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ORIGINAL PAPER

Understanding of leaning utility poles for visual monitoring of power distribution infrastructure

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Abstract
Protecting power infrastructure through visual surveillance can assure the safe operation of a power system, especially in unstructured environments where leaning utility poles are particularly inclined to cause large-area blackouts or even personal injury. Current methods place too much emphasis on detection and not enough on understanding leaning postures. However, due to the diversity and uncertainty of leaning utility poles, understanding them remains an urgent problem. Traditional posture estimation via three-dimensional (3D) point clouds is energy-intensive and costly, which limits its adoption in resource-constrained visual surveillance systems. In this study, we present a methodology to understand utility poles, and to estimate their leaning postures using a low-cost monocular camera. Edges and lines are extracted. Through their corresponding proximity and orientation, potential lines of utility poles are estimated. By analyzing relative geometric constraints between potential lines, utility poles are segmented and corresponding leaning angles are estimated, which is helpful to make risk-informed decisions to make leaning utility poles resilient. The approach requires neither prior training, nor calibration or adjustment of the camera's internal parameters. It is robust against color and illumination associated with severe weather conditions. The percentage of correctly segmented pixels was compared to the ground truth, demonstrating that the method can successfully understand utility poles, meeting safety monitoring requirements for power infrastructure.

Keywords Utility pole · Visual monitoring · Power distribution infrastructure · Vulnerability · Smart grid

1 Introduction

Ensuring stable power transmission is of great importance. Electrical departments at all levels must conduct regular inspections of power lines to prevent damage caused by illegal activities, adverse weather conditions, natural wear and tear, and other factors [1–3]. The rapid identification of leaning utility poles through visual monitoring is important to ensure the safe operation of the power system. Although many solutions, such as deep learning-based methods, have been proposed, these have many shortcomings and cannot meet the low cost and high efficiency requirements of power companies. Therefore, the use of limited computing, memory, and energy resources to understand the leaning postures of utility poles remains a challenge.

Unlike structured scenes, most leaning utility poles are located in unpredictable and unstructured environments where structural and dimensional changes are irregular and unstable, and environmental information is non-fixed, unknowable and indescribable, as shown in Fig. 1. This makes it difficult to apply existing structured scene understanding methods [4–6]. Leaning utility pole road scenes include pedestrians, vehicles, buildings, trees, and power lines. Unlike road scenes captured by light detection and ranging (LiDAR), these scenes are subject to interference from vehicles, trees alongside the road, and power lines on tilted utility poles, which affects the recognition of a leaning utility pole's outline. However, tilted utility poles have distinct characteristics: they are not vertical or horizontal, and two of their lines are relatively long and parallel. We can

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Fig. 1 Diverse leaning utility poles in unstructured environment

understand them by combining the length and corresponding angles. These geometric features, extracted through the combination of length and angles, maintain specific characteristics in terms of integrity and direction, enabling us to understand them in such environments.

Public utility companies have various methods for detecting utility poles. Cetin proposed a method that locates utility poles by detecting their shadows in aerial images [7]. However, this method is limited by the requirement of clear shadows in flat terrains. With the advancement of drone technology, Sharma developed a method that extracts the two-dimensional geometric shape of utility poles using shape-based templates, where a long trapezoid intersects vertically with at least one trapezoid representing the crossarm [8]. The method presents a low-cost, non-contact, vision-based multipoint displacement measurement system [9]. Another method was presented for the estimation of the location of power lines in space from point clouds, but not leaning poles [10]. Avila proposed an autonomous drone system that combines state flow machines with image recognition neural networks to make decisions on search, identification, and flight along utility poles and power lines [11]. Due to weather and vegetation interference, some utility poles cannot be detected through drone-based methods. Therefore, Gonzalez combined mobile laser scanning (MLS) and handheld mobile laser scanning (HMLS) to identify utility poles along roadways [12]. Landa proposed a novel method for detecting pole-like objects from laser scanning data, and utilized directional vectors to detect pole-like structures in unordered point clouds [13]. Talebi and Kang presented multiple methods for detecting utility poles using mobile laser scanning data in complex urban scenes [14, 15]. However, the high cost of handheld mobile laser scanning, and radar hinders their widespread use by utility companies.

