Automatic Extraction of 3-D Building Roofs by Data Snooping from Airborne LIDAR Data

Shih-Hong Chio
Department of Land Economics, National Chengchi University
64, Chih-nan Rd., Sec. 2, Wenshan, Taipei 11623, Taiwan
chio0119@nccu.edu.tw

Abstract: Terrain information is implied in airborne LIDAR data, therefore algorithms should be developed to extract meaning information from them for subsequent application. Especially the building roofs in airbore LIDAR data are very important for 3-D building reconstruction. The difficulty of building roof extraction lies on how to exclude the irrelevant data and to exact them automatically. Therefore, this paper will present an approach to automatically acquiring the 3-D building roofs from airborne LIDAR data based on the data snooping theory. Firstly, coarse and fine TIN structures are constructed based on pyramided LIDAR data that are constructed from original airborne LIDAR data with different spacing distances. On the assumption that roofs are composed of either horizontal or slope planes, some better plane information, called TIN planes, are extracted by means of least squares fitting among coarse TIN structure where cover some fine TIN structures. Forward selection algorithm is used in data snooping, therefore a airborne LIDAR dataset of one best fitting plane is selected from the extracted TIN planes. Afterwards, the neighboring fine TIN structures of this dataset are selected and verified TIN by TIN if they could be merged into this dataset by the data snooping theory. If any one could be included into the dataset, new plane information is calculated by the least squares fitting. Using this new plane information again, neighboring fine TIN structures of the new dataset are selected and verified by the same approach. Until no fine TIN structure could be included, the entire plane information is extracted completely. By utilizing the same procedure, another better dataset is selected from unprocessed TIN planes. The same procedure is used to merge the fine TIN structures into a same plane. After all planes are extracted, the related planes should be merged into more complete planes. Then the object knowledge of 3-D building roofs are employed to differentiate the building roofs with other terrain objects or terrain surfaces. From the experiments, this paper will show the efficiency and feasibility of proposed approach.
Keywords: Airborne IDAR data, TIN, Building Model, Data Snooping, Least Squares Fitting.

1. Introduction

Airborne LIDAR scanning system is a whole new surveying technique that captures extremely detailed and abundant terrain surface information [1;16]. Therefore lots of terrain information is implied in airborne LIDAR data. Many algorithms have been developed and proposed to extract important terrain information, such as digital elevation model, 3D building model, and trees [3;4;9;12;14;19]. Especially for 3D building models, building roof plane should be extracted firstly. Most extraction methods transform distributed LIDAR data into grid data through interpolation procedures and then apply image processing techniques for building detection and reconstruction [8;13]. Thus some important spatial information may be lost [4], especially in height accuracies. Therefore, some methods are developed for acquiring building roofs or models by using the original airborne LIDAR data [1;2;7;9;14;18;19]. For example, Lee [11] applies perceptual organization to analyze geometric structures of airborne LIDAR data in space and group them into planes. Wang and Tseng [15] present an octree-structure-based split-and-merge segmentation method for organizing airborne LIDAR point cloud into clusters of 3D planes. Although the usage of original airborne LIDAR data can keep the original accuracies, it is still expected that the irrelevant airborne LIDAR data, e.g. noise or points on the water tower or other constructions, should be removed during the extraction processing. Therefore, the difficulty of building roof extraction from airborne LIDAR data lies on how to exclude the irrelevant data and to exact them automatically. For accurate acquisition of building roofs, this study will use the data snooping theory [5] to remove the irrelevant data and automatically extract building roofs for subsequent process. That is, this paper is going to present an approach to automatically acquiring the 3-D building roofs from airborne LIDAR data based on the theory of data snooping. Section 2 will describe the planar extraction method from airborne LIDAR data and the theory of data snooping. Then the methodology will be presented in Section 3. The experiments and results will be depicted in Section 4. Finally, the conclusion and suggestion will be made in Section 5.

2. Plane Extraction and Data Snooping

This section will explain how to extract planar information by least squares fitting and the theory of data snooping.

1) Plane Extraction

In this study, on the assumption that building roofs are composed of either horizontal or oblique planes, any plane can be described by the following mathematic equation

$$Z = aX + bY + c \tag{1}$$

Where a, b, and c are planar parameters; X,Y, and Z are the coordinate components.

