AUTOMATIC GENERATION OF BUILDING FOOTPRINTS FROM AIRBORNE LIDAR DATA

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ABSTRACT ... Airborne LIDAR (Light Detection and Ranging) technology has reached a degree of the required accuracy in mapping professions, and advanced LIDAR systems are becoming increasingly common in the various fields of application. LiDAR data constitute an excellent source of information for reconstructing the Earth's surface due to capability of rapid and dense 3D spatial data acquisition with high accuracy. However, organizing the LIDAR data and extracting information from the data are difficult tasks because LIDAR data are composed of randomly distributed point clouds and do not provide sufficient semantic information. The main reason for this difficulty in processing LIDAR data is that the data provide only irregularly spaced point coordinates without topological and relational information among the points. This study introduces an efficient and robust method for automatic extraction of building footprints using airborne LIDAR data. The proposed method separates ground and non-ground data based on the histogram analysis and then rearranges the building boundary points using convex hull algorithm to extract building footprints. The method was implemented to LIDAR data of the heavily built-up area. Experimental results showed the feasibility and efficiency of the proposed method for automatic producing building layers of the large scale digital maps and 3D building reconstruction.

KEY WORDS: LIDAR, building footprint, convex hull algorithm, automatic extraction.

1. INTRODUCTION

Utilizing building footprints is essential for many applications such as building and modeling, digital mapping, urban planning, establishment of spatial data infrastructure, telecommunication analysis, environment monitoring, *etc* (Jensen, 2000). Building footprints, especially with height values can be also used to generate three-dimensional building models. Traditionally, aerial photos and high resolution satellite images have been considered as effective data sources to acquire and to extract building footprints (Jensen and Cowen, 1999).

In general, image based methods for extracting building footprints require significant levels of computational steps and the results are highly dependent on the image quality which is affected by various conditions. During the past two decades many researchers have been trying to develop automated methods to extract building footprints (Mayer, 1999; Strassopolou *et al.*, 2000; Lee *et al.*, 2003). However, automation is limited due to the influence of shadow and relief displacement of the buildings appeared in optical sensor images.

In recent years, airborne LIDAR technology has been developed for providing dense point clouds with accurate 3D coordinates, and it makes possible to extract building footprints more efficiently. Unlike the optical images, LIDAR data have the advantages such as all-weather operability, no influence of shadow and relief displacement, and orthogonally projected 3D data. However, voluminous and irregularly distributed point clouds make it difficult to apply automatic scheme for data processing including automatic extraction of building information from LIDAR data (Zhang *et al.*, 2006).

Many researchers have investigated automated extraction of building footprint from LIDAR data. The previous methods can be classified into two main categories. One is to separate the ground, buildings, trees, and other features from LIDAR point clouds simultaneously (Maas, 1999). The other is to extract building footprint data from non-ground measurements after separating ground and non-ground data, which is more popular method than the former one (Morgan and Tempfli, 2000; Rottensteiner and Jansa, 2002). However, these methods surfer from various problems. For example, the results are significantly influenced by segmentation algorithm.

The main objective of this paper is to propose algorithms for automatic extracting building footprints solely from airborne LIDAR data. To extract building footprints, the irregularly spaced LIDAR measurements are to be included in meshes created in the data coverage to facilitate computation. The ground and non-ground data were separated from the gridding data using histogram analysis. Finally, building footprints were extracted from the ground data using convex hull and tracing algorithm.

The paper is organized as follows. Chapter 2 explains building footprints extraction algorithm in detail. In

Chapter 3, the results and discussion are presented. Finally, conclusions are provided in Chapter 4.

2. EXTRACTION OF BUILDING FOOTPRINTS

The proposed scheme for extracting building footprint consists of six processes; data gridding, extraction of building outlines, grouping of building outlines, rearrangement of building outlines, extraction of building corner points, and simplification of building outlines. Figure 1 represents the proposed work flow of processing for automatic extraction of building footprints.

