Automatic As-is 3D Building Models Creation from Unorganized Point Clouds

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ABSTRACT

Building information models (BIMs) are increasingly applied throughout a building's life cycle for various applications, such as building renovation, energy simulation, and performance analysis in the Architecture, Engineering Construction, and facility management (AEC/FM) domain. In a traditional approach, as-is BIM is primarily manually created from point clouds, which is labor-intensive, costly and time consuming. This paper introduces a method to automatically create as-is 3D building model from unorganized point cloud collected by a 3D laser scanner. The collected raw data are downsized and segmented to individual plane segments. Then, boundary estimation method and building component recognition method are applied to recognize all building components as individual objects and visualize them as polygons. The proposed method was tested on outdoor point cloud data to validate its feasibility and evaluate its performance. The analyzed results showed that the proposed method would simplify and accelerate the as-is building model creation process.

INTRODUCTION

Architecture, Engineering, Construction, and Facility Management (AEC/FM) have relied on paper-based drawings for a very long period of time. This situation has changed significantly with the introduction of Building Information Models (BIM). BIM includes not only 3D geometric models, but also more specific information or attributes on a wide range of building elements. It can provide a data-rich, object-based, intelligent and parametric digital representation of the building. In the design phase of a building, BIM can assist the decision makers on cost analysis, construction sequencing, constructability test, and building performance test (Anil et al. 2012). BIM has been widely applied to a design phase by the construction companies, and people increasingly expect building designs to be energy efficient and conform to known or predictable performance levels. However, BIM is not available for most of the current old buildings. Even though some existing buildings may have BIM, it could be incorrect since the buildings keep being renovated. The preparation for new BIM is usually labor-intensive, costly and slow. In addition, it is inevitable that different modelers could create different models even though modeling the same building using the same software (Bazjanac 2009). Nowadays, the difficulty of as-built measurements of building geometries has been solved using the laser scanning technology due to its ability to acquire building spatial data in three dimensions with high fidelity and low processing time. The output of the laser scanning is an as-is point cloud which is composed of millions of individual points in which each point has its 3D relative coordinate information.

In recent years, many studies have been done on object recognition from the point cloud. Objection recognition algorithms have been used in construction sites to detect construction equipment, steel structures for the purpose of safety, 3D visualization and quality control (Tang et al. 2011; Lytle 2011). The newly developed 3D laser scanning system has started providing color information for each point which can be also used for object recognition based on color segmentation (Sapkota 2008; Son and Kim 2010). Besides its usage in the construction sites, it can be also applied to the buildings. Pu and Vosselman (2009) presented a knowledge based method to reconstruct the building models from terrestrial laser scanning data, and the features and the outline of the building were extracted, while the geometric model of the building was made based on several assumptions because only facades on the street side were scanned. A context-based modeling algorithm (Adan et al. 2011; Xiong, et al. 2013) was also introduced to create a complete as-is building model of the interior of the building. However, not much research efforts have been done on how to generate exterior building model due to the irregular building shape or complicated roof. In this paper, a methodology is developed for recognizing the building envelope components as individual objects by only using the coordinate information of the point cloud. In the following sections, the developed methodology and the preliminary field test results are explained.

UNORGANIZED POINT CLOUD COLLECTION

Point cloud collected from different devices can be categorized into organized and unorganized one. Organized point cloud has an organized data structure like an image or matrix, and each point of the point cloud has its index in rows and columns. Such point clouds include data collected from stereo cameras or Time of Flight cameras. The advantage of the organized point cloud is that data processing is more efficient by knowing the relationship between adjacent points or nearest neighbor. For unorganized point cloud, no data structure or point reference exists between points due to varied size, resolution, density and point sequence. Hence, usually more time is consumed in processing unorganized point cloud data.

In this paper, all the point cloud data were collected from our self-developed hybrid LiDAR system (Gai, et al. 2012). This system is composed of two 2D laser scanners which can be rotated 360 degrees to obtain 3D point cloud data. The point cloud processed in this study was collected in a residential area, as shown in Figure 1, four scans were made to cover one residential house. The collected point clouds were registered into one point cloud before data processing started. The residential house collected data from is a two-story building with full basement. In the following section, the proposed as-is 3D building model creation method is introduced and validated through processing the collected point cloud data of this residential house.

Figure 1. Collected point cloud of a residential house (stars indicate four locations of data collection)

OVERVIEW OF THE PROPOSED METHOD

The proposed solution is comprised of three steps:

(1) In the first step, collected raw data is downsized to reduce the processing time. As a result, a picture of the downsized point cloud would be generated.

(2) Upon completing data pre-processing, two methods of boundary point detection algorithms are applied to detect boundary points from the downsized point cloud data. The boundary points detected from both methods will be merged to increase the completeness and robustness of the final results.