Additionally, if the plane is consisted of *n* LIDAR points and only random error are occurred in the Z coordinate component, the least squares adjustment of plane fitting can be expressed in matrix form as

$$L + V = AX \tag{2}$$

Where $A = \begin{bmatrix} X_1 & Y_1 & 1 \\ X_2 & Y_2 & 1 \\ \cdots & \cdots & \cdots \\ X_n & Y_n & Z_n \end{bmatrix}_{n*3}$ is the coefficient matrix, $X^T = [a \quad b \quad c]_{1*3}$ is the estimated planar parameters vector. $L^T = [Z_1 \quad Z_2 \quad \ldots \quad Z_n]_{1*n}$ is the observation matrix. $V^T = [v_1 \quad v_2 \quad \ldots \quad v_n]_{1*n}$ is the residual vector. The observation is regarded as the identical weight, therefore, Eq.(2) has a covariance matrix $W_{n*n}^{-1} = S_0^2 Q_{ll}$. After adjustment, the goodness of plane fitting can be verified by the sigma naught, i.e. standard deviation.

2) Data Snooping

Data Snooping was proposed by Baarda [5] for blunder detection. In this study, this theory is used to detect and isolate airborne LIDAR data with large error from an extracted plane at some confidence level. The detailed derivation of this theory can also be found in the book [17]. As mentioned in previous subsection and according to Wolf and Ghilani[17], the relation between the residual vector and the true error vector can be expressed as the following form

$$V = -Q_{vv} W \varepsilon \tag{3}$$

where

$$Q_{vv} = W^{-1} - AQ_{xx}A^T = W^{-1} - Q_{ll}$$
$$Q_{xx} = (AWA^T)^{-1}$$

Now consider the case when all measurements have zero errors except for a particular observation Z_i which contains a blunder of size ΔZ_i. A vector of the true errors, $\Delta\varepsilon$, can be expressed as

$$\Delta\varepsilon = [0 \quad 0 \quad \ldots \quad 0 \quad \Delta Z_i \quad 0 \quad \ldots \quad 0]^T$$
$$= \Delta Z_i [0 \quad 0 \quad \ldots \quad 0 \quad 1 \quad 0 \quad \ldots \quad 0]^T$$

If the original measurement are uncorrelated, the specific correction for Δv_i can be expressed as

$$\Delta v_i = -q_{ii} w_{ii} \Delta Z_i = -r_i \Delta Z_i \tag{4}$$

where q_{ii} is the *i*th diagonal element of the Q_{vv} matrix, w_{ii} is the *i*th diagonal term of the weight matrix, W, and $r_i = q_{ii} w_{ii}$ is the observational redundancy number.

From Eq.(4), the expected correction v_i to an observation can be calculated and used to isolate measurement blunders by computing the standardized residuals from the diagonal elements of the Q_{vv} matrix as

$$w_i = \frac{v_i}{\sigma_{v_i}} = \frac{v_i}{\sigma_0 \sqrt{q_{ii}}} = \frac{v_i}{\sigma_{l_i} \sqrt{r_i}} \tag{5}$$

where w_i is the standardized residual, v_i the computed residual, q_{ii} the diagonal element of the Q_{vv} matrix, σ_0 is the known unit weight standard deviation (sigma naught). When the σ_0 is unknown, the *ti* test statistic can be defined from Eq.(5) by replacing σ_t with

$$t_i = \frac{v_i}{\sigma_t \sqrt{q_{ii}}} \sim t_{n-u-1} \tag{6}$$

As Eq.(6) defined, where

$$\sigma_t = \frac{1}{n-u-1}(V^T W V - \frac{w_i v_i^2}{r_i})$$

In this study, the σ_0 is supposed to be unknown and the *ti* test statistic is calculated and used to isolate measurement blunders.

3) Strategy for Data Snooping

Three strategies can be used for data snooping [11]. Forward selection strategy is used in this study, therefore a better dataset is needed whenever extracting a planar information. An airborne LIDAR dataset of one best fitting plane is selected from the extracted TIN planes. The following section will explain what is the TIN plane and how to extract it.

3. Methodology of Plane Extraction from LIDAR data

As mentioned in previous section, *ti* test statistic will be used in data snooping method for detecting the blunder. This section will describe the methodology of plane extraction from airborne LIDAR data. The flowchart is shown as Fig. 1.

As shown in Fig.1, because forward selection strategy is used in data snooping, therefore a better plane dataset is needed for extracting complete planes. As shown in Figs. 2a and 2b, coarse and fine TIN structures are constructed from original airborne LIDAR data with different spacing distances. 2-D TIN structures are constructed in terms of Delaunay method[6], then the height of each LIDAR point is attached to become the coarse and fine TIN structures used in this study. Fig.2a shows the coarse TIN structures and Fig. 2b the fine ones. On the assumption that roofs are composed of either horizontal or slope planes, one coarse TIN structure, called coarse TIN plane, can cover several fine TIN structures, as illustrated in Fig.2c.

