Extraction of power lines from mobile laser scanning data

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ABSTRACT

Modern urban life is becoming increasingly more dependent on reliable electric power supply. Since power outages cause substantial financial losses to producers, distributors and consumers of electric power, it is in the common interest to minimize failures of power lines. In order to detect defects as early as possible and to plan efficiently the maintenance activities, distribution networks are regularly inspected. Carrying out foot patrols or climbing the structures to visually inspect transmission lines and aerial surveys (e.g., digital imaging or most recent airborne laser scanning (ALS) are the two most commonly used methods of power line inspection. Although much faster in comparison to the foot patrol inspection, aerial inspection is more expensive and usually less accurate, in complex urban areas particularly. This paper presents a scientific work that is done in the use of mobile laser scanning (MLS) point clouds for automated extraction of power lines. In the proposed method, 2D power lines are extracted using Hough transform in the projected XOY plane and the 3D power line points are visualized after the point searching. Filtering based on an elevation threshold is applied, which is combined with the vehicle's trajectory in the horizontal section.

Keywords: Mobile laser scanning, power line, automated inspection, feature extraction, 3D model

1. INTRODUCTION

The world electric power grid becomes more and more important as the networks provide electricity to millions of homes and businesses. As the 2nd largest exporter and the 5th largest producer of electricity in the world, the bulk transmission network of Canada consists of more than 160,000km of high voltage power lines. Automatic protective relays detect the high current and quickly act to disconnect the faulted line from service. All the key corridor objects like power lines, towers, insulators, splices, switches and other components as well as terrain, buildings and trees require precise power lines change monitoring, especially after the northeast blackout in 2003, which is the largest power outage in decades throughout parts of the Northeastern and Midwestern United States and Ontario, Canada [1].

The traditional power lines inspection and maintenance mainly depend on manual survey and construction or aerial digital imaging, which are inefficient, high cost and poor security. In recent years, methods for power lines extraction are focused on laser scanning systems, especially the airborne laser scanning (ALS). The power line extraction method using ALS is approximately 1.5 times higher in cost per circuit mile but 2 times higher in accuracy for correctly detecting vegetation-related violations compared to the conventional method [2]. However, ALS systems are expensive and predominately belong in the realm of government and large corporate institutions due to their higher infrastructure cost. The terrestrial laser scanning (TLS) system uses the same principle as ALS, except it is ground based. The scanner is located on the ground so that it is more convenient to capture discrete objects from multiple angles, and is within the reach of a much broader range of practitioners [3]. These systems can measure thousands or even millions of points per second. For example, a Riegl VMX-450 mobile laser scanning (MLS) systems can collect 1.1 million points per second, which is far in excess of the traditional surveying techniques. Considering the less expensive and usually more accurate comparing with the ALS system, especially in complex urban areas, it is possible to determine the spatial relationship between power lines and corridor features (particularly corridors vegetation) in an accurate measurement with MLS systems. In this study, the MLS point cloud is processed to extract the power line features in the city area.

For the ALS data and aerial images, techniques proposed can be divided as three categories: 1) 3D point-based approaches [1,4-7]; 2) 2D image-based approaches [8,9]; and 3) fusion of ALS data and aerial imagery which is mainly

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used in building extraction. Reference [9] proposed a new method of power line extraction from Unmanned Aerial Vehicles (UAVs) using a classical edge detector, Hough transform and the Pulse Coupled Neural Filter (PCNF) to reduce noise. As the latest state-of-the-art laser scanning data acquisition system, the MLS system can quickly scan the whole urban areas and get denser laser scanning points with not only the height information but also the side information and trajectory information comparing with ALS. This calls different methods to process MSL data.

As for MLS data, a method for classifying terrain points and off-terrain points had been presented in [10]. 3D street-scene modeling developed rapidly with emerging expansion of location-based services, pedestrian and vehicle navigation, traffic accident, or crime case investigation [11,12]. However, rarely specific papers present the extraction of power lines using MLS data. In this paper, some tests of a preliminary power line extraction will be addressed to fill in this research gap.

2. METHOD

In the proposed method, a 3D power line model will be built from the MLS data mainly based on procedures of elevation filtering, 2D segmentation and point searching based on vertical projection. Figure 1 shows the flowchart of our method.