Surveillance cameras are ubiquitous on the streets. These ordinary monocular cameras can be used to take video footage at intersections, streets, and other areas. Using these low-cost street cameras to understand tilted power poles on the side of the road is more convenient and efficient than three-dimensional (3D) point cloud or drone detection methods, because 3D point clouds are costly to acquire, and drones are susceptible to meteorological and other factors such as wind and rain during flight, and require battery replenishment. Unlike semantic information with weak interpretability, interpretable visual clues are crucial for scene reconstruction. Depth perception is a reflection of how far or near different objects in space are to humans. Depth perception does not require additional information because it is innate in the human visual system [16–19]. It is difficult to obtain an accurate absolute depth of field through image recognition alone, but it is possible to infer relative depth and direction of spatial structures through geometric features captured in two dimensions (2D), which is crucial for understanding scenes.

Deep learning methods, such as the convolutional neural network (CNN) [20–22] and YOLO [23], have been proven to be effective in power pole detection. With the maturity of the technology, researchers have made improvements to better identify power poles. Huang developed and released a large-scale power grid labeling dataset using DCNN deep learning networks, and reported baseline results for power pole detection [24]. Jeddi proposed a lightweight CNN architecture, PDP-CNN, featuring multi-scale feature operations and anchor-free power pole detection [25]. Abid proposed an unsupervised deep learning framework for power pole detection [26]. Chen introduced a CNN-based backlight image enhancement algorithm and constructed a novel network architecture that integrates decomposition, restoration, and adjustment to recognize power poles under backlight conditions [27]. Kim proposed a novel data-driven approach to estimate and detect roadside power poles from Google Street View (GSV) images and estimate their angles, so as to support risk-informed decision-making for utility maintenance under extreme wind conditions [28]. However, most deep learning networks require training and manual labeling, which requires significant human resources and makes it challenging to generalize in power inspection systems.

With the continuous development of CNNs, semantic segmentation (extracting several specific regions of an image) has been applied in various fields. In structured