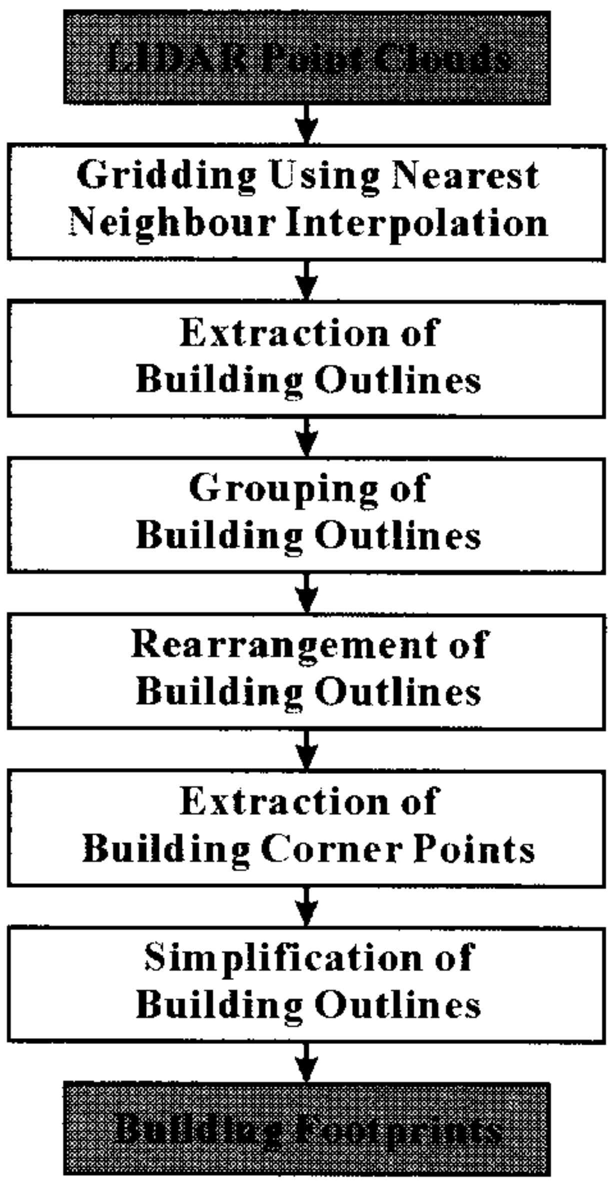

Figure 1. Algorithmic structure and work flow of the proposed method.

2.1 Data Gridding

LIDAR data consist of three-dimensional cloud of points (X, Y, Z) with irregular spacing. First, the point data were interpolated into regular grid data. There are various interpolation methods such as nearest neighbour, inverse distance, kriging interpolation, *etc*. Nearest neighbour interpolation was chosen in this study because the purpose is to extract buildings rather than to construct a smooth surface.

2.2 Extraction of Building Outlines

Classifying ground and non-ground measurements is an important step for extracting building outlines. The ground and non-ground measurements were separated by histogram analysis. The histogram analysis is based on the fact that the first peak of histogram comes from the ground measurements. The points with lower height values than the first peak of histogram are considered as the ground data, while points being higher height values than the first peak are regarded as the non-ground data (see Figure 2). The non-ground data extracted from the gridding data are trees and buildings or other objects. Trees in the non-ground feature data are usually removed using a progressive morphological filter (Zhang *et al.*, 2003).

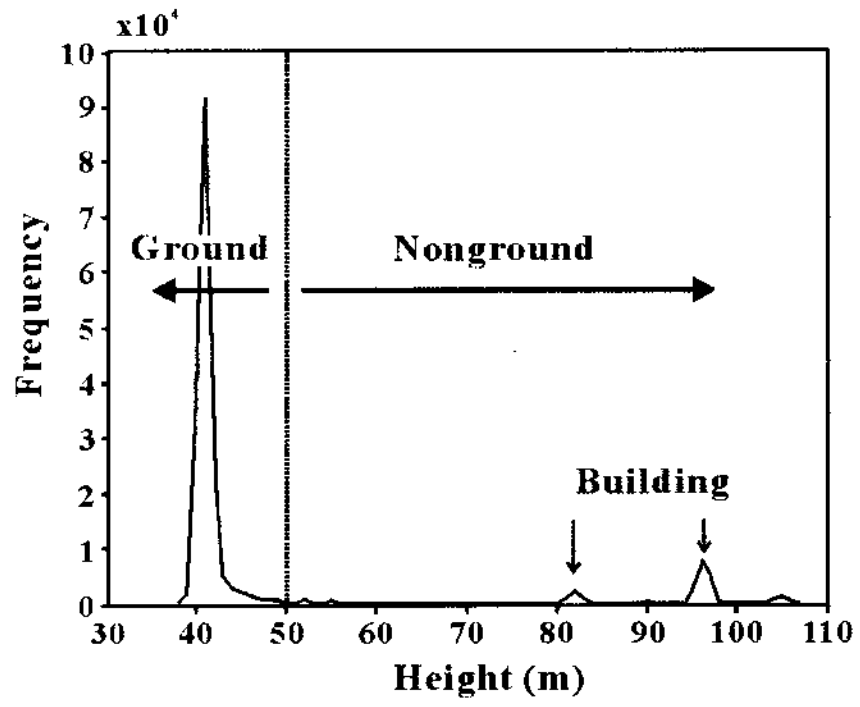

Figure 2. An example of separating ground and non-ground data using histogram analysis.

