AUTOMATIC RECOGNITION OF RIVERS FROM LIDAR DATA BY PROFILE FACTOR

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Commission VI, WG I/2

KEY WORDS: LiDAR, Automatic river recognition, Profile factor function, Edge extraction, Skeleton generation

ABSTRACT:

Laser infrared Detection and Ranging (LiDAR) has become one competitive remote sensing (RS) and photogrammetry technique. Extracting rivers' distribution from LiDAR's point cloud is one of its important research directions. But traditional methods are not completely suitable for the ranging data of LiDAR. Novel algorithm with profile factor as the kernel circle is proposed for rivers' automatic recognition. Image unification, edge extraction and skeleton generation are the premier three steps. The profile factor of morphology can be expressed as shape functions for concrete judgement. Natural rivers' profile is like "U" form, and artificial water-body's can be simplified as "M" figure. While highway's section can be considered as "W" shape. Then corresponding profile factor functions (PFF) can be established for determination. The experimental comparisons show that the results by the proposed algorithm are close to which from high-resolution RS images by manual interpretation.

1. INTRODUCTION

Laser infrared Detection and Ranging (LiDAR) has become one effective and competitive technique in remote sensing (RS) and photogrammetry fields, as LiDAR can acquire information with high ranging precision and high sampling density. The laser echoes stored in point cloud mode also supply the possibility of data processing as image. Among, extracting rivers' distribution status from LiDAR data now is one important research point (David, 2006), as this function avails many applications of LiDAR, such as water and soil conservation, flood control, hydrology fine investigation, precision agriculture, pollution abatement and etc.

For above applications, some river detection algorithms based on optical RS images have been developed (Lina, 2006). But the traditional methods are not completely suitable for LiDAR images which transformed from ranging data. LiDAR image pixels reflecting elevation feature is different with the spectral characteristics of RS images, i.e. SPOT5. Particular recognition algorithms need to be established for this new type of RS & photogrammetry mode.

Simultaneously the requirement of non-human-interference and in-time process increases gradually, as more and more situations ask for immediate process and decision. The trends of on-satellite and on-board processing also advance the development of related concrete algorithms. Automatic process has become an ignorable factor in feature detection techniques, especially in flood control system. Novel algorithm for rivers' recognition needs to be explored for LiDAR images.

Based on the analyses above, this paper proposes one automatic recognition algorithm based on profile factor function (PFF) for rivers. The following contents include three parts. Firstly PFF is introduced. Secondly real data is assumed for testifying the algorithm. Finally conclusions are given.

2. ALGORITHM

The proposed river detection algorithm comprises three steps of pre-process, and category judgment by PFF is the last but kernel circle for rivers' automatic recognition.

2.1 Pre-process

The pre-process is for constructing the frame suitable for PFF's implementation. The first step is to acquire the corresponding images by equal-interval transition from ranging values to grey scales. Secondly edge extraction based on wavelet transform with the Prewitt operator is carried out. Then improved Hilditch thinning algorithm for rivers' skeleton building is assumed.

Actually between the edge extraction and skeleton generation false edges' removal is one necessary circle. For RS images, this is especially difficult. In avoidance of struggling on the detailed and complex removal techniques' discussion, such as distance threshold or circle removal (Guido, 2004), this paper describes this part without details' introduction. The removal methods used in image processing of this paper will be introduced in authors' another manuscript.

2.1.1 Image unification

The premise of all processing for river recognition is that point cloud has been regulated as clear grid set. Then the cumbersome point cloud can be converted into grey images for following operations. And this also avails the comparison of LiDAR images with high-resolution RS images.

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The conversion assumes equal-interval mapping of elevation parameter to grey scale, as showed by the formula (1). The variance of grey pixels actually reflects the up and downs of terrain surface. PFF can be implemented directly based on the pixels' grey scale value, if the mapping isn't greatly smoothing the elevation information.

$$G_{ij} = \frac{h_{ij} - h_{\min}}{h_{\max} - h_{\min}} \cdot 255 \tag{1}$$

where h_{ij} = current point's elevation value
h_{max}, h_{min} = area's largest and least elevation value
G_{ij} = current point's corresponding grey scale

From the counterpart aspect, the equal-interval conversion also has the effect of noise-filtering for elevation-measurement data, which reduces the influence of earth surface's fine fluctuations, such as little potholes, low shrubs and etc.

2.1.2 Edge extraction

Edge extraction is the key circle for automatic determination of rivers' location and distribution. Simultaneously it establishes the bridge between LiDAR data and RS images embodying the terrain objects' spectral information.

