Wavelet-Based System for Classification of Airborne Laser Scanner Data

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***Abstract*— A new semi-automatic processing system for classification of airborne laser scanner cloud points is developed. To mitigate the difficulty caused by the complex distribution of objects on earth's surface, wavelet was adopted in size-based clustering of laser points. A hybrid method of processing laser scanner data in both grid and raw formats was also adopted to speed up the processing time and adjust the smoothing effect of interpolation. The processing focused on processing the data acquired over urban area. This paper presents and explains the components of the system using the test data acquired over Shinjuku area, Tokyo, Japan.**

Keywords-wavelet; airborne laser scanner; classification

I. INTRODUCTION

Airborne Laser Scanner has growing its operation in the fields of remote sensing, surveying and mapping. However, the post-processing, usually called filtering or classification, is challenging due to the complication of object's distribution on earth's surface. The problem has been investigated so far with varieties of algorithms, but they suffer from different magnitudes of drawbacks. The first group of developed algorithms employs the image processing techniques in classification of laser points as [1] and [4], which suffers from the interpolation effect. On the other hand, the second group classifies the laser points directly on irregular cloud points. It could avoid the problem caused by interpolation but it pays the cost of computation time and has been implemented in recent studies as [2], [5], and [9]. Generally, all the developed methods classify the laser points based on the distribution of their elevation in the local area. The critical problem is how to select the right size of this local area. It is tightly related to the scale (or resolution) property of the objects. The analysis of objects in the image or the cloud points at different resolutions has been proved as an excellent approach to detect and extract the target objects as [6] and [8]. The key point is that the objects appear only at a certain range of scale or resolution. This study proposed a new and improved method, based on a multi-resolution approach with wavelet to cluster the laser points. This enabled the classification of objects based on their size and perfectly filters out unwanted information at a specific resolution. Based on the proposed method, this study implemented a new processing system to classify airborne laser scanner data into the overlying object points and the terrain points.

II. SYSTEM STRUCTURE

Fig. 1 shows the components of the developed system, which was developed using Interactive Data Language (IDL). The details of the components are described below.

A. Interpolation

There are myriads of the interpolation methods. How to find out the best and suitable interpolation method is beyond the scope of this study. The planar interpolation method on the triangulated irregular network (TIN) gives the most accurate interpolated image [3]. It is employed to serve as the first step of processing.

B. Wavelet analysis

A trous algorithm [7] is applied to build up a multi-resolution framework. Let $\Phi(x)$ and $\Psi(x)$ are scaling and wavelet functions, respectively. The scaling function is chosen to satisfy the dilation equation as follows:

$$\frac{1}{2}\Phi(\frac{x}{2}) = \sum_u h(u)\Phi(x-u) \tag{1}$$

where h is a discrete low-pass filter associated with scaling function Φ and u is its size.

This equation shows the link between two consecutive resolutions, which are different by a factor of 2, by the low-pass filtering. The smoothed data $c_j(k)$ at a given resolution j and at position k can be obtained by the method of convolution:

$$c_j(k) = \sum_u h(u)c_{j-1}(k+2^{j-1}u) \tag{2}$$

The difference between two consecutive resolutions is calculated as

$$w_j(k) = c_{j-1}(k) - c_j(k) \tag{3}$$

The wavelet function $\Psi(x)$ is defined by

$$\frac{1}{2}\Psi(\frac{x}{2}) = \Phi(x) - \frac{1}{2}\Phi(\frac{x}{2}) \tag{4}$$

The cubic B-spline with the properties of compact support, symmetry, differentiability and one zero-crossing was chosen to be a scaling function. The implementation for 1D data is the convolution with the mask $\left[\frac{1}{16}\ \frac{4}{16}\ \frac{6}{16}\ \frac{4}{16}\ \frac{1}{16}\right]$. The *a trous* algorithm is easily extensible to the two-dimensional space. This leads to a convolution with a mask of 5x5 pixels for the wavelet connected to the cubic B-spline scale function. The coefficients of the mask with all the elements scaled up to 256 are:

$$\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$$

It is noted that wavelet is one kind of the linear multi-resolution (or multi-scale) analysis, which suffers from the distortion of the objects at a coarser resolution. To mitigate this problem, Median filter is applied prior to wavelet filtering. The wavelet analysis, therefore, is outlined in terms of pseudo codes as follows:

