BUILDING RECONSTRUCTION FROM LIDAR DATA

C.Y. Wang [a,] *, Z.M. Zhao [a]

[a] National Engineering Research center for Geoinformatics, Institute of Remote Sensing Applications, Chinese Academic of Sciences, Beijing, China – wangcycastle@163.com

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ABSTRACT:

Since the traditional building extraction from the common optical images is highly labor-intensive, time-consuming and very expensive. With the wide use of LIDAR System, it is possible to acquire buildings in cities in a fast way. In this paper, we present a new method to detect the outline of buildings and how to reconstruct them based on works of other scholars in this area. Two main steps (building outline detection and building reconstruction) are described. An experimental study has been conducted. Our preliminary Experimental results indicate that the method is feasible.

1. INTRODUCTION

1.1 Motivation

Cities are regions where mankind visits frequently, it is very important to monitor such areas. However, the urban environment is extremely complex for many objects with different features and heights within it; further, towns and cities are characterized by a fast change rate. Consequently practical monitoring of the urban environment is especially difficult. Automation in data acquisition for 3D city models is an important topic of research with the goal of reducing the costs of providing these data at an appropriate level of detail. In addition to photogrammetric techniques relying on aerial images, the generation of 3D building models from point clouds provided by LIDAR sensors is gaining importance. This development has been triggered by the progress in sensor technology which has rendered possible the acquisition of very dense point clouds using airborne laser scanners. Using LIDAR data with high point densities, it is possible not only to detect buildings and their approximate outlines, but also to extract planar roof faces and, thus, to create models which correctly resemble the roof structures. Nevertheless, the traditional manual building extraction from the common optical images is highly labor-intensive, time-consuming and very expensive. With the wide use of LIDAR (Light Detection and Ranging) System, it is possible to acquire buildings in cities in a fast way.

1.2 Related Work

There have been several attempts to detect buildings in LIDAR data in the past. Brenner uses interpolated raster DSMs (usually from laser scanning) and 2D ground plans as data sources for an automatic and/or semiautomatic reconstruction process (Brenner and Haala, 1998). Aerial images can be used to facilitate the interpretation by a human operator when semi-automatic post processing is performed, however they are not used for measurement. Vosselman extracts faces from non-regularized laser scan data using a Hough transform, followed by connected component analysis (Vosselman, 1999). No ground plans are used as additional information, however since jump edges cannot be determined very well from laser scanning. Vosselman and Dijkman's method (Vosselman and Dijkman, 2001) is similar to Vosselman (1999), however to prevent spurious roof faces, ground plans are introduced as additional information. Concave ground plan corners are extended to cut the building area into smaller regions. The Hough-based plane extraction is constrained to those regions. Split-and-merge is used to obtain the final faces. The approach used by Rottensteiner and Briese (Rottensteiner and Briese, 2003) extracts roof races using seed regions and region growing in a regularized DSM. Similar to Vosselman (1999), intersection and step edges are detected and a polyhedral model is derived. It is proposed to detect regular structures automatically and to introduce them as constraints into a global adjustment. The authors also suggest using additional aerial images to detect small planar segments and to fit the wire frame models obtained from the laser scanning data to aerial images in order to improve their geometric accuracy. Dr GuoTao presents a robust data fusion scheme for image and range data， and A novel method for 3D building automatic extraction is also presented (GuoTao,2003).

All the methods mentioned above have their ideas; however flaw also exists when used in applications. Some methods need additional information besides LIDAR data. Others may fail in complicate situation. So we have suggested a approach which is explained in the following paragraphs. It may present a new way to solve the problem using LIDAR data and we can find it is very robust. The task is solved by classifying the LIDAR points according to whether they belong to the terrain, to buildings or to other object classes, e.g., vegetation. We kick off other objects step by step, in the end, buildings are obtained and 3D building models are generated.

2. SOURCE DATA AND PROCESSING

2.1 The Nature of Data

The data set we use in this paper is a raw LIDAR point file; The

* wangcycastle@163.com, phone: 86-10-64842108

LIDAR System is LH System ALS40 LIDAR system including an inertial measuring unit (IMU) and a dual frequency airborne GPS receiver. LIDAR data was collected with 2.0 to 2.2 meter nominal post spacing, 25 percent field of view and a 30 percent overlap. The working wave length of it is near infrared.