If several fine TIN structures can constitute a TIN plane that may be one fraction of one complete plane, this TIN plane can be extracted by means of least squares fitting according to section 2-1. In this case, the average coordinate of three LIDAR points in each fine TIN structure, as shown in Fig. 2d, is regarded as the observation value. Several TIN planes will be extracted by least squares adjustment. Their goodness is described by sigma naught (standard deviation). The better plane dataset will be selected from those TIN planes and based on the smallest sigma naught. Actually, this better plane dataset is a group of fine TIN structures.

After a LIDAR dataset of one best fitting plane is selected from the extracted TIN planes. The neighboring fine TIN structures are selected and verified individual TIN by TIN if they could be merged into this dataset by the data snooping theory. The choices of neighboring fine TIN structures are constrained by height difference and by the angle difference of normal direction between fitting plane and fine TIN structures.

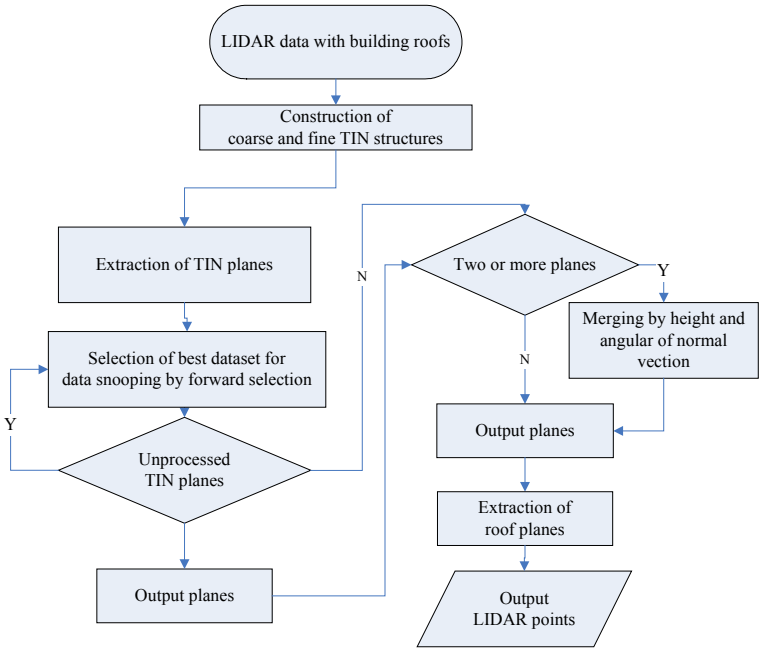


Fig. 1 The study flowchart

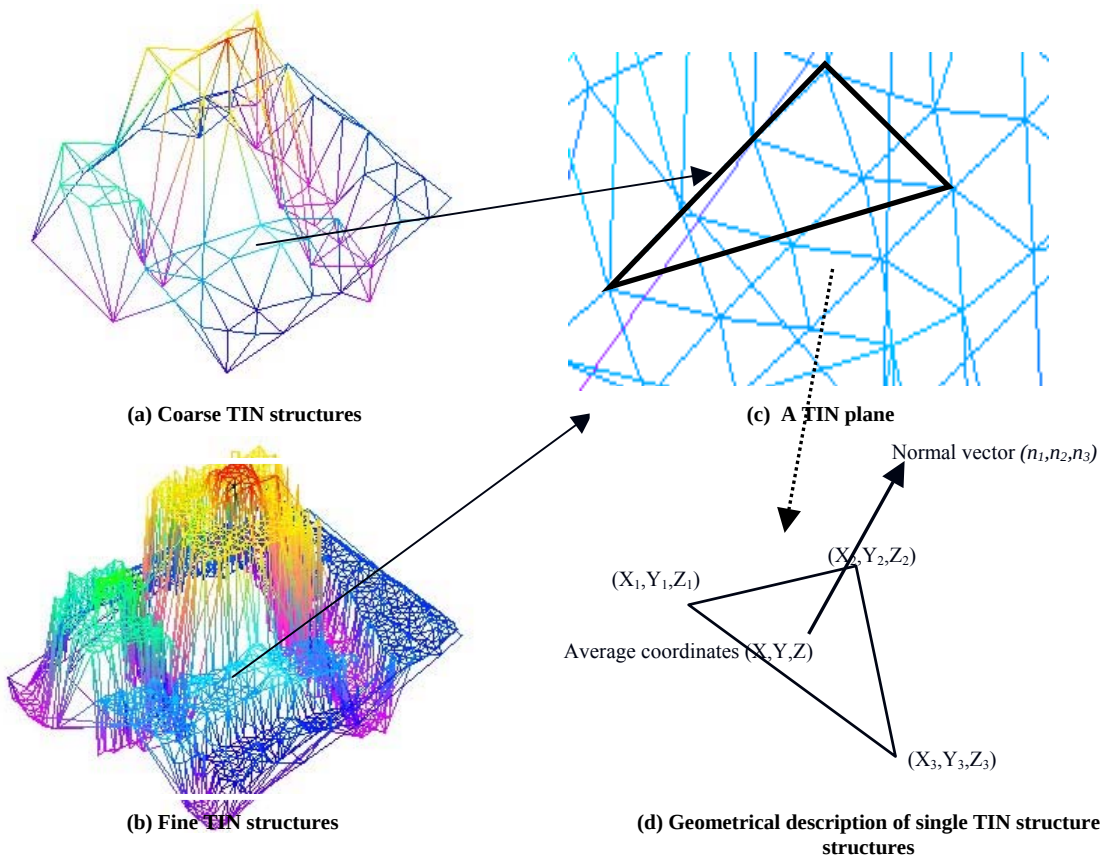


Fig.2 Diagram of coarse and fine TIN structures as well as TIN plane

If any fine TIN structure could be included into the dataset, new plane information is calculated by the least squares fitting. Using this new plane information again, neighboring fine TIN structures of the new dataset are selected and verified by the same approach. Until no data could be included, the entire plane information is extracted completely. By utilizing the same procedure, another better dataset is selected from extracted TIN planes. The same procedure is used to merge the fine TIN structures into a same plane. After all planes are extracted, the related planes should be merged into more complete planes if the related planes belong to a same plane. Then the object knowledge of 3-D building roofs are employed to differentiate the building roofs with other terrain object or terrain planes.

Briefly, all the procedure is divided into 1.Selection of better plane information, 2.Merging of individual fine TIN structure, 3.Merging of related planes (if necessary), 4.Extraction of roof planes. The experiments and the test results will be described in the next section.