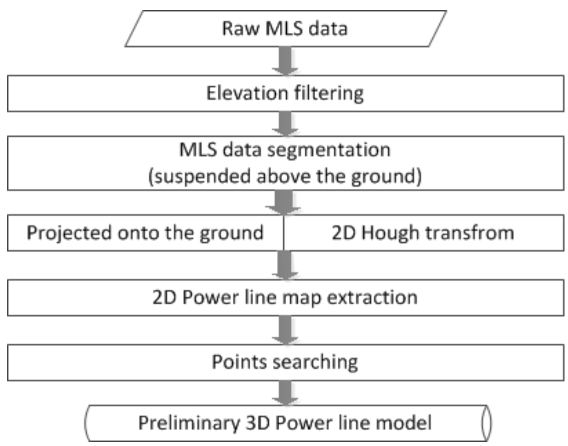


Figure 1. Workflow of our method.

2.1 Elevation filtering

Filtering is a key step of the entire process as the subsequent power line extraction and fitting will be based on this procedure. According to the characteristics of the distribution of the power line scanning data elevation, the elevation threshold segmentation algorithm is used to eliminate ground points and simplify the data to improve the extraction efficiency in this study. The elevation threshold segmentation algorithm uses the optimal threshold methods to find the optimal elevation data as the threshold to split the ground points and non-ground points. Optimal threshold methods include the P-median method, iterative optimal threshold value method, histogram concave analysis, Otsu method, entropy method, minimum error thresholding method and etc. [13]. As the iterative optimal threshold value method can quickly obtain a satisfactory result, and the small amount of computation can also meet the less precision image segmentation [14,15], it is applied in this experiment to deal with the elevation thresholding. Threshold segmentation of the iterative method is using iterative thinking mainly looking for the best segmentation threshold based on the statistics of the global points average. The iterative method is conducted as follows:

(1) Select the average elevation of all the data (T_0) as the initial threshold (T_k), that is $T_k = T_0$;

(2) Divide the data set into two sets based on the initial threshold T_k by calculating the average elevation of the two sets respectively: the results which are less than T_k will be put in the T_A , and the opposite which are greater than T_k will be put in the T_B ;

(3) Recalculate the new threshold T_{k+1} based on formula (1), then set $T_k = T_{k+1}$:

$$T_{k+1} = \frac{T_A + T_B}{2} \tag{1}$$

(4) Repeat the above procedure until $T_{k+1} = T_k$, then T_k will be the final elevation threshold T;

(5) Segment the data into two parts based on the final elevation threshold T.

2.2 2D line extraction

After elevation threshold filtering, all the points are divided into two groups: ground points and non-ground points. As the high elevation, the power line points are located in the non-ground part. For the consideration of there would be other points like parts of the tall trees and road lamps in the non-ground points, the segmented non-ground point cloud will be projected onto the ground from 3D to 2D for straight line detection as the trees will be in a cluster of points and the road lamps will be individual points separately in the XOY plane.

Hough transform is one of the basic methods of image recognition, and it is a commonly used linear detection algorithm. The main advantage is the ability to detect the geometry less affected by the interference of intermittent points and does not require pre-combination or connected edge points [16]. According to the characteristics of the power line distribution in the MLS data, a classic linear feature extraction, Hough transform with the best point chosen in the grid is applied in this experiment.

The Canny algorithm is chosen to use in this experiment as it meets the three performance criteria addressed by Canny in 1986 that it is good detection, good localization and only one response to a single edge [17]. The function cvCanny uses Canny algorithm to find the edges of the input image and identify those edges in the output image. The smaller threshold within threshold1 and threshold2 is used to control the edge access connection, and the larger one is used to control the initial segmentation of the strong edge.

2.3 Point searching

Figure 1 shows the workflow, in which the point searching is conducted when doing the transformation from the XOY plane to the extracted 3D power line model. When doing the projection from 3D to 2D, the coordinates of the 3D points will be recorded on 2D plane.

For a better management of the point data, a K-dimensional tree (KD tree) of data index was built to organize the MLS data and establish the relationship between them before performing filtering process. In this study, the Approximate Nearest Neighbour (ANN) Library, which includes a KD tree implementation, is applied to build the data indices. It is easier to find each MLS point and in the projection from 2D to 3D, it will be efficient to find the required elevation of some certain points with the KD tree.

