An Automated Method for Individual Wire Extraction from Power Line Corridor using LiDAR Data

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Abstract—The speedy development in electricity infrastructure due to urge in domestic and business usage requires a safe and secure maintenance of power line corridor (PLC) for the delivery of uninterrupted power supply to consumers. Inspection of PLC using light detection and ranging (LiDAR) has gain importance in the recent decade. In this paper, we have presented a new method for automatic extraction of wires from PLC using LiDAR point cloud data. Firstly, the pylon and vegetation points around the PLC are removed by using their shape and area properties. Then, pylon locations are used to extract the wire points in the form of span between two consecutive pylons. These spans are divided into several segments such that each segment has slice of wires from the span. A clustering algorithm based on the Euclidean distance is used to separate wires which are at different height levels in each segment and the number of wires in each cluster is counted. Points in each cluster are projected into a plane perpendicular to the direction of wires. Finally, wires are separated by fitting a 2D line and by using point and line distance formula. Results are presented on different spans from complex and semi-complex data sets with low point density. Experimental results show that the proposed method is able to extract the single or bundle wires with completeness and correctness of 99% and 100%, respectively.

Index Terms—Wires, segmentation, clustering, span, pylon

I. INTRODUCTION

Electricity plays a vital role in activities of modern society. For reliable delivery of electricity, it is very important for utility companies to monitor and maintain the power line corridor (PLC) effectively. The monitoring of PLC primarily includes two following groups of objects: electrical components such as wires and pylons, and surrounding objects, such as vegetation. For reliable transmission the stability of wires and pylons, and monitoring of vegetation near PLC is important. High vegetation (trees) may touch the wires and pylons and cause power failure during windy weather and storms. Thus, there is a need of the regular monitoring and maintenance of power lines (PLs) for assurance of reliable passage of electricity [1]. The conventional methods for an inspection of electric network to patrol PLs have limitations such as participation of ground personnel which is time consuming and expensive. With the advancement in remote sensing technology many researches have been employed primarily including

optical satellite [2] and synthetic aperture radar (SAR) [3], aerial and thermal images to extract PLC objects. But these sensors have limitations such as weather dependency and occlusion. Light detection and ranging (LiDAR) has been proven a powerful tool to overcome these limitations to enable more efficient inspection in recent years. Active airborne LiDAR systems directly capture the 3D information of power infrastructure and surrounding objects [4]. The Airborne laser scanning (ALS) technique is useful for the monitoring of narrow corridors such as railways, dikes, pipelines and overhead transmission lines [5] [6]. Due to an improvement in LiDAR technology, the small objects with small diameter such as PLs and Pylons can be extracted with accurate measurements [7]. Many researches have shown good results in extraction of PLC objects in urban and non-urban areas [8].

II. RELATED WORK

The methods used for detection, extraction and reconstruction of PLs can be initially divided into two groups: 2D image-based [5] and 3D point-based [9] approaches. The 2D image-based methods use the optical images under the assumption that PLs have uniform brightness, linear property and are parallel to each other. They highly depend on the contrast of the image, i.e., the background and foreground pixel difference in order to detect linear features for PLs. However, these methods are hard to automate and not suitable for 3D modeling. In contrast, methods in the 3D point-based approach first classify different objects within the PLC. Then, the 3D modeling of the corridor is based on several unique properties of the LiDAR data such as accurate height data, multiple echoes and intensity of the returned laser ray. Depending on how the data is processed the methods using 3D point-based approach can be categorised into two: grid-based [10] and point-based [9] methods.

The grid-based methods interpolate the 3D point cloud data into a 2D grid space, where each grid cell (pixel) represents information such as point height or laser intensity values. It makes the processing fast but at the cost of information lost. The point-based methods aim to extract or classify individual

objects considering every single point. Thus, they carry out a full investigation of all 3D points to label each point with an object class. The PL extraction methods in 3D point-based approach are further classified into three types based on how the input points are clustered or classified into individual objects in the scene [11]. Methods involving statistical analysis use height, density and number of pulses [12] [13]. Line-based methods typically employ Hough Transform (HT) and RANSAC (RANdom SAMple Conseus) algorithms [11]. Supervised classification-based methods first extract several features from the input data and, then, apply a classification algorithm [9].

Majority of the PL extraction methods fall into two or more of the aforementioned categories. For example, Melzer and Briese [7] applied an iterative HT on the grid data to extract lines and clustered them together to get positions of pylons. Liu et al. [14] separated ground points from the non-ground points using a statistical analysis and applied an improved HT algorithm to the gridded data to extract wire points. Zhu and Hyypä [12] used statistical analysis involving height, density and histogram thresholds to separate PLs from other objects. Jwa et al.