4. Experiments

Four test datasets, as shown in Figs.3 through 6, were extracted from an airborne LIDAR data set collected with Leica ALS40, in Hsinchu, Taiwan, on April 14th, 2002. Each dataset covers at least one building and each building contains at least one roof plane. Moreover, the airborne LIDAR data is purely surface data after filtering. Basic data characteristics are listed in Table 1. Figs. 3(a) through 6(a) illustrate the vertical view of original LIDAR data. For visualization, the heights are displayed by different colors and the point sizes are enlarged moderately.

Table 1 Description of four test datasets

	Dataset 1	Dataset 2	Dataset 3	Dataset 4
Point Number	1282	3801	21560	15826
Area m^2	2633	13003	18932	20352
Point Density (points/m^2)	0.5	0.2	1.1	0.8

According to the proposed procedures, coarse and fine TIN structures, as shown in figures 3(b) through 6(b) and 3(c) through 6(c), are constructed based on pyramided LIDAR data. Coarse TIN structures shown in figures 3(b) through 6(b) are constructed from original LIDAR data with 6m, 11m, 6m, and 7m spacing distance, respectively. Fine TIN structures illustrated in figures 3(c) through 6(c) are constructed from original LIDAR data with 1.4m, 4m, 2m, and 2m spacing distance, respectively.

On the assumption that roofs are composed of either horizontal or slope planes, some better plane information, called TIN planes, are extracted by means of least squares fitting from coarse TIN structures where cover some fine TIN structures. For acquiring these TIN planes, at least 6 fine TIN structures should be covered by one coarse TIN structure. Figs. 3(d) through 6(d) show the extracted TIN planes. From them, one LIDAR dataset for the best fitting plane is selected and employed in forward selection strategy of data snooping. The neighboring fine TIN structures of this better dataset are selected based on the 5m proximity, which is the maximum distance to the contour of this better dataset. Meanwhile, the height difference between the average height of each fine TIN structure and this fitting plane should be less than 0.6m. Besides the above-mentioned two constraints, the other constraint is to request the angular difference of normal vector between each fine TIN structure and this fitting plane should be below 3°.

