A MULTI-LEVEL SPAN ANALYSIS FOR IMPROVING 3D POWER-LINE RECONSTRUCTION PERFORMANCE USING AIRBORNE LASER SCANNING DATA

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ABSTRACT:

In the previous research, a new method for automatic 3D power line modeling related to rapid risk management in a power line corridor using airborne LIDAR data was proposed. The method of piece-wise propagation of catenary curve model provided robustness and reliability for 3D automatic power line reconstruction. Although the previous method demonstrated its high success rate of power line generation, it still produced under- and over- reconstruction errors under the circumstance of high-degree of power line scene complexity with irregular distribution of point clouds. This research focuses on correcting incompletely reconstructed power line models by applying a multi-level span analysis which utilizes the benefits of topological relations within inner-span and across neighbouring spans. The inner-span analysis is developed based on Minimum Description Length (MDL) theorem for rectifying under-reconstruction over bundled wires and over-reconstruction errors of partially detected lines. The across-span alaysis aims to adjust the parameters of power-line models by detecting precise location of POAs (Position Of Attachment). The POA detection is performed by analyzing a line-connectivity of conjugated paired lines found around a power tower. The proposed method also demonstrates a localization and prismatic modelling of power tower by a incremental searching of voxel space. The localization of power towers is used for final POA detection and adjustment of power-line parameters for completing power-line models.

1. INTRODUCTION

The North American electric power distribution network comprises a vast critical infrastructure of interconnected grids and power lines. Effective management of this system requires timely, accurate power line mapping and monitoring. Scene analysis for power-line change monitoring requires precise detection of all key corridor objects (i.e., power-lines, towers, insulators, splices, switches and other components as well as the terrain, buildings, trees, etc.) after the northeast blackout of 2003, especially. Maintenance of transmission line corridors called the Right-of-Way (ROW) in terms of rapid risk management focuses on supporting immediate response for possible dangerous situation by delivering rapid mapping products such as violation reports to the utility firms, which include hazard trees, vegetation encroachments, physical transmission structure information and so forth. However, since utility companies normally depend on a manual process with a few automatic steps as a primary methodology to analyze an urgent situation in ROW, the workflow for maintenance would be costly, slow, tedious and expensive. For example, Hydro One in Ontario sends off ground crews to the field who inspect its ROW manually, rarely surveying the area aerially, while other utilities firms like American Electric Power or FirstEnergy in the U.S. use airborne surveys to inspect its ROW (Ituen et. al., 2008). In recent years, since the state-of-the-art data acquisition systems, especially airborne LIDAR system integrated with digital cameras, are introduced for rapid mapping, utility companies become expecting more cost-effective automated approaches to extract critical and meaningful deliverables from the data source. They also expect the whole workflow of data acquisition, processing, analysis, and ROW clearance to be completed within 72 hours for providing rapid mapping service uninterrupted (Neal, 2009). The data processing step in the conventional maintenance procedure normally spends the most of the time to classify features and validate the relationship between power line infrastructure and other features. Thus, in order to meet an efficient and rapid risk analysis between corresponding features, main researches during the last five years have introduced on automatic power line scene classification and modeling using 3D point clouds and imagery data acquired from up-to-date airborne remote sensors. According to the primary data sources used, the proposed techniques can be divided into two categories: 3D point-based approaches (Melzer and Briese (2004), Clode and Rottensteiner (2005), McLaughlin (2006), Vale and Gomes-Mota (2007), Jwa et. al. (2009)) and 2D image-based approaches (Yan et. al. (2007), Li et. al. (2009)). The authors proposed a new method to automatically reconstruct 3D models of power-lines using airborne LiDAR data (Jwa et al., 2009). Although the method showed successful modelling achievement, there are still errors in power-line models produced which requires a rectification process to improve the algorithm's performance. This study proposes a multi-level span analysis for correcting under- and over-reconstruction errors in power-line modelling based on the authors' previous achievement. The following section introduces the previous study related to the model-based 3D power line reconstruction automatically mainly based on Jwa et al's work. Next, we outline post-processing step to use topological relations of line connectivity within each span and across spans. The experimental results are presented to validate the performance of our algorithm. Finally, the paper finishes with some concluding remarks and recommendations for future research.