2.2 Data Processing

Raw LIDAR data is a collection of mass points XYZ coordinate. In this paper, in order to make it easy to detect buildings, the point data have to be interpolated into regular grid data. There are several surface interpolation methods such as inverse distance weighted interpolation, kriging, polynomial regression etc. Our purpose is extracting buildings rather than constructing a smooth surface, therefore, we should preserve the sharp difference between buildings and their surrounding ground. Although a nearest neighbour interpolation method can do, it also has saw tooth effect in the edge regions, while TIN interpolation method can avoid such problem. Thus TIN interpolation method is chosen. Figure1 is DSM image generated using the method.

Figure 1. DSM image

3. METHODS

3.1 Work Flow for Building Extraction

The work flow for the extraction of buildings from LIDAR points is presented in Figure. 2.

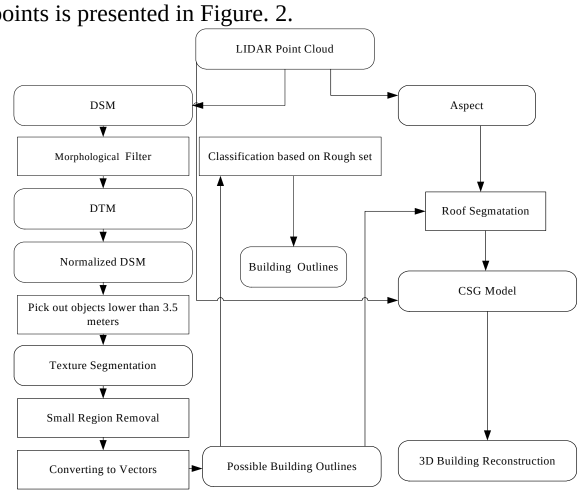


Figure 2. Work flow for building reconstruction from LIDAR data.

There are two main steps in the workflow, the first step is building outline detection, and the other step is building reconstruction. They are described in details in this paper as the following.

3.2 Building Outline Detection

Building outline detection is one key step for building reconstruction. This paper makes use of one way which picks off non-buildings step by step. Firstly, terrain is separated from DSM (Digital Surface Model) using morphological filtering, and Normalized DSM is acquired through subtraction of DSM and DEM. Because Normalized DSM includes objects which are above terrain, and then objects (such as cars, bushes and so on) which relative height is lower than 3.5 meters is picks out(as we know, most buildings is higher than 3.5 meters, so buildings which are lower than 3.5 meters can not be extracted with this method). In this context, it is hard to separate building and trees nearby. When buildings and trees are very close to each other, some buildings may be mixtures of them, so it is necessary to deal with such cases. Texture analysis is adopted and Gabor filter is used because the texture of buildings is quite different from trees. After removing isolated trees, street lamps and other small objects through a novel small region removal algorithm, we convert the binary image to polygons which represent possible buildings. In the end, rough set method is used to distinguish between buildings and non-buildings based on knowledge gained from training data; rough set is a supervised learning methods used for classification and regression. Parameters (Contrast, Energy, Entropy, Homogeneity) used in rough set are obtained from texture characters acquired through Co-occurrence Matrix. Thus, the outlines of buildings can be detected. Three main processes are described in this part: Normalized DSM Extraction, Texture Segmentation and Classification based on rough set.

3.2.1 Normalized DSM Extraction

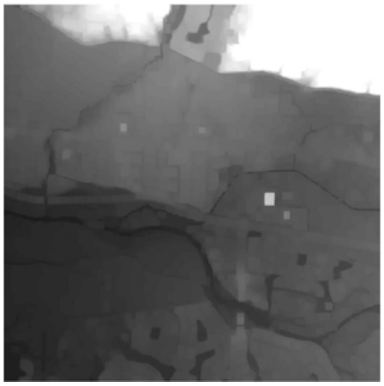
In order to acquire Normalized DSM, DTM should be extracted from DSM. Morphological filtering is an ordinary way to solve the problem. We Assume the DSM to be a matrix containing the heights z (i,j), with integer matrix indices i and j. For morphological filtering of the DSM, a structural element W, i.e., a digital image w (m,n) representing a certain shape, has to be defined. Restricting ourselves to symmetrical structural elements having constant values, thus w (m,n)=w(-m,-n) and $w(m,n) = 0 \forall [m,n] \in W$, morphological opening is performed by first carrying out an morphological erosion,