(3) The final step is to categorize all detected boundary points into its own building element category and create as-is 3D building model.

Figure 2 presents the work flow of the proposed method. In the sections that follow, three major sections of data pre-processing, boundary point detection, and as-is 3D building model creation process are briefly introduced and the results of each section are presented.

Data pre-processing

The basic goal of data pre-processing is to increase the data processing speed by downsizing the quantity of the raw point cloud data. The space is divided into a 3D voxel grid, which can be considered as a set of tiny cubes. The bigger the voxel is, the more points are eliminated. After locating all the points into their corresponding voxels, all the points present in the same voxel are approximated by its centroid point. Then the new downsized data are the input of the following processes. To maintain the accuracy of the results and reduce the processing time at the same time, the size of the voxel has to be adjusted properly. 10 cm was set as the edge length of the voxel in the preliminary tests, and the number of the points in the raw point cloud data was reduced from 1,965,312 to 55,867, more than 97% of the raw data was eliminated (see Figure 3.).

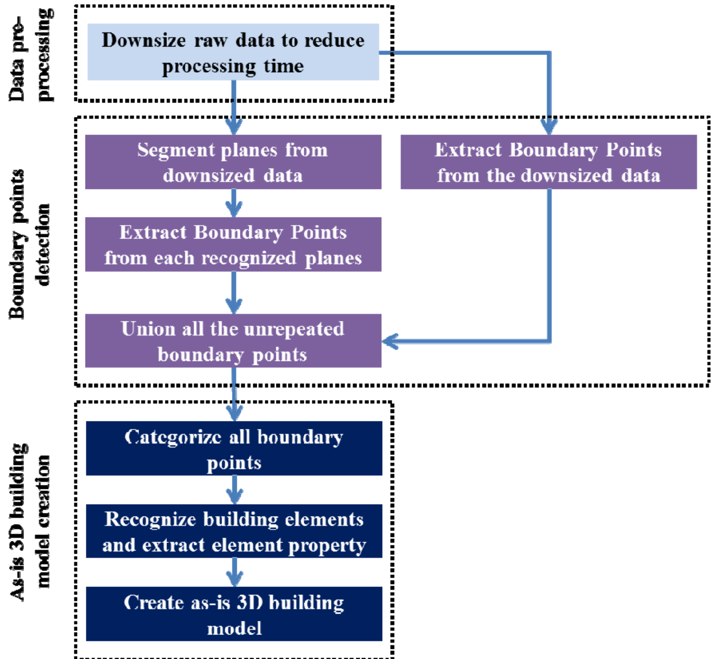


Figure 2. System process and the work flow

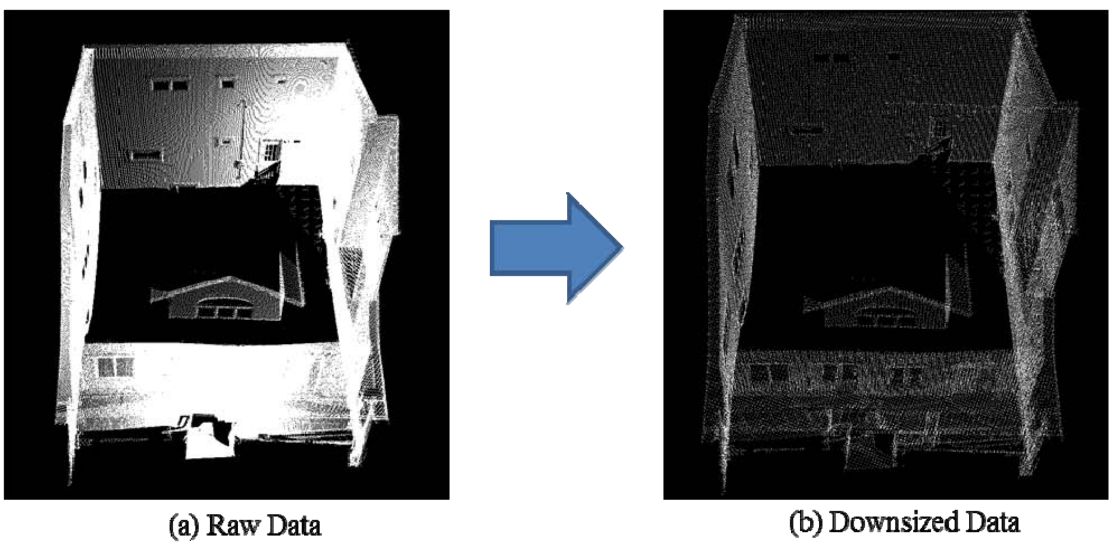
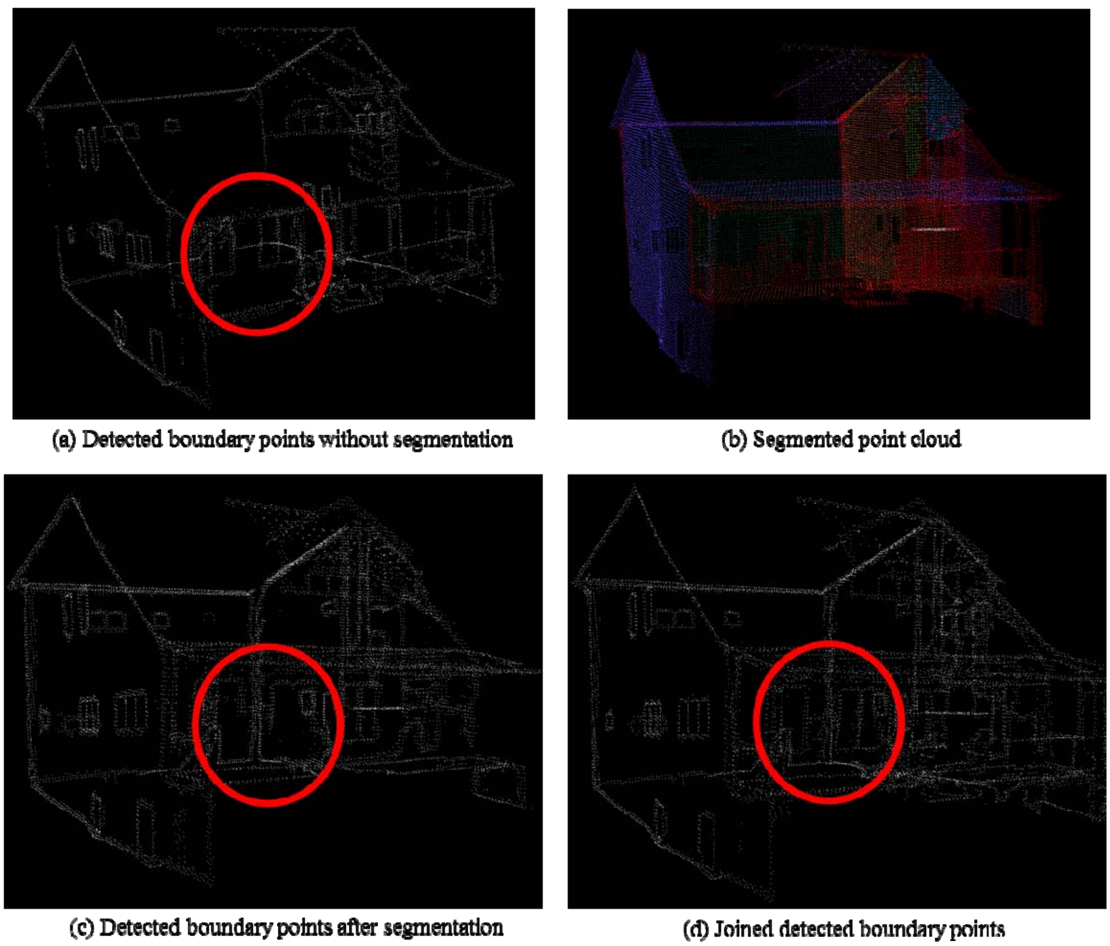


Figure 3. Bird view of the raw data and the downsized data

Boundary point detection