Adaptive wavelet transform-based edge extraction methods give solutions for river edges' acquiring. LiDAR images are duller compared with optical images, because pixel element reflects ranging and suffers less disruption factors. The relative process of de-noising is less complex. So edge extraction is usually based on Prewitt operator applicable of lower frequency (Hong, 2006).
The concrete parameters are achieved as the first derivative of the smoothness function, and the two elements of 2-dimensional 2-grade wavelet transform is equivalent to the two elements of signal's gradient vector after smoothness, as formula (2).

$$\begin{pmatrix} W^x S(2^j, x, y) \\ W^y S(2^j, x, y) \end{pmatrix} = 2^j \begin{pmatrix} \frac{\partial}{\partial x}(S * \overline{\theta}_j)(x, y) \\ \frac{\partial}{\partial y}(S * \overline{\theta}_j)(x, y) \end{pmatrix} \tag{2}$$
$$= 2^j \nabla (S * \overline{\theta}_j)(x, y)$$

$$MS(2^j, x, y)$$
$$= \sqrt{\left| W^x S(2^j, x, y) \right|^2 + \left| W^y S(2^j, x, y) \right|^2} \tag{3}$$

where $\theta(x, y)$ = smoothness function
(W^x, W^y) = 2-dimensional 2-grade wavelet transform
$S(x, y)$ = signal deployment
$MS(2^j, x, y)$ = maximum value function
$\nabla(S*\overline{\theta}_j)(x, y)$ = gradient vector

The value of gradient vector keeps direct ratio with the parameter *MS*. From equation (3) multi-scale edge detection using 2-grade wavelet transform at last lies in the local maximum value's calculation.

But edge extraction can't identify similar terrain characteristics, which means that the recognition function should be enhanced. Natural rivers and artificial rivers have the similar edge results. And simple utilization of the elevation information is also not promising. On the surface with some extent of slope, the water surface of upstream probably is higher than the road surface of downstream. And this embarrassment enhances the necessity of automatic recognition factor's introduction, such as profile.

2.1.3 Skeleton generation

Skeleton generation supplies the reference for following profile factor functions' implementation. Edge detection of a channel will generate two anti-parallel edges from either side of it. Nevatia and Babu (Nevatia, 1980) describe an algorithm to associate edges together. After parallel edges' association, the skeleton can be determined.

As we know, the regions between two borders are generally highway surface or water surface, which are relatively flat. And the median regions can be considered as element sets with equivalent characteristic amplitude. So the traditional but stable Hilditch algorithm (Lam, 1992; Abe, 1994; Jonathan, 2007) suitable for binary image can be improved for skeleton generation in this pre-process.

Simple Hiditch algorithm possibly adds false thinning sections, and its skeleton results sometimes are not in coincidence with the real centrelines. The improvements assume horizontal and vertical average individually as formula (4). Then the averaged point sets are used to modify the skeleton from the traditional Hiditch algorithm.

$$(i, j) = \left(i, \frac{1}{2}\left(m\big|_{P_{i,m} \neq 255} + n\big|_{P_{i,n} \neq 255} \right) \Bigg|_{\substack{P_{i,m<t<n} \neq 255 \\ P_{i,m-1} = 255 \& P_{i,n+1} = 255}} \right) \tag{4}$$

where (i, j) = river's median point's horizontal location
$P_{i,j}$ = relating pixel's grey scale value

After the skeletons have been got, the equal-division points for given number of sections can be calculated. Then the cross-lines of the skeleton through the above segmentation points can be achieved. Then PFF can be carried out on the cross lines within the range of rivers' average length.

2.2 Profile statistics

Automatic recognition based on profile factor still arises from the problems left by pre-process operations, as the traditional methods can detect grey-scales' difference but can't distinguish roads, natural rivers and artificial canals. Considering that LiDAR data is composed of ranging information, profile factor is one good choice to represent and determinate different terrain topographical categories.
In river's identification, after edge extraction operation there are commonly three types of terrain distribution with the similar features, namely artificial rivers, natural rivers and highways, whose shapes are generally in long strip. Experience knowledge tells us that their profiles are in different shapes, and the following statistical analysis of profile shape from real LiDAR data is conducted, as shown in Figure 1, 2 and 3.

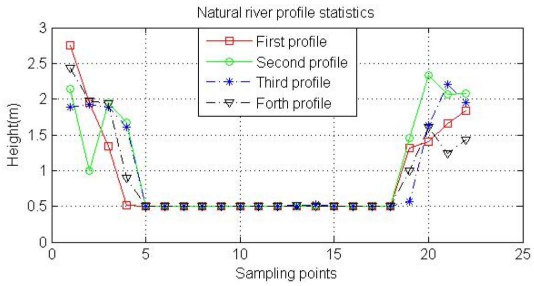

Figure 1. Natural river's profiles sampled on different sections

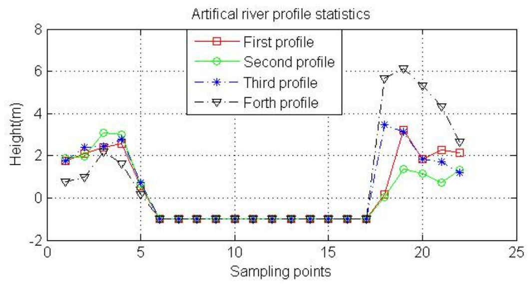

Figure 2. Artificial river's profile sampled on different sections (the sampling points with a certain distance)