2. 3D POWER-LINE RECONSTRUCTION

2.1 Method Overview

The method of automatic 3D power line reconstruction from LIDAR data based on piece-wise propagation of catenary curve model was presented in the previous study (Jwa et. al., 2009). A research outcome achieved by the proposed method can be summarized as follows; (1) using centenary line propagation model might be robust to relatively high-involvement of vegetations and power-lines belonging to the other towers; (2) a priori power line scene knowledge (i.e. pylon's position, line configuration subject to specific voltage and line analysis across spans) is not required in the process of power line reconstruction; (3) detection and modeling process of power line points are integrated in order to increase the efficiency of workflow without power line scene classification in advance.
The proposed model-based approach uses different types of features at different levels of perceptual grouping process. At the first level, the method starts to detect power-line candidate points from unlabelled LiDAR point of clouds which are potentially located on wires. The detection of power-line candidate points are accomplished by a hybrid decision filter integrating properties obtained by Hough Transformation, Eigen-value analysis and point density ratio. The next step is to attribute detected candidate points with line orientation using a compass filter. Based on the orientation similarity, candidate points are grouped into a number of line primitives based on a statistical outlier testing. An initial estimation of the power-line model parameters represented with catenary curve is done by non-linear least-square adjustment. This initial model is propagated to some extent based on stochastic constrained least square adjustment. Rather propagating one model, a multiple numbers of hypothetical models are predicted, each of which goodness-of-fit is measure. A final prediction is determined with give the minimum closeness between the model and LiDAR observations. Thus, the parameters of the power-line model are updated from the initialization result. This prediction and update process continue till an adjustment solution is converged within expected modelling accuracy. Figure 1 illustrates a schematic diagram describing the proposed incremental propagation of catenary line models. More detail description was provided in Jwa et al's work (2009).

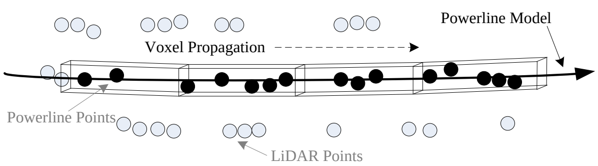


Figure 1. Illustration of piecewise propagation of catenary power-line model (Jwa et al, 2009).

2.2 Limitations

Although the proposed reconstruction method demonstrated its success, there are still errors left to be rectified. Figure 2 shows main limitations of the proposed automatic approach due to power line scene complexity and irregularity of data distribution, which result in under- and over- power line reconstruction. Figure 2(a) shows a problematic scene where power-line is captured by airborne LiDAR with low point density and large data gap due to occlusion effect. This problem often occurs over low-voltage power-lines (e.g., 13Kv conductors) or where many power-lines with different voltages run over together causing heavy occlusions. Under this circumstance, the reconstruction suffers difficulties of under-reconstruction problem where line modelling is early terminated which produces wrong localization of line ends. On the other hand, the method causes over-reconstruction problems in a situation where lines are too closely located each other to split them with separate models. Figure 2(b) illustrates this type of errors which often occurs over the bundled wires that are physically separated within less than 1.5 feet. As the point clouds are also distributed with random errors (i.e. normally more than 0.5 feet 3D accuracy), the distance between lines in the bundle becomes closer than the gap of real lines. Over-detected power lines on the same power line due to irregularity of data distribution and data gap are illustrated in Figure 2(c). Figure 2(d) presents problematic situation where a power-line is completely missed during the reconstruction process since power-line candidate points are not able to be detected sufficiently for modelling purpose due to heavy involvement of vegetation.