Those selected fine TIN structures will be verified one by one to check if they could be merged into this dataset by the data snooping theory. If any fine TIN structure could be included into the dataset, new plane parameters are calculated by least squares adjustment. Using this new plane information again, neighboring fine TIN structures of the new dataset are selected and verified by the same approach. Until no fine TIN structure could be included, the entire plane information is extracted completely. By utilizing the same procedure, another better dataset is selected from extracted and unprocessed TIN planes. The same procedure is used to merge the fine TIN structures into a same plane. The extracted LIDAR points of complete planes are illustrated from Figs. 3(e) to 6(e). The sigma naught (standard deviation) for each extracted planes are listed in Table 2. After all planes are extracted, all the planes are verify by both plane proximity and the height as well normal direction to check if they should be merge into a much more complete plane. In this study, no one should be merged into another one in each dataset. Afterwards the object knowledge of 3-D building roofs are employed to differentiate the building roofs with other terrain objects or terrain planes. In this study, the plane with lowest elevation in each dataset is viewed as ground elevation. In Table 2, it tabulates the planes that are viewed as ground surface, i.e. the mark GROUND in remark column. We suppose that the roof planes should be at least 3m higher than ground surface. Then after removing the non-roof planes, mark X in Remark column in Table 2, that height are less than ground surface at least 3m, Figs 3(f) through 6(f) show the final extracted roof planes.

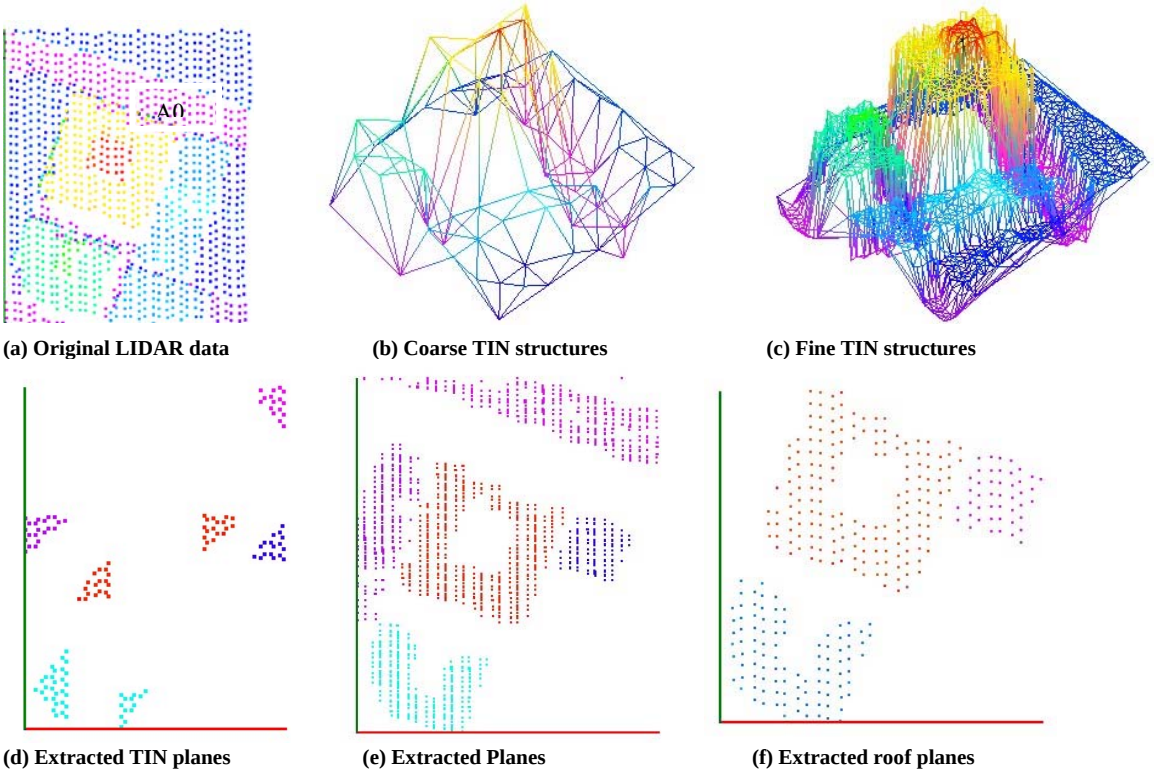
Besides the test Dataset A, all the roof planes in other three test datasets are extracted completely. As far as Dataset A is concerned, the actual ground surface is not extracted actually based on the proposed methodology. In this study, one