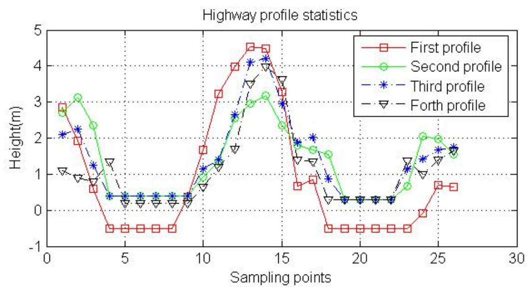

Figure 3. Highway's profile sampled on different sections (the sampling points with a certain distance)

The profile morphological factors can be expressed as shape functions for judging. Highways are commonly with gutters and the road surface is higher than the fields both sides, so its profile can be united into "W" shape. Natural rivers are like "U" without banks, while artificial water-bodys have riverbanks and its profile can be simplified as "M" figure. Then corresponding profile factor functions can be established for calculation and judgment accordingly.

2.3 Profile functions

For automatic identification, the distribution of rivers' profiles should be summarized into functions for logical judgement. Natural rivers, artificial rivers and highways are individually deduced as the shapes shown in figure 4. For highway and artificial river, the upper shapes are more common, but the lower ones still exist.

The concrete mathematical expression can assume sine function, which distinguishes by the fitting range in different phase and amplitude. The shape deployment also can be characterized by different degree polynomial functions with various coefficients as detection parameters. But these kinds of method above need sophisticated computation. This paper suggests using the logical relationship of the locations for different height sections on the profile, which can simplify the judgement process.

The following consideration about establishing the concrete judgement functions takes the skeleton as the initial reference, and ranges 2 times the distance from central line to the extracted edge. Based on the sum up about the typical forms of the profile distribution in the upper three figures, the logical relationship between initial position, end position, highest position and lowest position can be determined and be used for making sure of different profiles. Then the discrimination function can be summed up.

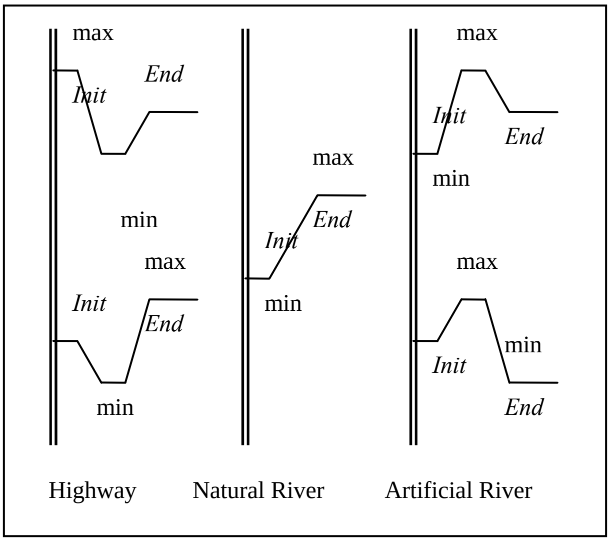

Figure 4. Profiles induction for river and highway

The profile factor logical function of natural river, highway and artificial river can be summed up as formula (5), (6) and (7) individually. If the real profile fits one of the conditions, then the object can be determined as the related terrain catogery.

$$\begin{cases} P_{\max} = P_{Init} \mid P_{\max} = P_{End} \\ P_{Init} < P_{\min} < P_{End} \end{cases} \tag{5}$$

$$\begin{cases} P_{\min} = P_{Init} \\ P_{\max} = P_{End} \end{cases} \tag{6}$$

$$\begin{cases} P_{\min} = P_{Init} \mid P_{\min} = P_{End} \\ P_{Init} < P_{\max} < P_{End} \end{cases} \tag{7}$$

where P_{init} = height of the point on the centreline
P_{end} = height of the point at the end of the profile
P_{max} = height of the point with largest elevation
P_{min} = height of the point with least elevation

The above discrimination functions need some pre-processes to ensure the reliability of the practical judgement. Firstly, the data for implementation should assume the average result of multiple profiles, which can weaken the impact of special circumstances. Secondly, as to the inconsistency condition of highway width or water surface width, the same number of samplings from the start line is adopted to get uniform sequence. Thirdly, after the positions related with the start point, the termination point, the highest elevation and the lowest elevation are sought, constant-value function is applied for fitting the neighbour points of given number. Then the nearest point on the fitting line replace the above four calculated points as the actual positions used in determination functions.