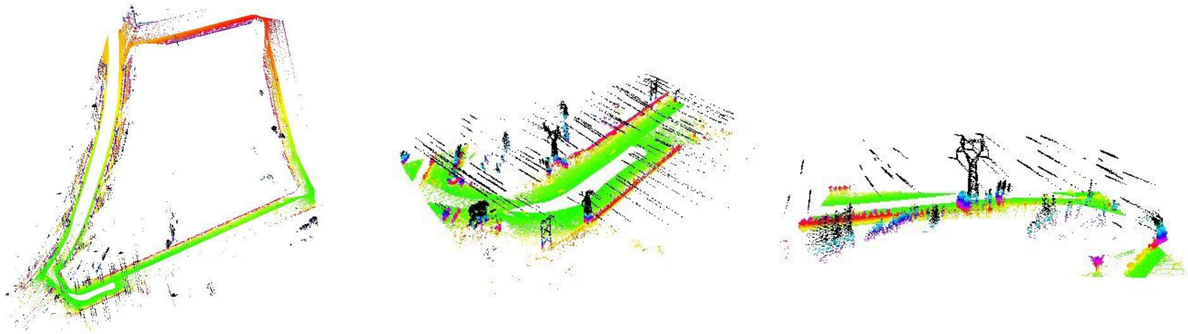
If several points are projected onto the same place, the point with highest elevation will be regarded as the recorded point. In this way, according to index of the extracted points in the XOY plane, the 3D coordinates of the power line model can be settled.

3. EXPERIMENTS AND DISCUSSIONS

3.1 Study area and data description

The RIEGL VMX-450 Mobile Laser Scanning System for 3D data acquisition from moving platforms is used in this experiment. The study area is a piece of urban area MLS data scanned in the Northern China. The format of the LAS point cloud is LAS 1.0, and the height range from 1026.4m to 1078.9m covered area 0.31 km2. The total entry points' number is 4,154,289 with the average density of 13.5 points/m². Figure 2 shows the MLS point cloud of the study area.

As shown in Figure 3, the elevation distribution of the MLS points ranges from 1026m to 1045m, and no point is as high as 1045m.



(a) (b) (c)

Figure 2. MLS point clouds: (a) Vertical view, (b) and (c) Side view.

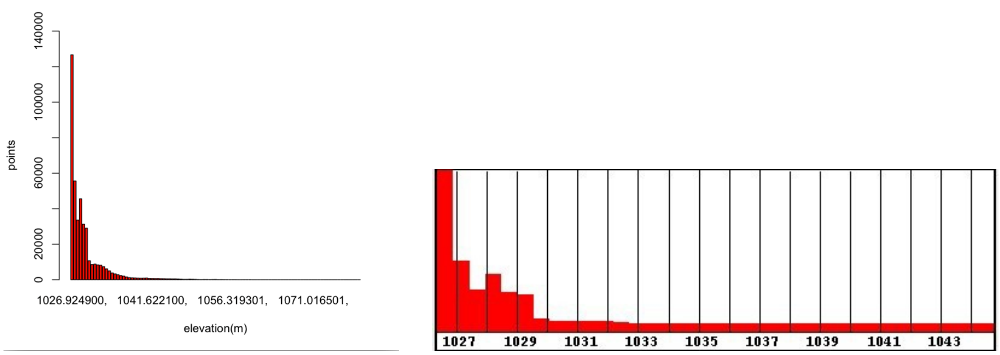
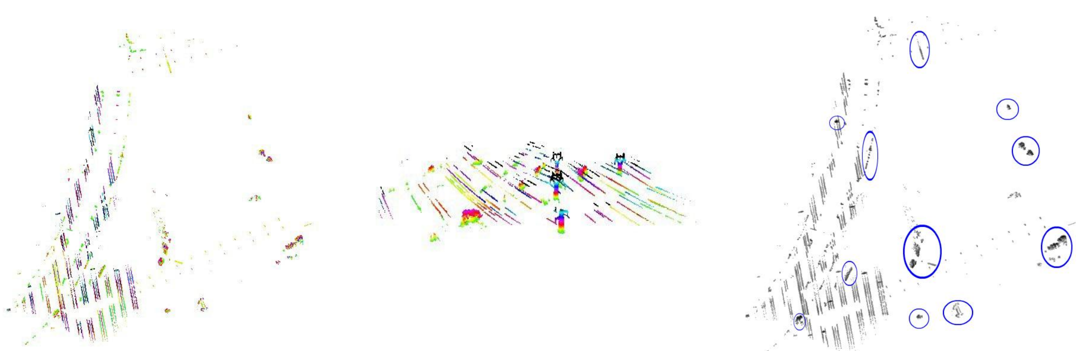


Figure 3. Elevation distributions based on the points of every 0.5m from 1026m to 1045m (X axis is the elevation, and Y axis represents point number on this elevation).

3.2 Filtering results

The optimal elevation threshold is chosen to be 10m after several tests.