[15] introduced a voxel-based piece-wise line detector (VPLD) for PL modeling from airborne point cloud data using a perceptual grouping framework which reconstructs a PL by grouping similar primitive features, i.e., points, segments and lines. The experimental results show a high success rate (93.8%) on a low point density. However, the method would not work in situations where the gap between the successive points on the same PL is large and when PLs change direction abruptly. McLaughlin [16] computed the Gaussian mixture model using the expectation minimisation algorithm and clustered the point cloud data into three clusters: transmission lines, vegetation and surfaces (e.g., buildings) using the elliptical neighbourhood whose size was determined the gap between the transmission lines in the input data.

Kim and Sohn [9] proposed another 3D point-based supervised classification using RF and divided the objects in the PLC into wires, pylons, vegetation, buildings and low objects. Guo et al. [17] first extracted 26 different features using three types of neighbourhoods: cylindrical, sphere and grid. Thereafter, they applied the JointBoost classifier to classify the objects into ground, vegetation, building, pylon and wires. Wang et al. [11] proposed a semi automatic method where the PLC direction was established using lines from the HT and the RANSAC algorithms which were applied on the 2D grid of non-ground PL candidate points. A total of 26 features were extracted using four local neighbourhoods and the SVM was used for classification. Yang et al. [1] applied Laplacian smoothing to extract the PL skeleton structure and used voxel-based latent Dirichlet allocation topic models with Markov random field (MRF) model to extract PLs. Cheng et al. [8] used vehicle-borne LiDAR data to extract PL from urban site by using an iterative clustering algorithm. Qin et al. [18] used cable inspection robot (CIR) to construct a new collection mode of LiDAR to generate the LiDAR data for PLs and single

PL spans were extracted by using voxel-based extraction and clustering.

In the literature, most of the algorithms demonstrates the extraction of single power line span or assumed bundle wires as single wire for extraction and less attention has been given to extraction of bundle wires in each span. Thus, in this paper a hierarchical and fully automated method is introduced to extract individual wires from bundle wires in each span. Firstly, standalone pylon and vegetation are extracted by using their shape and area properties. Then location of pylons is used to get wire segments in the form of spans. The span points are further segmented and projected to vertical plane for extraction of individual wires.

The remainder of this paper is structured as follows. Section II describes the proposed method in detail. Section III presents the data sets in detail with results and discussions for evaluation of the proposed method. Finally, conclusion is presented with a brief on future research directions in Section IV.

III. METHODOLOGY

The work flow for the proposed PL extraction is illustrated in Fig 1. First of all pylon locations are detected using their shape and area properties [19]. These pylon locations are used to extract the spans in PLC. For extraction of wires, each span is divided into several segments so that wires appear as straight lines in each segment. After a segmentation clustering algorithm based on the Euclidean distance is used to separate wires exist at different height levels. Finally, the clustered points are further processed for counting and separation of wires in each cluster.

Fig. 1. The work flow of the proposed method.

A. Detection of pylon location

First of all pylons with their locations are extracted using the method described in [19]. This method starts of with the removal of ground points from point cloud by using a height

threshold of 1 m [20]. The non-ground points contain three key objects, i.e., wires, pylons and vegetation. These non-ground points are separated into two classes by using the fact that pylons and trees in the data show vertical continuity, while wires hang over the terrain surface and thus show vertical discontinuity. Vertical profile features are computed over the voxel grid of $5\text{ m} \times 5\text{ m} \times 5\text{ m}$ by using the method described in Kim and Sohn [9]. Each voxel is divided into fixed segments of 1 m height. The number of “continuous on segments” and the number of “continuous off segments” are computed for each voxel. A binary mask is generated using the method described in Awrangjeb et al. [20] from vertical points i.e., trees and pylons. The resolution of M is set fixed at 0.25 m [?]. A connected component analysis is carried out on the filled image to obtain individual object boundaries. Assuming the maximum length or width of a pylon is 10 m, an area threshold $T_a = 100\text{ m}^2$ [20] is applied to remove trees with large horizontal areas.

To separate the trees whose area is comparable to pylons a connected component analysis is carried out. For each surviving connected component, the vertical points in each connected component within its boundary are taken and a 3D cuboid is formed based on the minimum and maximum easting (x), northing (y), and height (z) values. The cuboid is then divided into bins of equal size in the height direction. The value of n is empirically set 12 based on the input point density. Then, pylons are separated from small trees by counting the number of empty bins. Finally, for each pylon its location is obtained as the mean of its points.

The transmission wires in PLC is made up of numbers of spans. These spans are connected to each other through pylons. Thus the extraction of individual pylons with their locations is helpful in determining these spans. Once pylons with their locations have been identified they are used to obtain the region between, i.e., points between two successive pylons in a corridor. As the trees are already removed span points expected to contain only wire points. The span extraction reduced the size of data points and makes the further processing of wire points easier. Fig 2 shows the pylon locations of first five spans in two data sets.