Although the above functions utilize the common regulars, the real-world has some anomalies. The artificial river probably has a cross interface with natural river. One side-bank of artificial rivers sometimes makes use of natural terrain slope. The special situations also should be considered in the following work.

3. EXPERIMENTS AND ANALYSIS

The experiments will use real LiDAR ranging data to testify the algorithm proposed above. And some related analyses are made for further improvements, which aims at becoming one module of practical software.

3.1 Data

This paper applies Abbeville district's LiDAR ranging data in America to validate the proposed algorithm, at the same time rivers' distribution from the same area's high-resolution RS image is applied and extracted as comparison template.

Figure 5 and 6 illustrates the characteristic distribution of the chosen area. LiDAR samplings has 5 times grid-spacing than the spatial resolution of RS image (1m), which needs data compression for comparison.

The figures also show that LiDAR images are generally more homogeneous than RS images. This avails of automatic process when extracting information. And this also constitutes the foundation of whole algorithm.

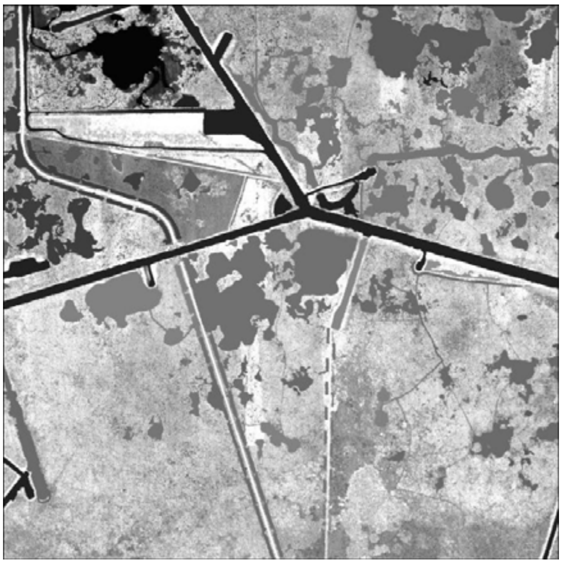

Figure 5. Typical LiDAR image for experiments

Figure 6. RS image of the same area for comparison

3.2 Results

After edge extraction, skeleton generation and PFF recognition, as showed in figure 7, 8 and 9, the areas related with artificial river, natural river and highway can be determined. The results indicate that although some long strips of terrain are picked out by edge extraction, PFF can recognize them.

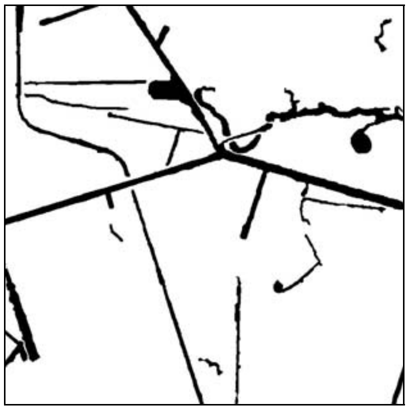

Figure 7. LiDAR image's objects extraction result

Figure 8. LiDAR image's skeleton generation result based on figure 7.

Figure 9. LiDAR image's PFF recognition result
●Artificial river ●Highway ●Natural river ●Other terrain

Then the areas of three terrain categories are segmented from RS image, which is showed in figure 10.

Figure 10. RS image's manual interpretation result
●Natural river ●Highway ●Artificial river

The comparison shows that the result acquired with the profile factor algorithm is close to from high-resolution RS images by manual interpretation.

Figure 11. RS and LiDAR recognition results' comparison
●Natural river ●Highway ●Artificial river ●Other terrain

The rivers can be distinguished with highways, and the artificial rivers also can be distinguished from natural ones. Artificial rivers' area is taken as criterion, and the extracted rivers' area occupies about 84% of the related area interpreted from RS images.

3.3 Analysis

The proposed algorithm based on profile factor adds criterion up to the automatic identification of rivers, but this can not be applied in all practical applications. The rivers' straightness can be used as the additive discrimination condition for artificial river and natural river, highway and natural river.

At the same time high-resolution remote sensing images and LiDAR data can also be fused to increase the accuracy of automatic recognition. During related software development, various proper factors should be used and integrated to enhance the accuracy and reliability of automatic identification.

4. CONCLUSION

This paper explores a new river automatic recognition method combined with terrain morphological distribution, based on the specialties of LiDAR ranging data. And the work supplements recognition function to feature extraction modules and supplies appropriate scheme for automatic application.

ACKNOWLEDGEMENT

This work was supported by the Wiser Foundation of IDC - Peking University (No. W08SI01). The authors also wish to thank LSU CADGIS Research Laboratory and Louisiana Oil Spill Coordinators Office of America for distributing laser scanning data and high-resolution RS images of Abbeville district.

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