$$\bar{z} = \min_{[m,n]\in W} z(i-m, j-n) \tag{1}$$

Followed by a morphological dilation,

$$\bar{\bar{z}} = \max_{[m,n]\in W} \bar{z}(i-m, j-n) \tag{2}$$

Yielding the morphologically opened height matrix $\bar{\bar{z}}(i,j)$ (Weidner, 1997). The resulting height matrix does not contain objects smaller than the structural element W. If W is chosen to be greater than the largest building in the dataset, all buildings are removed by morphological opening; however, if W is too large, terrain details might be removed, too. If W is chosen rather small, the results of morphological filtering will be closer to the original height matrix and, thus, to the terrain, but larger buildings will remain in the dataset (Franz Rottensteiner, 2003). After filtering of DSM, DEM can be obtained. The so-called normalized DSM, i.e., the difference between DSM and DTM can be calculated, resulting in a representation of objects rising from the terrain. Figure 3 shows the process.



(a) DTM Extracted from DSM

(b) Normalized DSM

Figure 3. Extraction of Normalized DSM

3.2.2 Texture Segmentation

In this paper, because texture of objects is different in the image, a texture segmentation algorithm based on directional Gabor filters is used in this paper (ZHAO Yin-di, 2006). When orientation characteristics of textures are taken into account. Incorporating into the human visual characteristics, a design approach of optimal directional Gabor filters is proposed. Each texture can be thought of as containing a narrow range of frequency and orientation components, By filtering an input texture image with Gabor filters tuned to the dominant frequency and orientation component of the textures, it is possible to locate each texture. Figure. 4 is the work flow of the texture segmentation. Figure 5 is the result of texture segmentation.

3.2.3 Classification based on Rough set

Figure 5 shows the possible building outlines. In order to obtain building outlines we want, what we should do is to judge which objects are buildings. While rough set is powerful tool to solve the problem, thus, it is adopted to classify them.

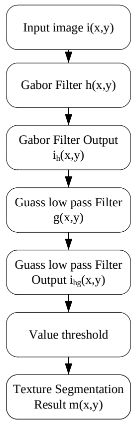


Figure 4. The work flow of texture segmentation

Figure 5. The result of texture segmentation

- **Basic concepts of rough set**

Rough set theory was developed by Zdzislaw Pawlak (Z.Pawlak, 1982) (Z.Pawlak, 1991) in the early 1980s.It deals with the classificatory analysis of data tables. The data can be acquired from measurements or from human experts

Information Systems

A data set is represented as a table, where each row represents a case, an event, a patient, or simply an object. Every column represents an attribute (a variable, an observation, a property, etc.) that can be measured for each object; it can also be supplied by a human expert or user. This table is called an information system. More formally, it is a pair A= (U, A), where U is a non-empty finite set of objects called the universe and A is a non-empty finite set of attributes such that a: U->V_a for every a∈A. The set V_a is called the value set of a.

Decision Systems

In many applications, there is an outcome of classification that is known. This a posteriori knowledge is expressed by one distinguished attribute called decision attribute; the process is known as supervised learning. Information systems of this kind are called decision systems. A decision system is any information system of the form A= (U,A ∪{d}), where A is the decision attribute.