Figure 3 (a) shows the building extracted using histogram analysis and progressive morphological filter, and Figure 3 (b) represents the building outlines extracted by the vertical and horizontal derivative filters.

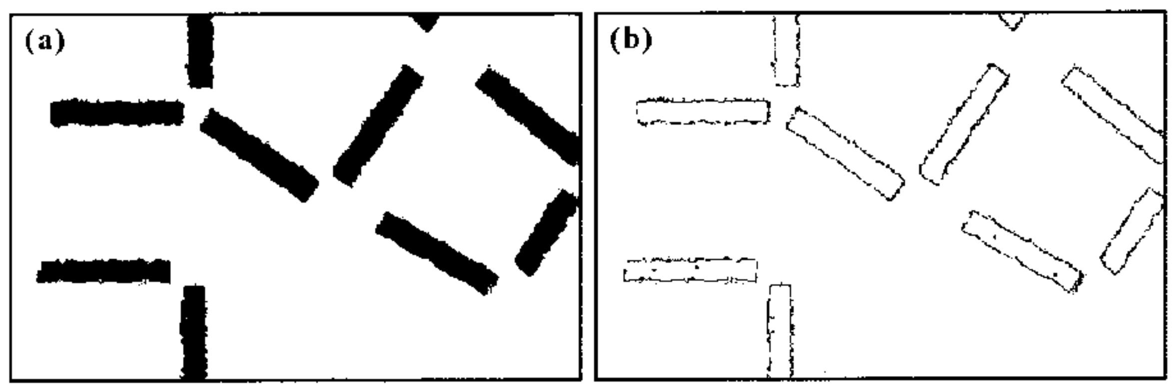

Figure 3. Extraction of buildings and building outlines from nonground data: (a) the extracted buildings and (b) the building outlines extracted from buildings.

2.3 Grouping of Building Outlines

All building outlines were separated by split-and-merge grouping process. After the grouping process, the boundary of the each building can be extracted. Figure 4 illustrates grouping process of building outlines.

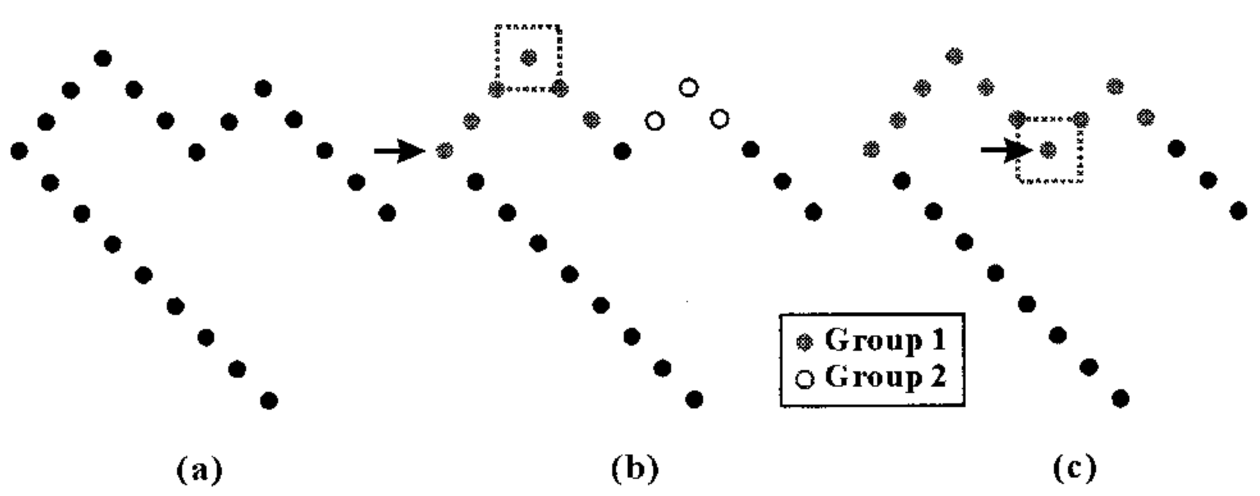

Figure 4. An example of grouping building outlines process. (a) Building outlines are presented, (b) each point on the building outlines is numbered by group ID of near points if its near points have the same group ID, and (c) groups 1 and 2 are merged if near points have different group ID.