coarse TIN structure has to cover at least 6 fine TIN structures, then least squares fitting might be used to extract TIN planes. In Dataset A, the ground surface A0, as shown in Fig.3a, is not extracted. Therefore the identification for ground surface in Dataset A is wrong. It leads only three roof planes to be extracted. Due to the limit of at least 6 fine TIN structures, the extraction approach of roof planes are not launched at the beginning of finding the TIN planes and it causes many roof planes are not successfully extracted based on the proposed methodology in Dataset A. This major reason is that the roof planes are a little bit small in Dataset A. This kind of little roof planes is typical in urban area. However, other roof planes in another three datasets are much larger than general roofs in shape. Therefore, they can be extracted completely. It leads to another issue to investigate how to use proposed approach to extracting typical urban building roofs more completely. In our thought, it is a possibility to integrate the aerial images and to use image segmentation method to acquire the better dataset for data snooping.

Another problem shown in this study is the extraction of the roof ridges. In theory, the roof ridges can be extracted by the intersection of relevant roof planes. However, because test statistics is used to extract the roof planes, the fine TIN structures close to roof ridges is great possibility to be judged to another roof plane. Just like the white ellipse shown in Fig. 5f, some LIDAR points are classified to the wrong roof plane. This may be resolved also by the integration of aerial images to detect the actual roof ridges in terms of image processing techniques in the future.

Additionally, the complete contour of each roof plane is not extracted in this study. If the accurate contour of each roof plane is expected, the other data source, e.g. aerial images or topographic maps, should be integrated into the proposed mythology.

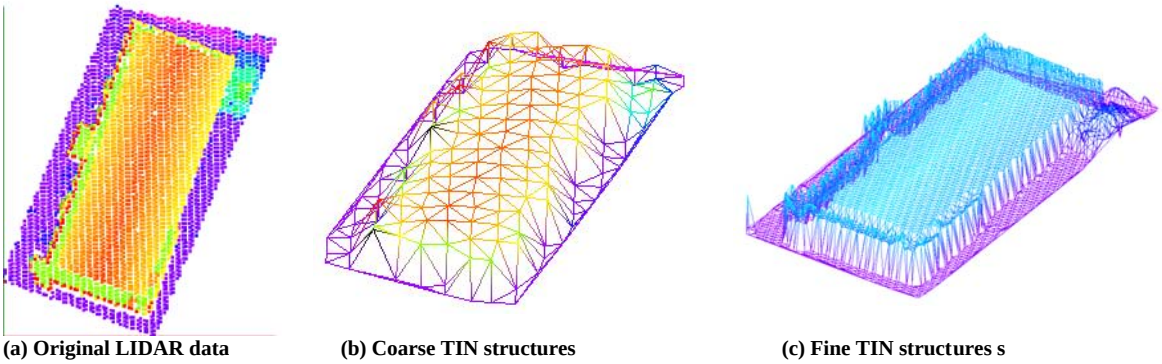
Despite of the above-mentioned discussion, from Table 2, the extracted roof planes are of good accuracies. Sigma naught all are below 0.15m. Also, this results show the efficiency and feasibility of proposed approach. However, the speed about this proposed methodology is really a vital problem because the computation time is huge for data snooping. Therefore, it's another issue to investigate hoe to reduce the computation time in the future study.



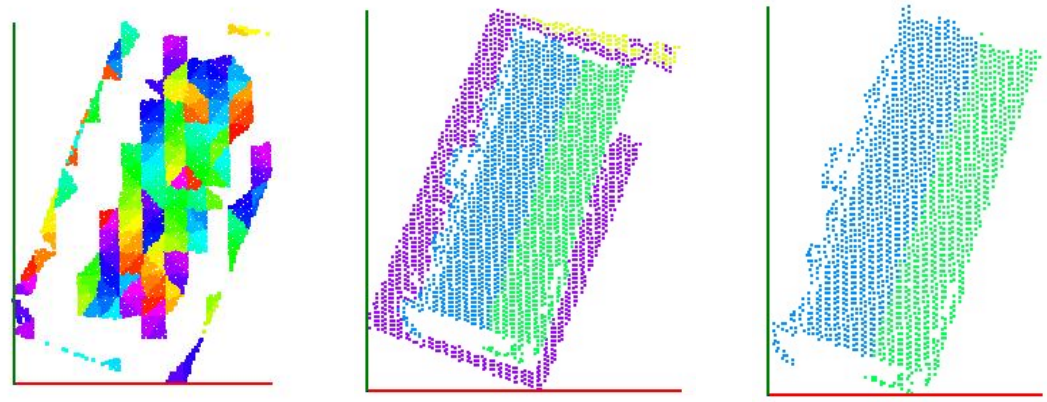
(a) Original LIDAR data **(b) Coarse TIN structures** **(c) Fine TIN structures**