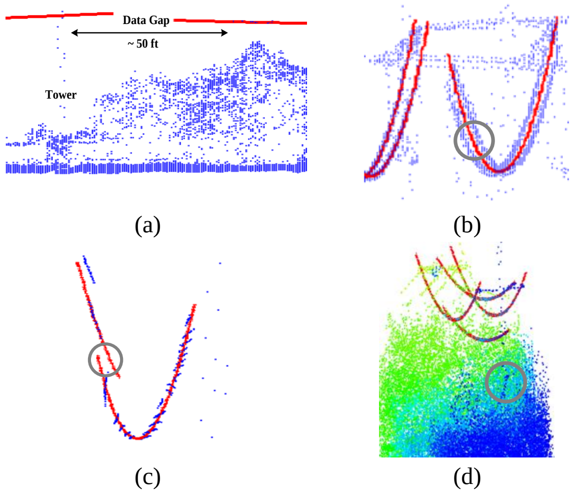


Figure 2. Examples of under- and over-reconstruction errors of automatic power-line reconstruction method proposed by Jwa et al. (2009).

In order to address these errors of the power-line reconstruction technique, we present herein a post-processing algorithm to rectify the under- and over-reconstruction errors of power-line models. The proposed post-processing is comprised of two main steps; inner- and across-span analysis. Under- and over-reconstruction errors shown in Figure 2(b) and (c) respectively are corrected by splitting and merging power-line models per one span ("inner-span analysis). This is accomplished by applying well-known MDL (Minimum Description Length) process. In addition, partially detected line shown in Figure 2(a) is rectified by extracting POA (Point of Attachment) which is accomplished by analysing a line-connectivity of conjugate paired lines across two spans. Errors in Figure 2(d) might be hard to recover it without manual processing due to significant deficiency of modelling cues. *A prior* knowledge to support the presence of missing line should be provided in advance or obtained during the post-processing procedure. A post-processing for handling errors in Figure 2(d) is not discussed here.

3. POST-PROCESSING OF 3D POWER-LINE MODEL

Post-processing with respect to power line reconstruction is defined as an additional step to improve robustness and reliability of the automation of the power-line modeling. We achieved a successful outcome by applying the automated technique of 3D power-line reconstruction discussed in Section 2. However, the result still produced errors which cause incompleteness of power-line modelling which requires a post-processing process. Figure 3 illustrates the overall workflow of the previously proposed power-line reconstruction method and currently studied post-processing technique. After extracting 3D power line models automatically, post-processing is applied for under- and over- reconstructed power line models. The proposed post-processing framework is comprised of main three steps: 1) inner-span analysis; 2) across-span analysis; 3) power tower modelling; 4) POA detection. The first step aims to rectify under-reconstruction and over-reconstruction errors by applying MDL (Minimum Description Length) principle to each power-line localized within one span. The MDL plays a role as an optimal scoring function to determine merging or splitting power-lines reconstructed in Section 2. The second step is to readjust power-line parameters by analyzing power-line connectivity between two consecutively connected spans. This process determines paired power-lines across a power tower and localizes the intersecting position of two lines, which is called as POA (Point of Attachment). By knowing the POA position, we are able to further adjust the parameters of power-lines which reconstruction are early terminated during the reconstruction process so their ends are far from the power tower. The last two steps aim to reconstruct the model of the power towers, with which further detection of POA and thus adjustment of the power-lines that are missed during the previous steps is achieved

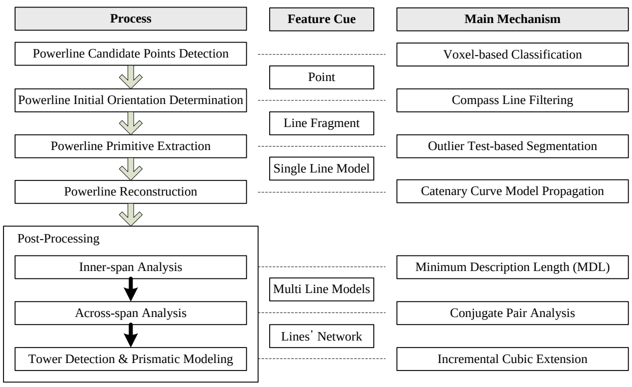


Figure 3. The overall procedure of the proposed 3D power line reconstruction and post-processing method.