In the second step, the boundary point detection algorithm is applied on the downsized point cloud data to find all the possible boundary points. The boundary points mentioned here could be the edge points between different surfaces and the points next to the empty space. Two different approaches are introduced to detect the boundary point clouds, one is detecting boundary points directly from the downsized point cloud data (Rusu, et al., 2007), and the other is segmenting the downsized data into several surface clusters and then detecting boundary points from each surface cluster. Eventually, the two estimated boundary point clouds are joined together as one to compensate each other's incompleteness.

Region growing segmentation algorithm (Farid and Sammut, 2012; Farid and Sammut, 2013) was implemented in the proposed method, and this algorithm can merge the points close enough to each other in terms of the smoothness constraint into one cluster. The output of this segmentation algorithm is several segmented point cloud clusters where points in the same cluster are considered to be a part of the same surface. As shown in Figure 4, segmented clusters are presented in different colors, and the circled areas show the comparison among each boundary point cloud and the joined one. The boundary points of the front windows are completely detected from the downsized data (Figure 4 (a)) rather than the segmented clusters (Figure 4 (c)), thus joint boundary point cloud was better integrated. After conducting boundary point detection algorithm, the size of the point cloud data decreased to 11,781 (Table 1.). These 11,781 points will be analyzed in the next step to create building elements.