For instance, let building outline be given in Figure 4(a). If a certain point has neighboring points without group ID, then a new group ID is provided to the point (Figure 4 (b)). On the other hand, if a certain point has neighboring points with previously provided group ID, then the point is belong to the neighbor group. If group

IDs of neighboring points are different each other, the group IDs are merged, otherwise split (Figure 4 (c)).

2.4 Rearrangement of Building Outlines

As seen in Figure 5(a), the points on building outline extracted using the method described in Section 2.3 are restored as grid data, therefore, it is necessary to rearrange the data along the building outline. It is difficult task because the outline data are not geometrically systematic and irregular. To rearrange the points along the outline, convex hull method and trace algorithms were employed. Convex sets were extracted from the points on building outline using convex hull algorithm (see Figure 5(b)), and then the points between two convex sets are rearranged using trace algorithm. This procedure was continuously repeated until the last convex set point was reached.

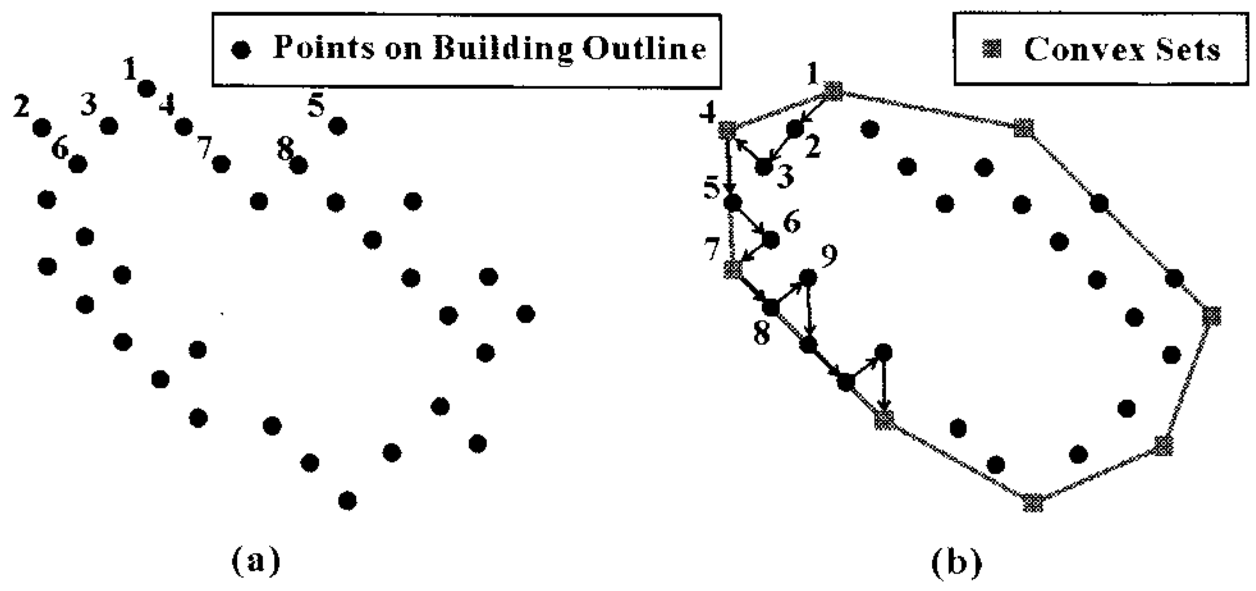

Figure 5. An example for rearrangement of points on the building outline using convex hull and trace algorithms: (a) before and (b) after rearrangement

Figure 6 represents points on building outline and convex sets estimated using convex hull algorithm. The points on building outline were rearranged using tracing of the points.