3.1 Inner-span Analysis

The proposed inner-span analysis is similar to a splitting-and-merging algorithm. In other words, the inner-span analysis aims to merge over-reconstructed lines into one single power-line or split under-reconstructed lines into two or more numbers of lines. Through our extensive visual inspection over experimental results, the over-reconstructed errors usually occur where LiDAR point density and spacing are very irregular so that lines are usually segmented into multiple line segments. However, the under-reconstructed errors can be found where power-lines are very closely located each other (e.g., bundled wires) so that two lines are modelled with one line. To resolve this problem, we adopt the MDL theorem for testing multiple hypotheses of merging and splitting over power-line models questioned. Li (1992) presented 2D shape description approach including straight and curved lines based on MDL criterion which can drive an optimal description between a given data set and generated models. Based on the theory of MDL, we select several terms as shown in Equation 1, which is from the MDL equation suggested by Li, to find the optimal 3D power line model in alternative hypotheses derived from a given data set. For each hypothesis, the description length, DL, is determined using goodness-of-fit criteria between the hypothesized model and its corresponding data set. Given a power line model, ϕ, and the observation, *D*, DL is defined as

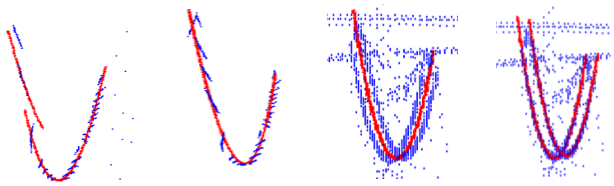
$$\begin{aligned} DL &= L(D\,|\,\phi) + L(\phi) \\ &= \frac{m}{2} lbn\left[lb\frac{l}{\varepsilon} + L_g(D,\hat{\sigma}) \right] + m\left(lb\frac{R_x}{\varepsilon} + lb\frac{R_x}{\varepsilon} \right) \end{aligned} \tag{1}$$

Where, $L(D\,|\,\phi)$ is description length of data on model (ϕ), $L(\phi)$ is description length of the parameters of model, L_g is error between observation and model which is with Gaussian distribution, *m* and *n* is the number of parameter and observation, ε is resolution to extract each line, *R* is range of data domain, *l* is length of power line.

The verification of power line model based on MDL is performed by generating two possible hypotheses: null hypothesis, H_0, and alternative hypothesis, H_a. In the given data domain, H_0 indicates a current power line model and H_a means power line model regenerated by merging or splitting the current power line models. Finally, the hypothesis with minimum DL is to be chosen as the best approximated power line model. Note that the merge and split step is terminated if null hypothesis is selected as the optimal model in global data domain as depicted in Equation 2.

$$H^* = \underset{\forall\{H\}}{\arg\min}\{DL\} \tag{2}$$

Figure 4 illustrates an example for determining an optimal power line model after generating H_a based on the theory of MDL in the local data domain. Figure 4(a) and (b) illustrate an over-reconstruction error which is corrected by the proposed method. DL is measured with a null hypothesis of H_0. After alternative merging hypothesis of H_a is produced with given data, alternative DL is measured and compared to the null hypothesis case. An optimal hypothesis is determined for merging over-reconstructed lines in Figure 4(b). Figure 4(c) and (d) show an under-reconstruction error. Similarly to the over-reconstruction error correction, a number of alternative hypotheses are produced by changing the numbers of power-lines models applied to the given datasets. DLs are computed per each hypothesis and an optimal one is selected which give the minimum DL value. Figure 4(d) shows that the MDL selected splitting over the datasets with two power-line models as an optimal decision. That is, the closeness between model and data lead to reduce the total DL despite increase of the number of model parameters for representation of power lines.