- **Parameters used to describe properties of Buildings**

To define the information system of rough set, parameters to describe buildings should be defined. Since the Two-dimensional co-occurrence (grey-level dependence) matrices, proposed by Haralick in 1973, are generally used in texture analysis because they are able to capture the spatial dependence of gray-level values within an image (Haralick, 1973). A 2D co-occurrence matrix, P, is an n x n matrix, where n is the number of gray-levels within an image. Four parameters are defined to describe textures:

Contrast (Con): Measures the local contrast of an image. The Contrast is expected to be low if the gray levels of each pixel pair are similar.

$$Con = \sum_{i=0}^{n}\sum_{j=0}^{n}(i-j)^2 \frac{P_{i,j}(d,\theta)}{\sum_{i=0}^{n}\sum_{i=0}^{n}P_{i,j}(d,\theta)} \tag{3}$$

Energy (Ene): Measures the number of repeated pairs. The Energy is expected to be high if the occurrence of repeated pixel pairs is high.

$$Ene = \sum_{i=0}^{n}\sum_{j=0}^{n}\frac{P_{i,j}(d,\theta)}{\sum_{i=0}^{n}\sum_{i=0}^{n}P_{i,j}(d,\theta)} \tag{4}$$

Entropy (Ent): Measures the randomness of a gray-level distribution. The Entropy is expected to be high if the gray levels are distributed randomly through out the image.

$$Ent = \sum_{i=0}^{n}\sum_{j=0}^{n}C_{ij}\log\frac{P_{i,j}(d,\theta)}{\sum_{i=0}^{n}\sum_{i=0}^{n}P_{i,j}(d,\theta)} \tag{5}$$

Homogeneity (Homo): Measures the local homogeneity of a pixel pair. The Homogeneity is expected to be large if the gray levels of each pixel pair are similar.

$$Homo = \sum_{i=0}^{n}\sum_{j=0}^{n}\frac{1}{1+(i-j)^2}\frac{P_{i,j}(d,\theta)}{\sum_{i=0}^{n}\sum_{i=0}^{n}P_{i,j}(d,\theta)} \tag{6}$$

Figure 6 shows the classification result.

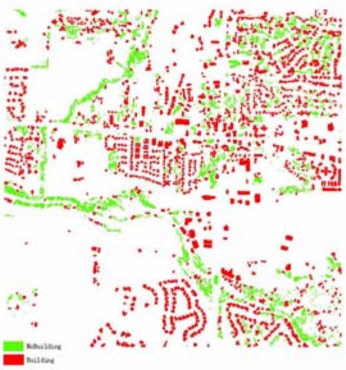


Figure 6. Classification based on rough set

3.3 Building Reconstruction

There are two primary methods for building reconstruction, one is data driven reconstruction, and the other is model driven reconstruction. data driven reconstruction method needs high accurate data and the demand of model driven reconstruction is the construction of a fine model database. In order to avoid the high demands of the two methods, the method used in this paper is one which combines the two primary methods and set CSG (Constructive Solid Geometry) (Tseng, Y.H., and Wang, S., 2003) model the target building model: First, regions inside building outlines are divided into basic 3D components, in order to attach this aim; slope information inside the building outlines is used. With basic 3D components (such as cuboids, tetrahedron and so on) and rules for assembling them together stored in model database, (for example, hipped buildings can be assembled with one cuboids object and one tetrahedron object).and basic 3D building models can be obtained, complex 3D building models are composed by basic 3D building models (such as flat buildings, hipped building and so on). With this approach, very complex buildings can be reconstructed. Figure 7 is the work flow of building reconstruction.

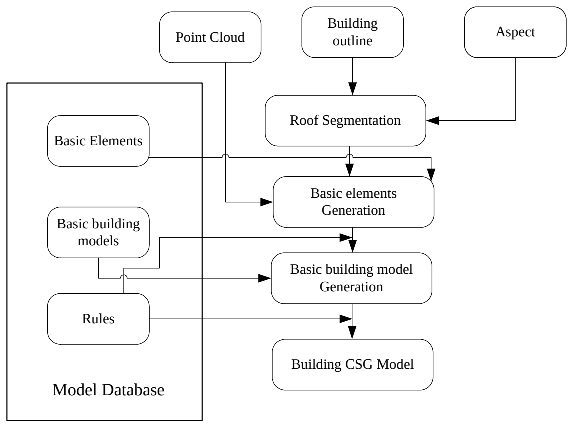


Figure 7. Work flow of building reconstruction

The key step of the work flow is roof segmentation. Since aspect is a important factor describe the roof, it is used to segment the roof. Figure 8 shows the work flow of it.