(d) Extracted TIN planes **(e) Extracted Planes** **(f) Extracted roof planes**

Figure 3 Test Dataset A , intermediate, and results

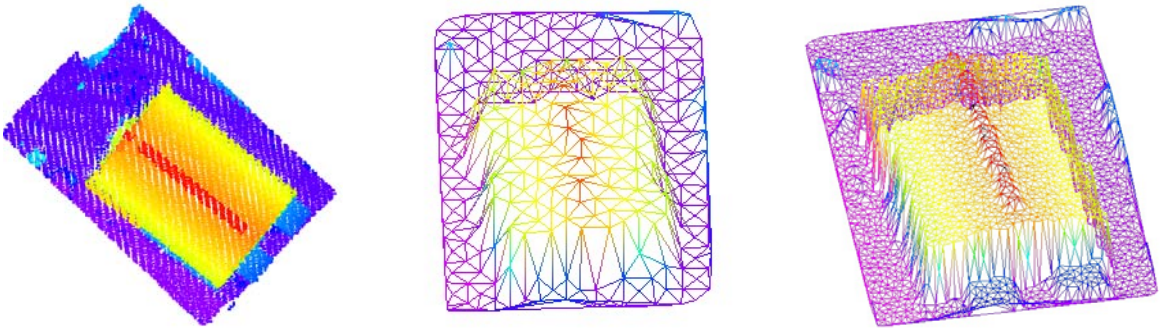


(a) Original LIDAR data **(b) Coarse TIN structures** **(c) Fine TIN structures s**