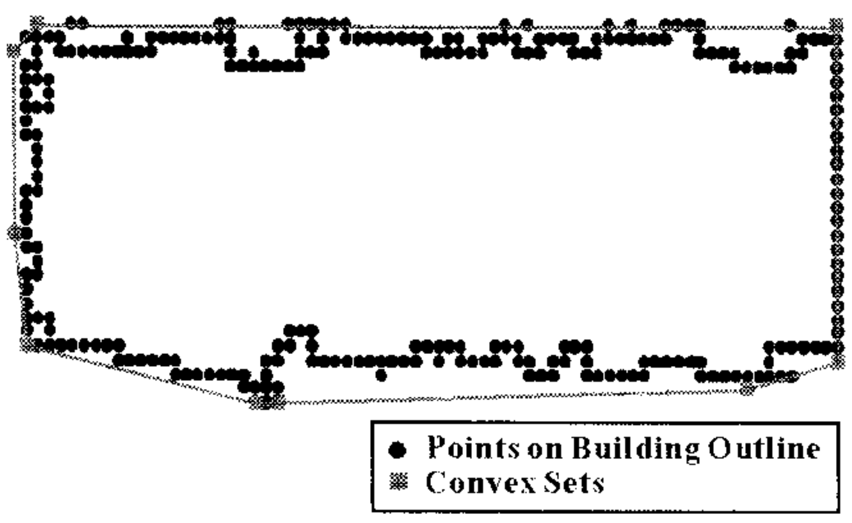

Figure 6. Points on building outline and convex sets estimated from them using convex hull algorithm.

2.5 Extraction of Building Corner Points

The extracted building outlines, as shown in Figure 6, are very noisy and rough because of the nature of raw LIDAR point clouds and interpolating irregular spaced LIDAR measurements to create gridded data. To depict the building outline more realistically, corner points of an building were obtained by using the fitting error, e_i, which is defined as given by:

$$e_i = \sum_{k=1}^{n} d_k = \sum_{k=1}^{n} \sqrt{(\hat{x}_k - x_k)^2 + (\hat{y}_k - y_k)^2} \tag{1}$$

where n is the number of points used in fitting, $\hat{x}$ and $\hat{y}$ are the estimated values of x and y. The corner points are represented as peaks in the graphical representation with point index *versus* normalized fitting error (see Figure 7). The building corner points were chosen from convex sets estimated from convex hull algorithm.