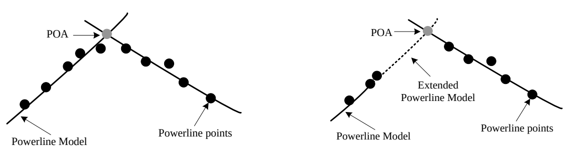


(a) H_0 (b) $H^* = H_a$ (c) H_0 (d) $H^* = H_a$

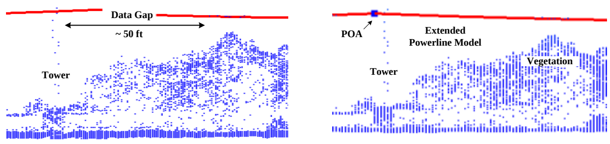
Figure 4. Illustration of the inner-span analysis for rectifying under- and over-reconstruction errors.

3.2 Across-span Analysis

The across-span analysis is a procedure to rectify errors in power-line reconstruction caused especially when the model solution is early converged, called as "partial reconstruction errors" in current study. This error is special type of under-reconstruction errors. Figure 5 illustrated two exemplary errors caused when paired line ends across spans are not linked each other. As a valuable by-product obtained by this process, precise POA (Point of Attachments) can be obtained. A POA is defined as a 3D point to which two consecutive power-line pairs is connected each other around the pylon. Conducting insulators are usually attached to the POA. It is critical to know precise POAs in the power-line network for many applications including derivation of current workload and simulating line-safety. Note that this process does not aim to find POAs for "dead end" lines where transmission lines between two spans are not directly linked thorough POA, but insulating guide-lines. As the first step of the process, all power-lines per a span were virtually extended to half of line lengths from each of line endings. Then, a 3D line connectivity analysis is performed to find conjugate line pairs by investigating closeness between two lines. 1-to-N analysis is done for finding a possible candidate of conjugate line pair pairs which provides an intersecting position and minimum distance deviation. A final decision is made to accept a paired line candidate as a real intersecting line if the deviation is less than two times of line modelling accuracy, σ_M ,which is derived from $\sigma_M = Max\{\sigma_1, \sigma_2\}$, where σ_1 and σ_2 are the goodness of fit between a line model and corresponding LiDAR observation used. Once all paired lines are obtained, the position of the POA can be calculated by intersecting two paired lines by minimising distance between two lines and considering average directions of all paired power-lines of the spans considered using least-square adjustment. After all the POAs are detected, the errors of partially reconstructed lines are rectified so that its length and position of the line end are corrected. Figure 5 illustrates the proposed POA detection procedure where a partially reconstructed lines shown in Figure 5(c) due to a large gaps of LiDAR point acquisition (i.e., no point acquired over 50 feet) is adjusted by the across-span analysis for POA detection. The result of POA detection is shown in Figure 5(d).



(a) (b)

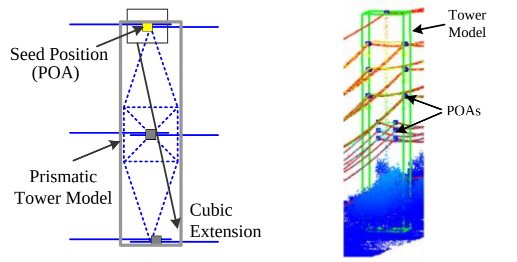


(c) (d)

Figure 5. POAs detection and complete reconstruction of partially extracted lines based on conjugate pair lines' analysis.

3.3 Power Tower Modelling

This process is to localize and model a power tower, often called as Pylon with a cubic-like prismatic model. After the POA detection process is finished, a small cubic searching space is produced from a detected POA as a seed point for reconstructing the model of power tower. This cubic searching element incrementally grows if either unlabelled point or another POA is found within the cubic space. This cubic growing process continues until no unlabelled point or POA cannot be found. Afterward, a final cubic model is reconstructed to encompass entire individual cubic elements and then final model parameter is adjusted to minimize its volume, but with maximal member points. Figure 6(b) depicts the example of tower model extracted as prismatic model based on the method of incremental cubic extension from a real data set. Point clouds which are unclassified and located within the tower model will be classified as the tower class. Note that this tower detection is developed based on the assumption that POAs are usually located around at the power tower.



(a) (b)

Figure 6. Tower detection based on the method of incremental cubic extension.