B. Extraction of bundle wires

For extraction of wires it is very important to understand the structure of PLC, i.e., the structure of pylons and wires attached to it. There are following facts about PLC: Wires do not intersect each other but maintain an adequate clearance to avoid unsafe contact themselves and they are hanged above the ground level at a certain height and carry the same direction in a span [21]. Bundle wires are usually used to avoid the corona discharge and reactance among the wires. Especially the high voltage transmission lines are constructed with bundle wires instead of single wires and fixed by spacers for their structural stability maintenance [4]. Fig 3 outlines the steps of wire extraction and their details is given below.

Fig. 2. Pylon locations in two data sets.

1) Segmentation: First step of wire extraction is segmentation. To perform the segmentation over the span, it is very important to understand the basic design structure of PLC. In each span the bundle wires are attached to pylon through arms at different height levels of pylons. We have used this contextual information of pylon as parameter from the dataset to do the initial segmentation. For example, if the bundle wires in a span are attached to the arms of pylon arms at left and right sides of a pylon, the points will be divided into left and right regions first. If the bundle wires attached to pylons at left, right and centre of the pylon, in this case the points will be divided into three regions i.e., left, right and centre.

The pylons can have maximum of four arms at each height level to carry the bundle wires, so the maximum number of regions can be four. After the initial segmentation, the regions are further divided into several segments. The number of segments are directly proportional to the length of the span. Fig 3(a) shows one of the segment. The purpose of making segments in each region is to make the bundle wires appear

Fig. 3. (a) Segment of wires, (b) Clustering result, (c) initialisation of vertical plane, (d) Projected versus non projected points, (e) Project points on XOZ plane, (f) Separation of wires into two sets, (g-h) Separation of wires into four sets, (i) Wire separation result on projected points and (j) Conversion to 3D points.

as straight lines in each segment (see Fig 3(a)).

2) *Clustering* : Each segment from the previous step expect to contain wires from different height levels. As mentioned earlier in previous step that, bundle of wires at certain height do not intersect with bundle of wires at different height, and must have adequate clearance between them. Using this property of wires in a span, the hierarchical clustering algorithm based on top-down approach is used which separate the points using Euclidean distance metric. Initially, all the points are considered belong to one cluster and splits into more clusters. As the points in each segment are located at different height levels and can be separated into different clusters by using the fact that points in each bundle are very close as compared to points in different bundle. The minimum distance between bundles of wire is believed to be atleast 3 m (from the dataset) in height (z) direction. Fig 3(b) shows clusters in different colours representing bundle wires at different height levels.

3) *Wire-count on each cluster*: Identifying the number of wires in each bundle is the premise to separate bundle wires. Typically, the number of bundle wires is not more than four in PLC and each wire in bundle is spaced at (0.25 - 0.5 m from the dataset). According to the given information, theoretically, the number of wires in each cluster can be identified by finding the mean point of a cluster and calculating the maximum and minimum distance (dist) of points to the mean point. The value of wire-count is calculated as :

$$\text{wirecount} = \begin{cases} 1 & \text{if max dist - min dist is } < 0.5 \\ 2 & \text{if max dist - min dist } > 0.5 \text{ and } < 1 \\ 4 & \text{otherwise} \end{cases} \quad (1)$$

Here, we are considering only maximum of four bundle wires in each cluster and minimum of one.

4) *Projection On vertical Plane*: After determining the wire numbers in each cluster the clustered points are projected to the plane which is perpendicular to the direction of wires in a segment. Fig 3(c) depicts the vertical plane (red rectangle). It is very important to choose a plane which is orthogonal to wires, for example, in our case XOZ and YOZ planes both are suitable to project the wires while XOY is not as it is parallel to direction of wires. Fig 3(d) show the original points and projected points on a plane and Fig 3(e) shows projected points on XOZ plane. Finally, a line of best fit based on least square approach that represents the data on each cluster is projected on the 2d space of a plane using an equation given below:

$$c = \bar{z} - m\bar{x}, \quad (2)$$

$$m = \frac{\sum(x - \bar{x}) * \sum(z - \bar{z})}{\sum(x - \bar{x})^2}$$

where, $\bar{x}$ and $\bar{z}$ are mean of the x coordinates of all the given points. m is slope of the line and Z intercept of the line. Distance of each point with the line is calculated and their location is determined "up" and "down" based on the sign of

the distance. All the wires usually does not have equal number of points. Identification of wire numbers in each cluster is very important here as if the wire-count is 1 then the clustered points are wire points. If it is 2, then points will be divided into "up" and "down" sets. If the wire-count is 4, then projecting line is not simple and straight procedure due to the fact that some wires may have more dense points while some wires have few points. The location of projected line on the plane depend upon the characteristics of wire points in a cluster. The projected line will always be formed on side dense points side. According to dense characteristics of wires, we have defined two cases.

