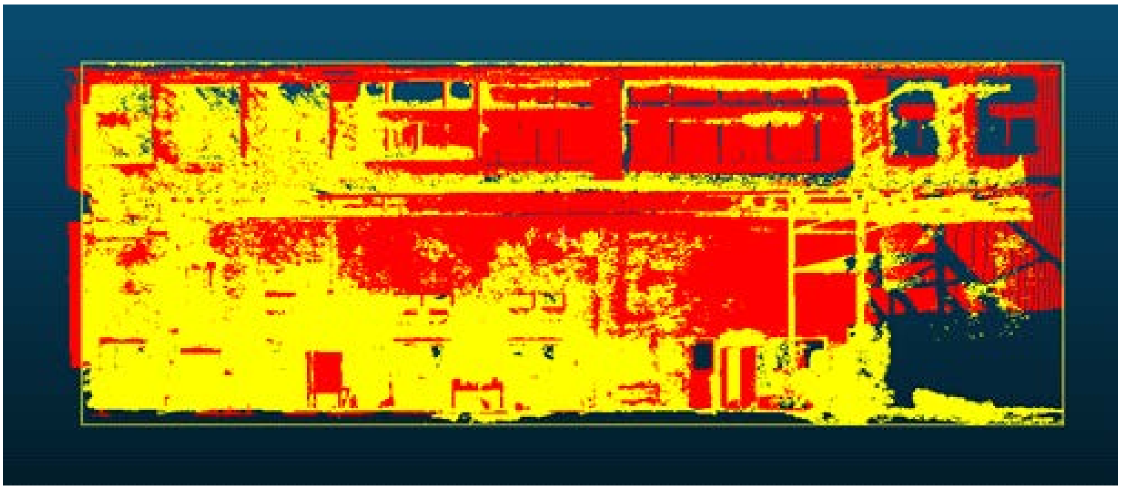

Fig.6 Registration between two the point clouds from the laser scanner and image-based method using Iterative Closest Point algorithm

create a BIM model. The xBIM toolkit creates a 3D model by using an Industry Foundation Classes (IFC) system, which is a Standard Format for creating BIMs. The BIM generation using xBIM is beyond the scope of this paper.

4. EXPERIMENTS AND RESULTS

Iterative Closest Point (ICP) method was used to register the point clouds from the laser scanner and from the image-based technique via the software package called CloudCompare. The algorithm minimizes the root of distance between compare points, which is called the Root Mean Square (RMS) errors. As shown in Figure 6 and Table 3, the point cloud from both method can be aligned well and the RMS error between the point cloud is 0.1967. This means that the average distance between the two point clouds is around 0.1967 m or 19.67 cm. The results are quite high, this may be caused by the difference in the point clouds as some regions were missing in the image-based based point cloud. Nevertheless, two-point clouds can be registered to have identical world coordinates.

The results of plane detection by the M-estimator Sample Consensus algorithm and modeling in xBIM are shown in Table 3, 4, and 5, and Figure 7 and 8. The algorithm detected 1 plane from point clouds. The detected plane is the main wall in the laboratory, the planes on the windows and doors are note detected. From Table 4, the cost function, which is the output from the algorithm shows that the cost function values from both datasets are similar, which is approximately 0.04. And as shown in Figure 7 and Figure 8, the detected plane from both datasets are identical. This can be concluded that the planes detected from the two datasets are identical, hence the point clouds from the two methods are similar when extracting planes from the point cloud.

Table 3 The root mean square errors between the point cloud from the laser scanner and image-based technique

Data Registration	RMS
Laser-Scan and Image-based	0.1967

Table 4 The cost function or mean square error from the m-sac algorithm for the point clouds from the laser scanner and image-based technique

Data type	Cost Function
Laser Scan / Automatic detection	0.0066
Image-based / Automatic detection	0.0078