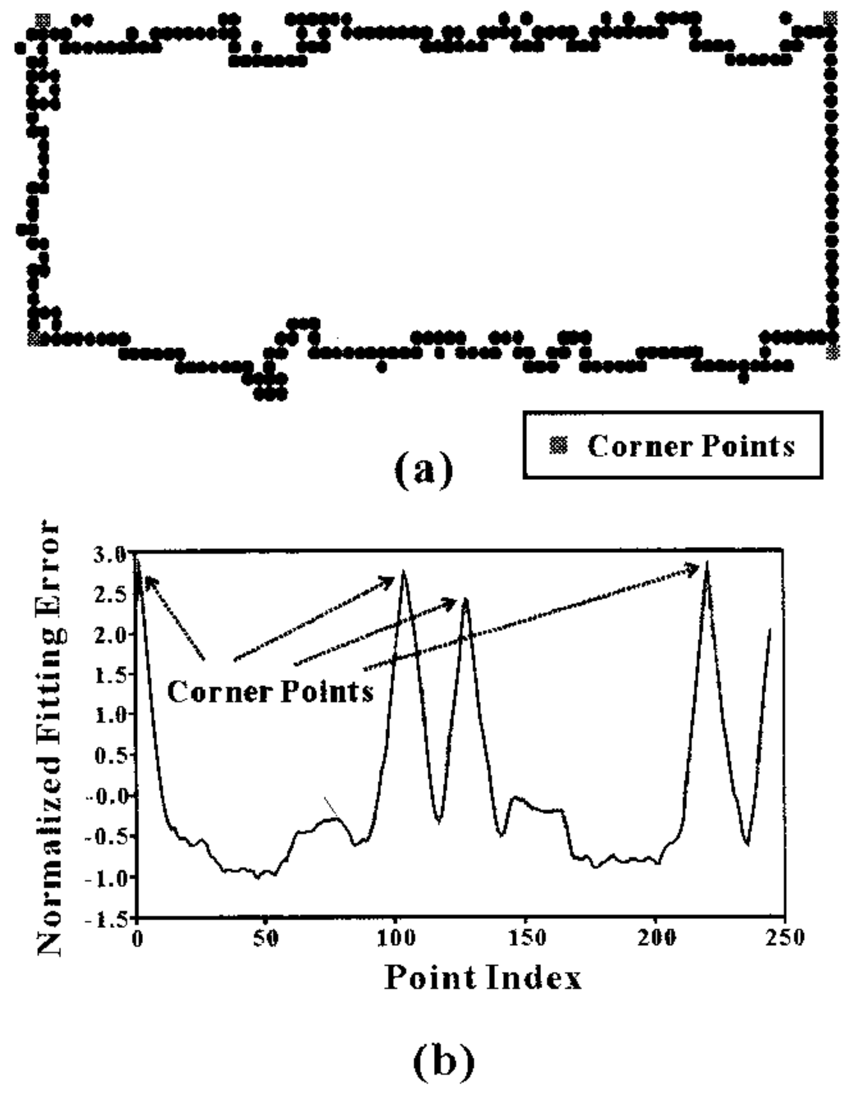

Figure 7. Corner points extracted from the convex sets and the points on building outline: (a) the extracted corner points and (b) determination of corner points using the normalized fitting error.

2.6 Refinement of Building Outlines

To generate fined building footprint, the best-fit linear equations were estimated from all of points on building outline between two adjacent corner points. The linear equation which represent building footprints is defined by

$$y = ax + b \text{ or } x = ay + b. \tag{2}$$

The parameters a, b can be derived by minimizing sum of squares due to deviations (SSD) as

$$\min(SSD) = \min \sum_{p_k \in M} (\hat{y}_k - y_k)^2 \text{ or } \min \sum_{p_k \in M} (\hat{x}_k - x_k)^2 \tag{3}$$

where M is a set for points on building outline, and $\hat{y}$ and y or $\hat{x}$ and x are estimated and observed values, respectively. The appropriate equation must be selected from the linear Equations (2) using the fitting error (e_i) given by equation (1).

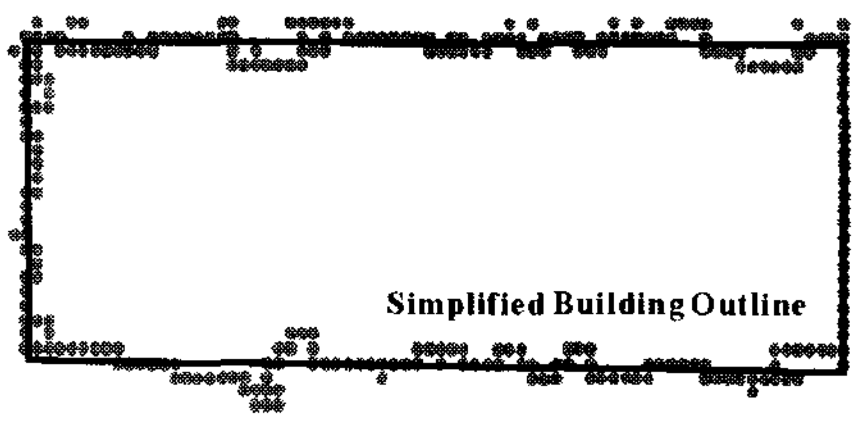

Figure 8. Refined building outline by least square fitting.

3. EXPERIMENTAL RESULTS

The proposed method was applied to the real airborne LIDAR data set. Figure 9 shows the aerial image of the buildings and results were shown in Figure 10. By comparing the results with the aerial image, proposed method for building extraction is feasible for automatic generation of building modeling and digital mapping.

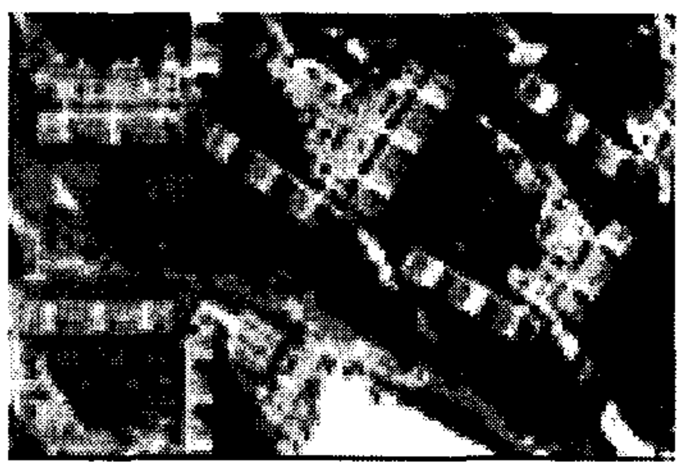

Figure 9. Aerial image of the buildings.