Case 1. In this case all the wires have more or less the same number of points. It means the projected line is formed and can be easily separated into "up" and "down" sets according to their positive and negative distances. The points in each set is further split up into two subsets by projecting a fitted line again in each set.

Case 2. In this case, some wires have very few points and projected line does not formed in the middle instead it formed where points are more dense and some of the points may pass from the projected line. As the wires have minimum of 0.3 - 0.5 m distance between them, so the points with the distance less 0.25 m the points are supposed as one of the line points else points are at up location and down location. The size of two sets is calculated and the set with big size is further separated into two wires as shown in Fig 3(f-i). Finally, the projected separated points are converted to 3D points (see Fig(j)).

IV. PERFORMANCE EVALUATION

In this section, the details of data sets and results are presented in detail.

A. Experimental data

To test the feasibility of the proposed method, two different data sets depicted in Fig 4(a) and (b) are used from Main-dample (MDP), Victoria and Bindebango (BDB), Queensland Australia with desnity of 23.7 and 56.4 points/m² respectively. The MDP has two transmission line corridors (TLCs). While the BDB has three TLCs. Table 1 shows the summary of the ground truth used for evaluation of results. The number of wires in Table 1 and 2 is calculated by counting the number of wires in each span.

TABLE I
SUMMARY OF THE DATASET I (MAINDAMPLE) GROUND TRUTH.

TLC	Points		Total	
Area	All	Wires	Span	Wires
900 × 330	46,219	40,510	5	45
557 × 430	352,042	38,965	5	45
Total = 1457 × 760	398,261	79,475	10	90

Fig. 4. (a) Maindample, (b) Magnified version (Maindample), (c) Bindebango, and (d) Magnified version of (Bindebango).

TABLE II
SUMMARY OF THE DATASET 2 (BINDEBANGO) GROUND TRUTH.

TLC Area	Points		Total	
	All	Wires	Span	Wires
350×330	50,862	40,211	2	28
250×330	24,317	19,364	2	10
250×330	22,094	18,110	2	10
Total = 850×990	97,273	77,685	6	48

TABLE IV
POINT-BASED EVALUATION OF WIRES IN TWO DATA SETS.

Data sets	Wires		
	Comp.	Corr.	Qual.
Maindample	98.6	99.1	98.4
Bindebango	99.7	99.4	99.63
Average	99.15	100	99.01

B. Results and discussions

For performance evaluation, object- and point-based completeness C_m , correctness C_r and quality Q_l and [11]. For object-based evaluation, the total number of extracted wires in both dataset of five spans from each of the TLCs in each data set are counted. Table 2 shows the object and point-based evaluation results for the dataset. All the wires from two given data sets are extracted. In both sites, some of the wire points are misclassified as pylon points as these wire points are very close to pylons and hard to separate using vertical profile features see Fig 2(c). All the wires are correctly extracted despite the shortage of points in some spans.

TABLE III
OBJECT-BASED EVALUATION OF WIRES ON TWO DATA SETS.

Data sets	Wires		
	Comp.	Corr.	Qual.
Maindample	98.5	100	98.1
Bindebango	99.6	100	99.5
Average	99.05	100	98.8

C. Comparison with existing methods

The novelty of this study is the individual wire extraction from complexed data sets unlike the previous research works which mostly focused on extraction of single wires or considered bundle wires as single wires due to very small distance among them. A few studies has given an automated solution for individual PL extraction but they present result on single wires. such as Jwa et al. [15] present an automated voxel-based solution for PL extraction with completeness of 93.4%. Zhu and Hyppä [12] provide an automated solution to detect PLs with 93.26% accuracy. Cheng et al. [8] proposed a method to extract PLS from urban areas using vehicle-borne LiDAR data with correctness and completeness of 100% and 97.2%. The proposed method has achieved better accuracy i.e., 99% and 100% in terms of completeness and correctness.

V. CONCLUSION

Existing methods mostly extract the single wires and limited solutions have been provided for bundle wire extraction which is very important for detailed PLC mapping and 3D modelling. An automated solution is provided in this paper to address the extraction of individual wires in complex and semi-complex environment with low point density. A hierarchical approach is adopted that first extract the pylon with their locations

(a)

(b)

(c)

(d)

(e)

Fig. 5. Extraction of wires in different spans from two data sets

which is used to extract the span points. The proposed method shows 99% and 100% completeness and correctness. Though it depends upon some parameters from data sets which can be automate by adding pylon contextual information. In future, we will investigate the reconstruction of PLs and pylons for automation of PLC. It will be very interesting to see the how pylon contextual information will improve the wires extraction and reconstruction results. Moreover, the location of pylons, wires and vegetation can be further used to monitor the vegetation near PLC to prevent risk from tall and growing trees closely to power lines.

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