Fig.7 The detected plane from the laser scanner

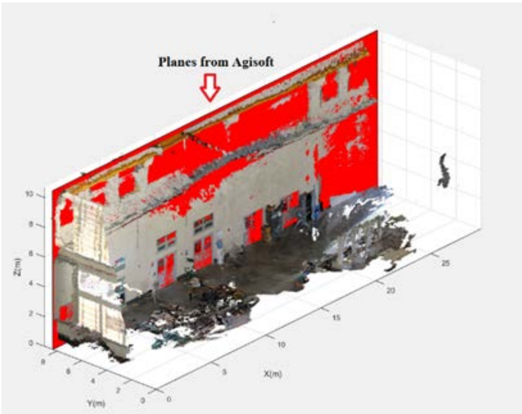

Fig.8 The detected plane from the images-based technique

As shown in Table 5, the result shows the angle of the normal vectors from the detected planes from the two sets of data. As can be seen, the angle is 0.89^{o}, which means that the two planes are very similar. It can be said that the results of plane detection from both sets of the point cloud are almost identical. This can be further confirmed by Figure 9 and 10, which is the results of constructed planes from xBIM for the two set of point clouds. The results are identical and hence it can be concluded that the point cloud from the image-based techniques can provide an equally good result for plane detection and can be used instead of a laser scanner. The image-based technique is much cheaper than a laser scanning technique and can be deployed faster. The image-based technique can also be used with a drone, which can collect data from a location, which is high and human cannot access. This is one of the main advantages for the image-based method as it uses image data which can be collected much easier, whereas the laser scanner cannot be collect from a high rise point.

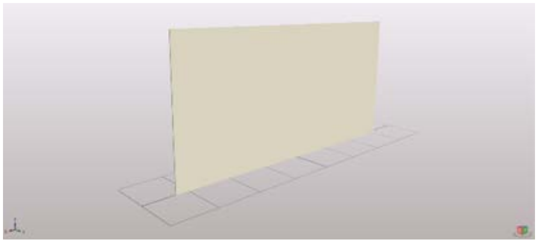

Fig.9 3D model from the image-based technique using xBIM

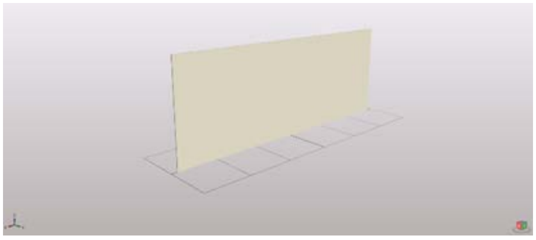

Fig.10 3D model from a laser scanner using xBIM.

Table 5 The parameters of detected planes from the point clouds from the laser scanner and image-based technique

Data type	Plane Equation	The angle between 2 planes
Laser Scan / Automatic detection	$\mathbf{-0.0118x + 0.9999y}$ $\mathbf{-0.0038z - 7.6457 = 0}$	$\mathbf{0.89°}$
Image-based / Automatic detection	$\mathbf{-0.0005x - 0.9999y}$ $\mathbf{+0.0029z + 8.3116 = 0}$	

5. CONCLUSION

In this paper, automated planar detection from the point cloud using the MSAC algorithm was applied to the point cloud obtained from the images-based and laser scanning techniques. The laser scanned and images-based point clouds were imported to CloudCompare to register the clouds together via an Iterative Closest Point (ICP) algorithm to allow the point cloud to have the same world coordinates. It was observed that the RMS error between the two clouds was approximately 19.67 cm. Although the number may be high, visually, the two-point clouds can be registered together well and sufficient for the next stage of processing.

The MSAC algorithm was applied to detect the planes between the point clouds from two techniques. As concluded in the results, the planes detected were similar for both the point cloud from the two techniques. The normal vectors from the two data differ by only 0.89o. This means that the quality of the point cloud from the image-based techniques is similar to the point cloud from the laser scanner. However, the image-based technique is cheaper and easier to apply and can be combined with a drone to obtain images where the laser scanner cannot reach. Therefore, it can be concluded that the point cloud from the image-based technique is an attractive method for BIM modeling. The detected planes from MSAC algorithm can be further modeled into BIM models using xBIM, which is demonstrated in this paper.

6. ACKNOWLEDGMENTS

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