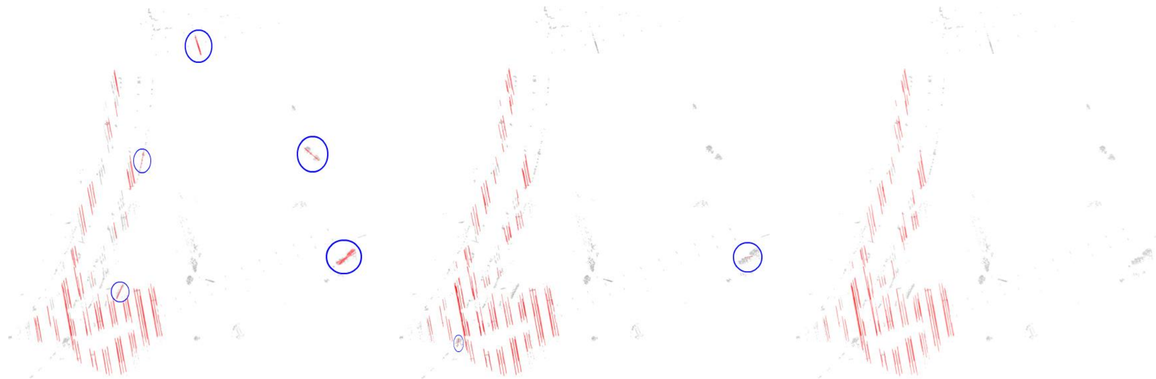
(a) (b) (c)

Figure 4. Filtering results with 10m elevation threshold: (a) top view, (b) side view, and (c) tree clusters.

Figure 4(c) shows the 2D transform map after filtering with the threshold of 10m. There are eleven main tree clusters and some point outliers including the individual road lamps marked in blue circles.

3.3 Extracted powerline maps from Hough transform

Figure 5(a) shows the extracted power lines by setting the (threshold, param1, param2) in Hough transform function as (50, 150, 30). It means that we set the minimum length of the line is 150m. When the interval between the two broken line segments on the same straight line is less than 30m, they will be combined on the same straight line. If the cumulative value is greater than the 50m, then the function returns the segment. We can find that five places in the blue circles have been wrongly extracted. As there are eleven clusters have the possibility to be misclassified in total, the error rate is 45.5%.

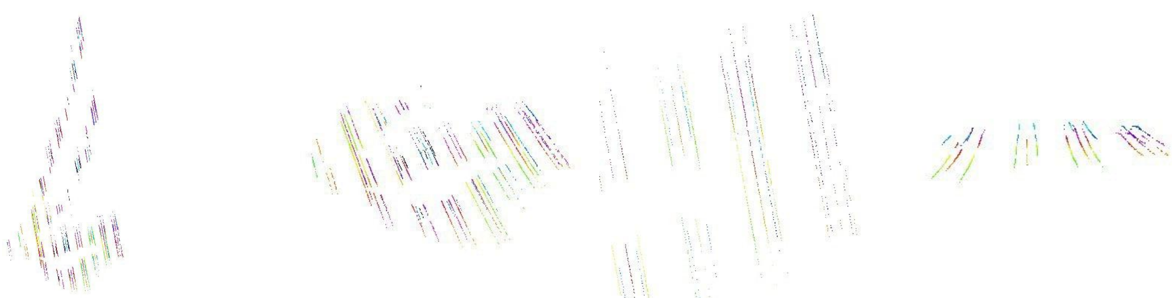


(a) (b) (c)

Figure 5. Extracted power lines using (a) 50, 150, 30; (b) 100, 50, 30; and (c) 100, 50, 50.

Figure 5(b) shows the extracted power lines using (100, 50, 30). We can find that two places in the blue circles have been wrongly extracted. The result is better than the one in Figure 5(a). The error rate of misclassified is 18.2%. After several tests, the parameters (100, 50, 50) are chosen as the relative optimal result it presents. In Figure 5(c), there are no wrongly extracted lines and the effects of the power line fitting are as well as which in Figure 5(a).

From 2D to 3D, points searching have been employed. From 3D point cloud using the result from Figure 5(c), we can see the power line model in different views. All the trees, road lamps, power towers and other outliers have been removed. Each group of the power lines has five exact lines been extracted, which can be seen in Figure 6 (d).



(a) (b) (c) (d)

Figure 6. 3D visualization of the extracted power line points. : (a) top view, (b)-(d) side view.

4. CONCLUDING REMARKS

By viewing the results of extracted power line maps from the Hough transform, the misclassified rate in Figure 5 is 45.5%, 18.2% and 0 respectively. So the proposed method of automatic power line extraction from MLS data by using grid searching projection and Hough transform works pretty well. However, as lacking of the reference photos and data of the study area, the validation and accuracy assessment cannot be completed in this experiment including the visual interpretation. As a matter of fact, the density of the point cloud especially on the power line points is a key factor influencing the accurate rate of extraction of the power lines.