- Input a parameter: the number of the resolutions to be analyzed, e.g. *kmax*.
- Init $k = 1$, e.g. scale equals 1
- Assign the original image to *im_in*
- For each k, k is increased by 1 until $k = kmax$
  - o Median filter *im_in* with the kernel size equals to $2^k + 1$, obtain *im_med*
  - o Detect the strong signatures by differencing *im_in* and *im_med* and thresholding with a threshold of 3σ, where σ is the standard deviation of the difference.
  - o Assign *im_in* to *im_tmp.*
  - o Replace the values of the strong signatures in *im_tmp* by the ones in *im_med.*
  - o Wavelet filter *im_tmp;* obtain *im_wave*, which is the wavelet-smoothed image at scale *k*.
  - o The wavelet coefficients or detailed image is the difference between *im_wave* and *im_in*.
  - o Assign *im_wave* to *im_in* for the next loop.

The wavelet coefficient images are used to detect the boundaries of the multi-resolution clusters, which depict the existence of the objects based on their size. Fig. 2 shows the result of wavelet smoothing across two consecutive resolutions. In the wavelet analysis, the only input parameter is the number of resolutions. It should be noted that more resolutions are employed, more information is obtained, and hence a longer time is required to process the algorithm.

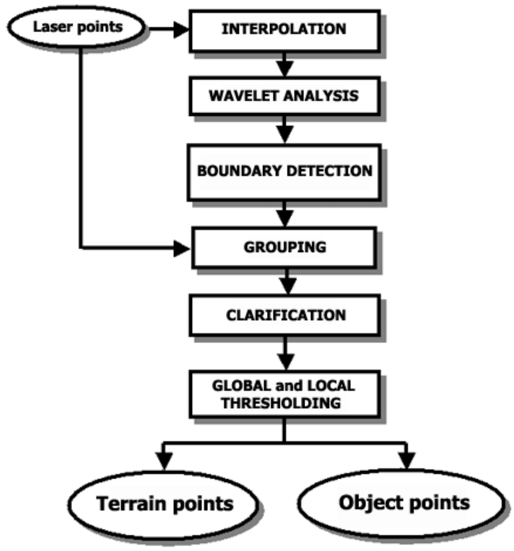

Figure 1. The components of the processing system

C. Detection of cluster boundaries

Across the multi-resolution space, the edge pixels are found as the cut points formed by the profiles of the consecutive resolutions. Fig. 3 illustrates the detected edges across two consecutive resolutions. The detected edges are converted to a vector format for grouping the laser points.

D. Grouping and clarification

By a spatial relation of fall-into-boundary, it is possible to distinguish between the qualified object points and the remnants. This processing step is a hybrid method in which the cloud points are grouped and categorized based on the results obtained from the interpolated images. However, there is ambiguity along the edges of objects. The classified laser points along the edges of the clusters might fall into the class named fuzzy edge points, which are the overlying object points but classified as the terrain points, or the class named the wrongly classified points, which are the terrain points but classified as the object points. Let OP is the object point set that has been detected and *P* as the remainders set of points. The wrongly classified point can be detected by the following equation.

$$WCP = \left\{ \begin{array}{l} OP_k : (OP_k \setminus in\ OP) \text{ and} \\ (P_i \setminus in\ \mathrm{P}) \text{ and} \\ (\mathrm{O}P_k \setminus in\ N_i) \text{and} \\ \left| Z(OP_k) - AveZ(N_i) \right| \le StdP \end{array} \right\} \quad (5)$$

where *WCP* is the wrongly classified point set, *StdP* is the given threshold, N_i is the Delaunay neighbor point set of terrain point P_i, $Z(P_i)$ is the elevation of the point P_i, $AveZ(N_i)$ is the average of elevation in N_i, *\in* denotes the “is-element-of” symbol.