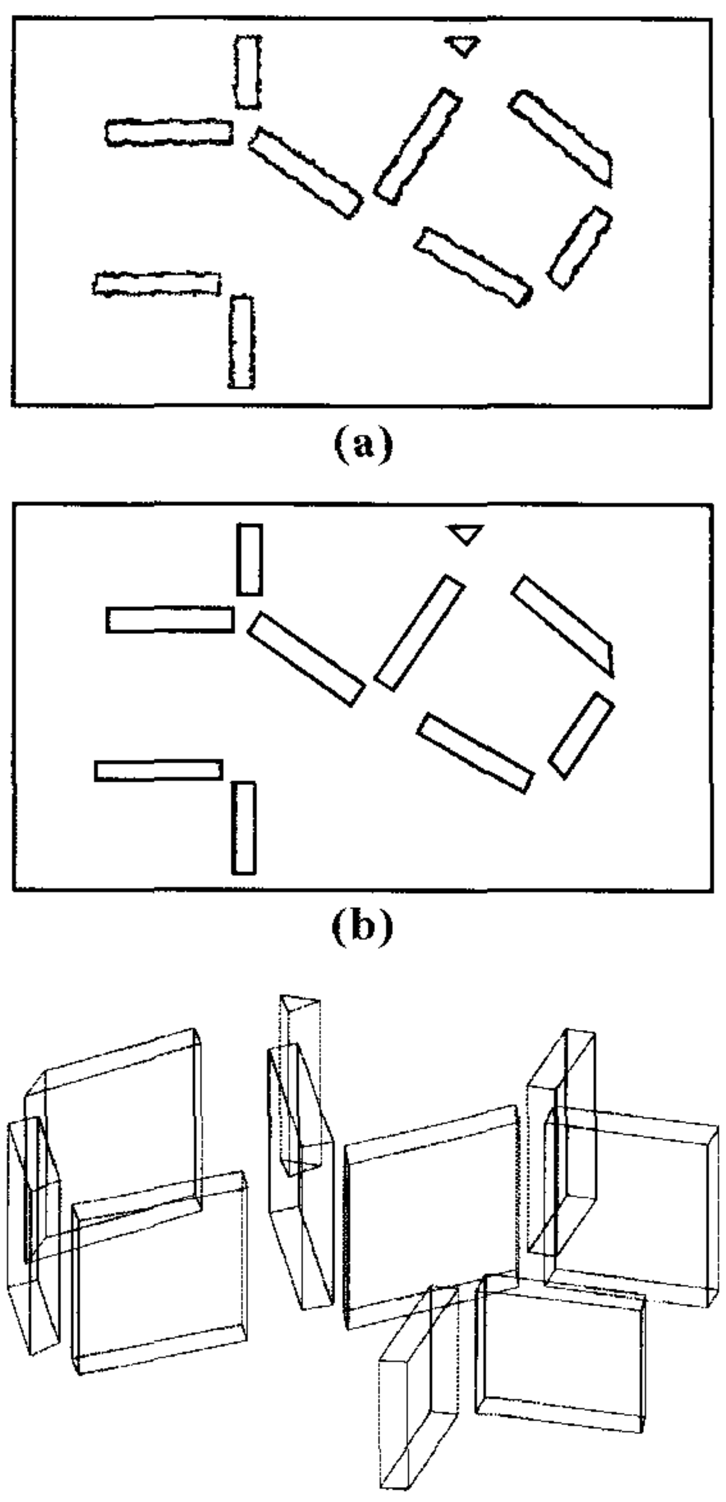

Figure 10. (a) Initial building footprints, (b) final building footprints, and (c) simple 3D building model.

4. CONCLUSION AND FUTURE WORKS

An efficient and robust method is proposed for processing LIDAR data to extract building footprints automatically. The method includes three major steps; (1) histogram analysis to separate ground and non-ground data, (2) rearrangement of extracted building outline by convex hull and trace algorithm, and (3) least square fitting method based on a local line fitting technique to refine building footprints. The method works well in the presence of noise.

For the future works, the accuracy of the building footprints and heights can be evaluated by using reference maps and/or surveying. This technique could be used to generate large scale and precise 3D city modeling by adding height values with appropriately segmented LIDAR data.

ACKNOWLEDGEMENTS

The material presented in this paper is based upon work supported by the Seoul R&BD program (10541).

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