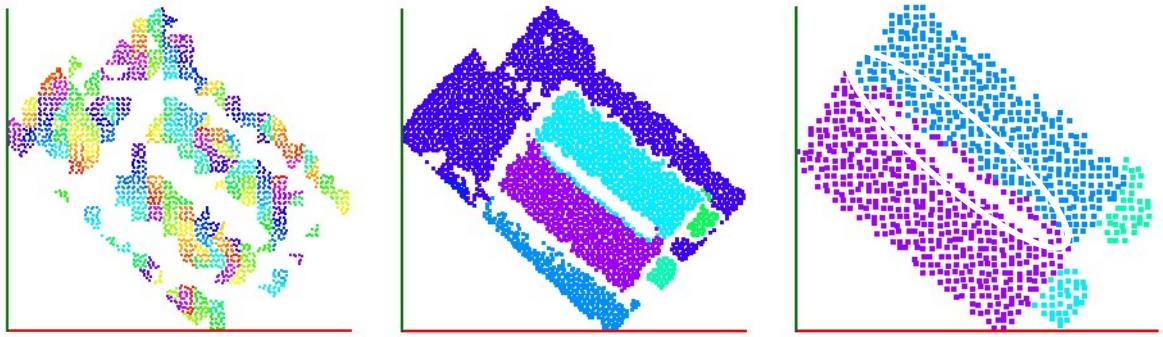


(d) Extracted TIN planes **(e) Extracted Planes** **(f) Extracted roof planes**

Figure 4 Test Dataset B, intermediate, and results

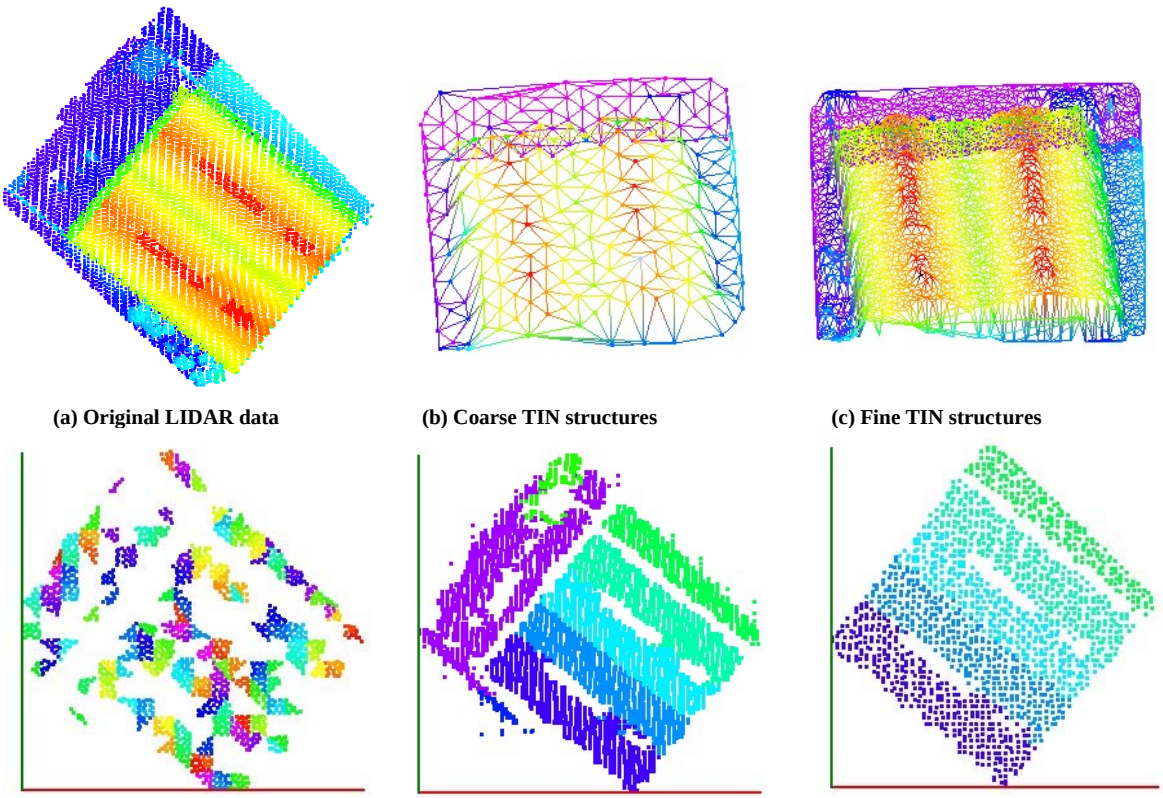


(a) Original LIDAR data **(b) Coarse TIN structures** **(c) Fine TIN structures**



(d) Extracted TIN planes **(e) Extracted Planes** **(f) Extracted roof planes**

Figure 5 Test Dataset C, intermediate, and results



(a) Original LIDAR data **(b) Coarse TIN structures** **(c) Fine TIN structures**

(d) Extracted TIN planes **(e) Extracted Planes** **(f) Extracted roof planes**

Figure 6 Test Dataset D, intermediate, and results

Table2 Result of extracted planes and roof planes for four datasets

Dataset A	Plane No.	Sigma naught(m)	Fine TIN numbers	Ave. Z(m)	Remark		Dataset B	Plane No.	Sigma naught(m)	Fine TIN numbers	Ave. Z(m)	Remark
	1	0.09	145	63.9				1	0.11	1826	45.8	X
	2	0.23	137	53.9	X			2	0.12	2025	58.4	
	3	0.10	257	79.3				3	0.09	1638	58	
	4	0.03	65	57.1				4	0.16	167	44.9	Ground
	5	0.26	261	52.9	Ground							
Dataset C							Dataset D					
	1	0.08	783	157				1	0.25	1082	135.5	X
	2	0.11	1703	136	X			2	0.10	597	157.5	
	3	0.17	463	134.8	Ground			3	0.23	93	134.8	Ground
	4	0.10	723	156.9				4	0.14	642	157.1	
	5	0.06	50	140.7				5	0.10	592	157.5	
	6	0.11	49	141				6	0.05	582	157.2	
								7	0.10	370	142.4	
								8	0.28	85	136.3	X

5. Conclusions and Outlooks

Building roof extraction from LIDAR data is an important task for 3-D building reconstruction. The difficulty of building roof extraction from LIDAR data lies on how to exclude the irrelevant data and how to extract them both accurately and automatically. This paper proposes an approach to automatically acquiring the 3-D building roofs from LIDAR data based on the theory of data snooping. Generally, the propped methodology does remove the relevant data from desirable roof planes from the experiment and the extracted roof planes are of good accuracies. Sigma naught all are

below 0.15m. Also from the experiments, it has shown the efficiency and feasibility of proposed approach although some problems have to be resolved in the further study. In the future study, the improvement will be made in order to solve the problems mentioned for acquiring the building models automatically and effectively. Meanwhile, subsequent studies will be conducted by the integration of different source data, e.g. aerial images, based on current results for much more complete reconstruction of building models.

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