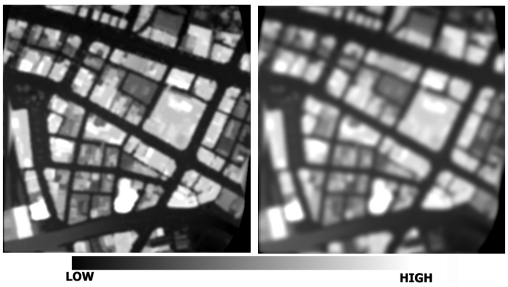

Figure 2. Smoothed wavelet images across two consecutive resolutions

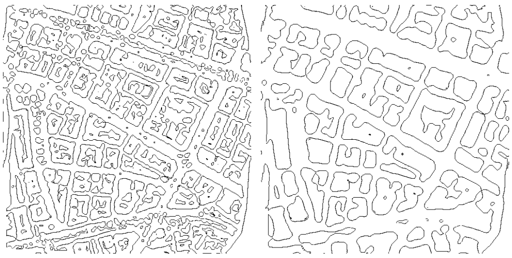

Figure 3. Detected edges across two consecutive resolutions

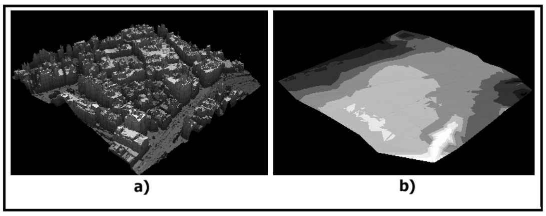

Figure 4. a) original surface ; b) filtered surface

The fuzzy edge point is a point that satisfies the following condition:

$$FEP = \left\{ \begin{array}{l} P_i : (P_i \setminus in\ P)\text{and} \\ (OP_k \setminus in\ \text{O}P)\text{and} \\ (P_i \setminus in\ N_k)\text{and} \\ \left| Z(P_i) - AveZ(N_k) \right| \le StdOP \end{array} \right\} \qquad (6)$$

where FEP is the fuzzy edge point set, $StdOP$ is the given threshold, N_k is the Delaunay neighbor point set of object point OP_k, $Z(P_i)$ is the elevation of the point P_i, $AveZ(N_k)$ is the average of elevation in N_k, *\in* denotes the "is-element-of" symbol.

E. Global and local thresholding

By the reflection from the complicated objects on the earth surface, there might appear some erroneous laser points with very high elevation on the terrain. These points were easily removed by a statistical thresholding applied on a cumulative histogram. Subsequently, a new Voronoi diagram is generated for the remaining set of points. There are a few object points that remain in this set of points and their elevation differs from their neighbors. A slope thresholding is carried out iteratively in the local Voronoi neighbor. As a result, the terrain points are detected which is ready for the reconstruction of the terrain surface. Fig. 4 presents the terrain surface filtered by the developed system along with the original surface.

III. COMPUTATIONAL TIME

During the processing of the airborne laser scanner data, most of the time is used for reading the data from and writing the data to files. This is due to the enormous amount of the laser points acquired in the data set. In this wavelet-based processing, the size of resolutions to be employed is the main factor that controls the computation time. If the time required for input and output of the data and the time needed for interactive processing is excluded, the total computation time for the processing will be substantially lower. For instance, the computational time for an image size of 512 m x 512 m carried out on a PC with CPU 600MHz and memory of 128MB is about 150 seconds. Till now, there are no reports regarding the computation time for the existing algorithms. Therefore, it is unable to compare the attained time efficiency with other algorithms.

IV. CONCLUSION

A newly developed system based on the wavelet analysis for classification of airborne laser scanner data has been presented. The implementation of the system has been carried out and is on the testing stage. It is required to test the system on various kinds of terrain as well as different acquired airborne laser scanner data in further studies.

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