3.4 POA Detection Using Power Tower Model

Although the most of POAs are detected by the across-span analysis, there are still some erroneous lines left as being partially reconstructed so that two consecutive lines are not intersected at a specific position. This error occurs to the cases where: 1) in reality there is no paired line so the across-span analysis fails to find conjugate pairs; 2) pre-defined threshold for the across-span analysis is not valid to some power-line scenes. For resolving the aforementioned problems, the reconstructed tower model is used for finding POAs which leads to the adjustment of the power-line parameters. We first estimate parameters of rotation matrix to adjust a tower model to the dominant direction of power-lines belonging to the model. An averaged direction of the member power-lines is calculated for the rotation parameter adjustment. The tower model is now rotated by achieving a maximal orthogonality to the member power-lines. The next step is to produce a 2D plane passing through the centre of the tower model which normal direction is parallel to the averaged power-line direction. The positions of

POAs that are missed in the previous steps are then computed by intersecting power-lines with no POA with the 2D centre plane of the tower model. Figure 7(a) and (b) illustrate POA detection procedure using a power tower model. Figure 7(c) and (d) show the result of updating power-line parameters of an over-extended line model by the proposed POA detection method.

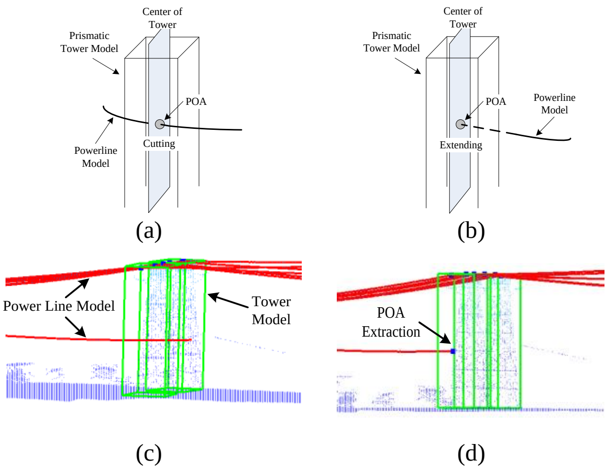


Figure 7. A schematic diagram to describe the proposed POA detection method using the tower model: before applying POA detection (a) and (c); after applying POA detection (b) and (d).

4. EXPERIMENTAL RESULT

We demonstrate the performance of proposed post-processing approach over the urban data set which was used in the previous study (Jwa et. al., 2009). The test data set obtained from Riegl Q560 covers an area of about 2094(length) × 385(width) ft^2. The average point density and average point distance on power lines are 5 (points/ft^2) and 1.03 feet respectively. Figure 8 and Table 1 illustrate the results of 3D power line reconstruction before and after the proposed post-processing method including POA detection and tower extraction. The experiment results indicate that 148 power-lines out of total 157 lines in 9 spans were successfully reconstructed which corresponds to 94.3% success rate. A final reconstruction result obtained without the post-processing is shown with black-coloured lines in Figure 8(c). We observed that there is one partially detected line model and 8 under-reconstructed power-line models in the low voltage power-lines which have high average point distance (i.e. > three times compared to the total average point distance). In the result, there are a number of bundled power-lines which are closely located to each other, less than 1.3 ft as shown in Figure 2 (a) and (b). This result was obtained by applying our previous line modeling method to the datasets.

The proposed post-processing algorithm was applied to the results of Figure 8(c). A final result after the post-processing is applied can be shown with red-coloured lines in Figure 8(d) and Figure 8(e). These two figures present post-processing results for two different power-line networks. As shown in Table 1, after performing post-processing, partial and under-reconstructed power line models are compensated successively. All the modelling errors were eliminated by the proposed post-processing method. In addition, we manually counted 125 POAs and 21 towers located toward main direction in the data set. The proposed methods for POA detection and tower extraction achieved high success rate of 99.2% and 85.7% respectively. Under- and over-detection of POA and tower mainly occur over the low-voltage power-lines which are usually captured by airborne LiDAR with low point density and many lines without having their conjugate pairs. A line with no its conjugate line pair leads to under-detection errors to find POA and tower. This is happened because the presence of POA is critical to extract towers and thus adjustment of POA position. We also found that the proposed post-processing still has a problem to over-detect towers, particularly over the low-voltage lines. In general, it is hard to localize the tower region well enough if sufficient amount of LiDAR points are not hit on the towers which leads to multiple-segmentation of one towers by the proposed method. This is the case for the low-voltage region.