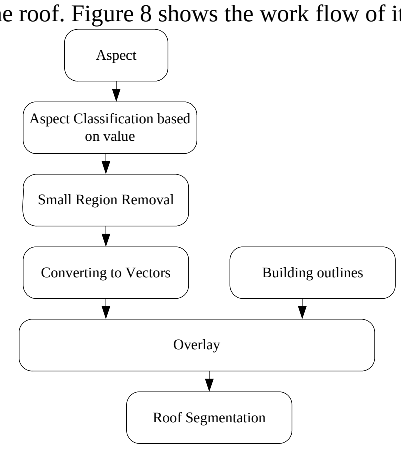
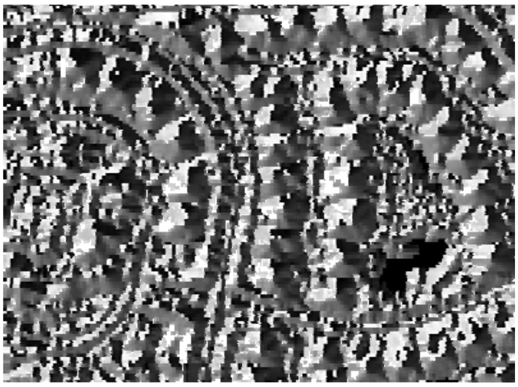


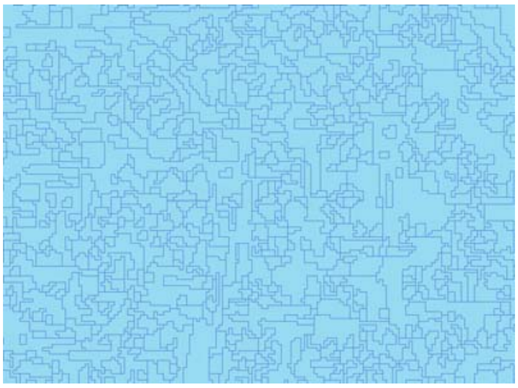
Figure 8. Work flow of Roof Segmentation

4. RESULTS

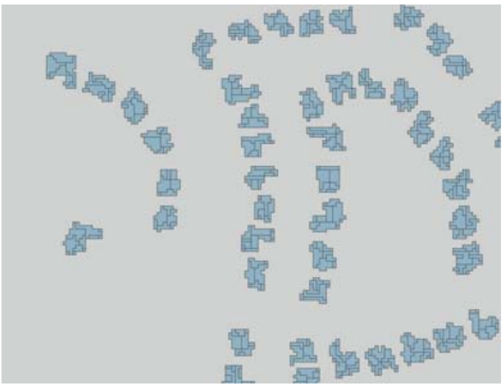
To illustrate the performance of the proposed method, Figure 9(a) shows the aspect of the region. Figure 9(b) shows the vectors after aspect classification. Figure 9(c) shows the overlay between building outlines and vectors of aspect.



(a) Aspect



(b) Vectors after aspect classification



(c) Result of roof segmentation

Figure 9. Roof Segmentation Results

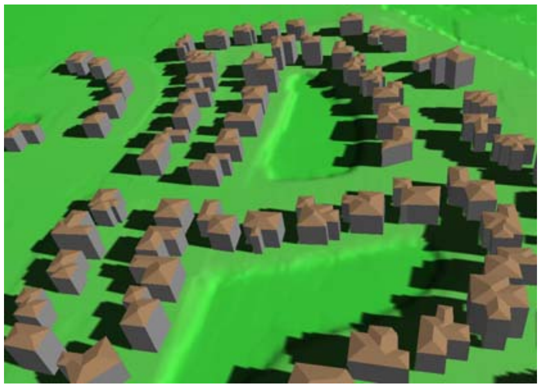


Figure 10. Building Reconstruction Result

Finally, Based on the knowledge stored in the model Database(such as basic elements, basic building models and Rules fro connecting them together), CSG building models can be built. The results are show as Figure 10.

5. CONCLUSION

The method demonstrates the efficiency of using LIDAR for a reliable building reconstruction. Although the method gets a good result in ordinary urban environment, it does not mean that the approach will work well in especially complex downtown areas. And some works are not involved in this paper, such as 3D building model refinement, building outline simplification and so on. The preliminary results encourage us to continue the research in this direction.

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