(a) Detected boundary points without segmentation (b) Segmented point cloud

(c) Detected boundary points after segmentation (d) Joined detected boundary points

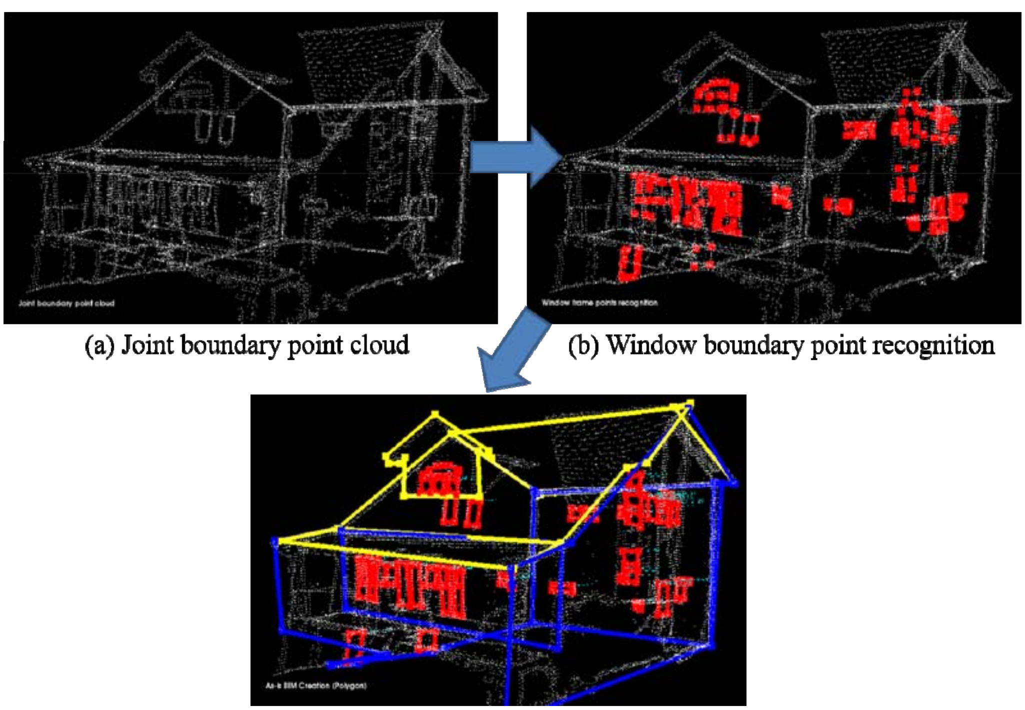
Figure 4. Boundary point detection

Table 1. Number of Points in the Boundary Point Cloud

Data	Quantity
Downsized data	55,867
Detected boundary points without segmentation	7,527
Detected boundary points after segmentation	8,440
Joint boundary point cloud	11,781

As-is 3D building model creation

Building elements are automatically created from the boundary points detected in the previous step. First, the boundary points are divided into two categories – window frame boundary and exterior wall boundary. It is unable to collect point cloud data from the low reflection material such as black object and glass due to the character of the laser beam. Thus, there is no point showing in the window glass area. The boundary points of the window frames can be separated from the joined boundary points based on the fact that the boundary points of the window frame surround an empty window glass area. Having the window frame points recognized, the windows and the exterior walls can be created by connecting the corresponding boundary points. Due to the incompleteness of the data on roof area, the roof is approximately created by connecting all the top edges of the exterior walls. Finally, the created as-is building model is rendered in different color according to the element types. Figure 5 demonstrates the process and preliminary results of the proposed as-is 3D building model creation algorithm.



(a) Joint boundary point cloud (b) Window boundary point recognition

(c) As-is 3D building model creation

Figure 5. As-is 3D building creation

Precision and recall (Olsen and Delon 2008) were estimated to evaluate the performance of the proposed algorithm. As shown in Table 2, True Positive (TP) indicates the number of correctly recognized components, False Positive (FP) means the number of wrongly recognized components, and False Negative (FN) is the number of components that were not recognized. Due to the incompleteness of the collected data, the precision and recall were only analyzed on recognized windows. In the preliminary test, 40 windows were recognized from the collected point cloud data, and the average error difference is 16.90% for width and 12.45% for length.

Table 2. Precision and Recall of the Created Building Element

Component	TP	FP	FN	Precision	Recall
Window	40	2	4	95.24%	90.91%

CONCLUSION

In this study, unorganized point cloud data were collected by a LiDAR system. First, more than 97% of the raw data are eliminated to reduce the data size so as to increase the processing speed. The downsized data were then processed through two different approaches of boundary point detection algorithms. Two sets of detected boundary points are joined together as one to compensate each other's incompleteness. As-is 3D building model was finally created by processing the boundary points to recognize the building components. The proposed method has been validated though the preliminary test with a residential house point cloud data.

Future work will focus on the improvement of the accuracy on processing incomplete data. In the current study, the accuracy mostly relies on the data integrity. Future work will discuss how to model the building components that are blocked by trees or bushes.

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