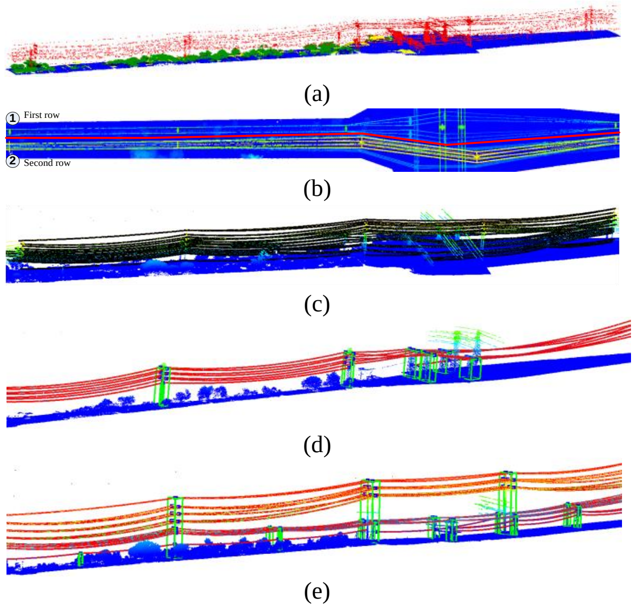


Figure 8. Raw LiDAR data set in (a) 3D and (b) 2D; 3D power-line modelling result in (c); post-processing results in (d) and (e).

Table 1. Experimental results of 3D power-line reconstruction; (a) before post-processing; (b) after post-processing; (c) first POA detection, (d) tower extraction, and (e) second POA detection

(a) Before post-processing			
	Complete Detection	Partial Detection	Under Detection
Number	148	1	8
Rate (%)	94.3	0.6	5.1
(b) After post-processing			
Number	157	0	0
Rate (%)	100	0	0
(c) First POA detection			
	Complete Detection	Under-detected	Over-detected
Number	117	8	0
Rate (%)	93.6	6.4	0.0
(d) Tower extraction			
Number	18	1	2
Rate (%)	85.7	4.7	9.6
(e) Second POA detection			
Number	124	1	0
Rate (%)	99.2	0.8	0.0

5. CONCLUSIONS

This paper proposed a post-processing method to automatically rectify under- and over-reconstruction errors in 3D power-line modeling. The proposed approach started with power line models reconstructed by automatic approach using catenary curve equation. Then, an inner-span line analysis was performed based on the MDL framework which rectifies under- and over-reconstructed power-line models by achieving an optimal balance between hypothesized model complexity and goodness of fit of the models hypothesized to observations. We also proposed the across-span analysis for re-adjusting power-line model parameters by detecting POAs and towers. Final results obtained by the proposed post-processing method showed that: (a) Under- and over-reconstructed power line models including partially detected lines could be corrected completely, 100% success rate in the test area. (b) The parameters of power line models are able to be updated so that more accurate information of line length and the positions of POA and sag point can be achieved. (c) Tower points can be classified by localizing tower with the prismatic models. It is critical to know precise measurement of power-line structure (length, numbers of power-lines, gaps between lines, sag position, POA and so forth) in order to keep up high-quality maintenance of power-line safety to unforeseen risk factors. The researches discussed here is that an automation of 3D power-line reconstruction can be achievable using high-density LiDAR data. However, in order to apply the proposed algorithm for practical operations, more extensive throughput test to evaluate the efficiency (cost-saving), reliability (accuracy compared to the ground truth) and robustness (testing over more diversified voltage types and structures) should be required as our future research direction.

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