One of the problems should be considered is the overlapping even though there is no overlapping power lines in the dataset of this experiment. The proposed approach based on 2D image analysis depends strongly on image gradient, which is the contrast of pixel values. “As the lack of 1D (i.e., z-axis) in 2D images, occlusion occurs along the height direction”, it is difficult to detect overlapping power line projections [2]. However, in the ALS data, the overlapping phenomenon is more common than the MLS data because of the scanning approaches. It is also much easier and more convenient to scan in different view with the MLS system if there is overlapping than the ALS.

In the proposed method, we can also try the interpolation before filtering, it may enrich the point cloud especially the area have fewer and sparse points. In the area with a lot of categories of non-ground objects, we can also apply the k-means algorithm to first segment the clustered non-ground objects.

The RANdom SAmple Consensus (RANSAC) method can be applied in the further study for more accurate and consistent power line extraction and fitting. By using a catenary curve equation, a power line model can be reconstructed with the parameters estimated robustly using RANSAC [2]. This kind of method has not yet been employed in the MLS power line extraction. By using the power line model to extract and fit the power line points directly will be much a future trend in the power line extraction.

REFERENCES

[1] Jwa, Y. and Sohn, G., "A multi-level span analysis for improving 3D power-line reconstruction performance using airborne laser scanning data," ISPRS Archives 38, 97-102 (2010).

[2] Jwa, Y. and Sohn, G., "A piecewise catenary curve model growing for 3d power line reconstruction," Photogramm. Eng. Remote Sens. 78(12), 1227-1240 (2012).

[3] King, B. and Li, J., "Introduction to the PE&RS Special Issue on Advances in Terrestrial LiDAR Techniques and Applications," Photogramm. Eng. Remote Sens. 78(4), 307-308 (2012).

[4] Melzer, T. and Briese, C., "Extraction and Modeling of Power Lines from ALS Points Clouds," Proc. 28th Australia Assoc. Pattern Recog, 47-54 (2004).

[5] Clode, S. and Rottensteiner, F., "Classification of trees and powerlines from medium resolution airborne laserscanner data in urban environments," Proc. WDIC 2005, 97-102 (2005).

[6] McLaughlin, R.A., "Extracting transmission lines from airborne LiDAR data," IEEE Geosci. Remote Sens. Lett. 3(2), 222-226 (2006).

[7] Vale, A. and Gomes-Mota, J., "LiDAR Data Segmentation for Track Clearance Anomaly Detection on Over-head Power Lines," Proc. IFAC Workshop, 5-9 (2007).

[8] Yan, G., Li, C., Zhou, G., Zhang, W. and Li, X., "Automatic extracion of power lines from aerial images," IEEE Geosci. Remote Sens. Lett. 4(3), 387-391 (2007).

[9] Li, Z., Liu, Y., Walker, R., Hayward, R. and Zhang, J., "Toward automatic power line detection for a UAV surveillance system using pulse coupled neural filter and an Improved Hough Transform," Machine Vision and Application 21(5), 677-686 (2010).

[10] Habib, A. F., Chang, Y. C. and Lee, D. C., "Occlusion – based methodology for the classification of lidar data," Photogramm. Eng. Remote Sens. 75(6), 703-713 (2009).

[11] Kutterer, H., [Mobile mapping, Airborne and terrestrial laser scanning], Whittles Publishing, UK, 293-311 (2010).

[12] Yang, B., Fang, L., Li, Q. and Li, J., "Automated extraction of road markings from mobile lidar point clouds," Photogramm. Eng. Remote Sens. 78(4), 331-338 (2012).

[13] Sezgin, M. and Sankur, B., "Survey over image thresholding techniques and quantitative performance evaluation," J. Electron. Imaging 13(1), 146-168 (2004).

[14] Ridler, T.W. and Calvard, S., "Picture thresholding using an iterative selection method," IEEE Trans. Syst. Man Cybern. 8(8), 630-632 (1978).

[15] Leung, C.K. and Lam, F.K., "Performance analysis of a class of iterative image thresholding algorithms," Pattern Recognit. 29(9), 1523-1530 (1996).
[16] Castleman, K.R., [Digital Image Processing], Prentice Hall, Upper Saddle River, New Jersey, (1995).
[17] Canny, J., "A Computational approach to edge detection," IEEE Trans. Pattern Anal. Mach. Intell. 8(6), 679-698 (1986).