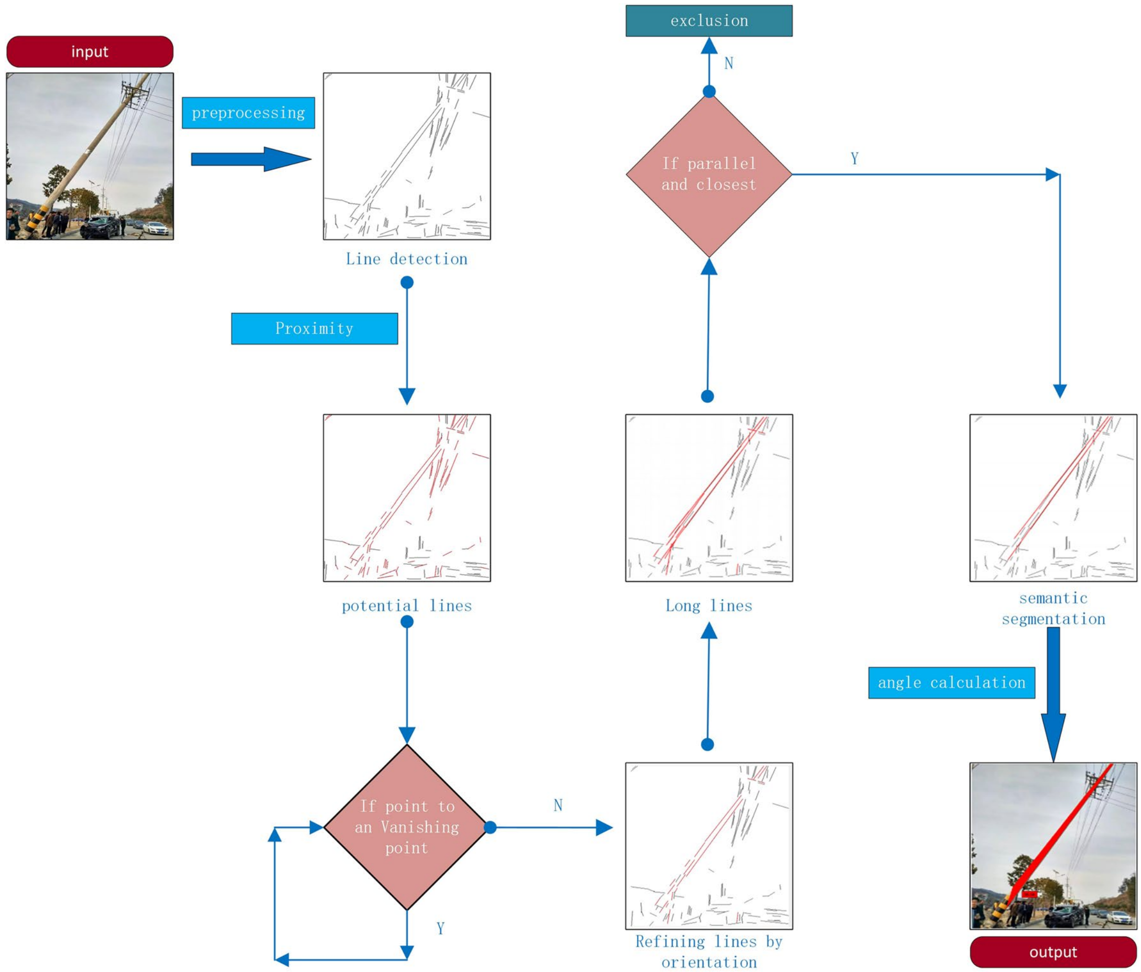

Fig. 2 In our system architecture, edges and lines are first detected. The proximity and orientation of lines are then combined to estimate potential wires of leaning utility poles. Finally, we analyze the relative geometric constraints between potential wires and vanishing points to approximate the segmentation of tilted utility poles

urban scenes, Vasavi proposed a deep learning-based U-Net semantic segmentation method using ResNet-34 as the backbone network for classifying urban buildings [29]. Chen introduced an object-guided distillation method and spatial-aware adaptation approach, using synthetic data for semantic segmentation of urban scenes [30]. Feng presented a semi-supervised learning framework, InvSSL, for medical image segmentation, utilizing GAN inversion to generate corresponding variants from labeled images [31]. Another model, DualANet, combines dual-branch encoders, multi-scale skip connections, and adaptive receptive field selection decoders to improve the accuracy of medical image segmentation [32]. Cano-Solis and Hu proposed U-Net-based methods for segmenting power lines in drone images, facilitating related power line research [33, 34]. Liao proposed a risk information quantification framework for non-structural nest risks on transmission towers based on HRNet [35], and Dosso presented a segmentation method for critical electrical infrastructure in ground images based on HRNet [36]. HRNet has also been modified for pole recognition. Suzuki proposed HRNet-OCR to identify power poles in urban areas [37]. Singh evaluated the semantic segmentation performance of the HRNet-OCR model on ground images of utility poles under Arctic weather conditions [38]. Although deep learning has been used to identify power pole scenes, its performance is poor, and it requires much training, which can consume system memory. This means that in situations where memory is limited, it is necessary to use a method that identifies tilted power poles through visual features captured in images.

We propose a method to detect the tilt posture of electric poles using a single low-cost camera. We achieve this by extracting edges and lines, and estimating the potential lines of a tilted electric pole based on their respective proximity and direction. We approximate the segmentation of the tilted electric pole by analyzing the relative geometric constraints between the potential lines and the vanishing point, and estimate its tilt angle. This simple and effective method can facilitate the safety inspection of utility poles.

In contrast to deep learning methods, the proposed approach requires no pretraining and has lower hardware requirements. By utilizing interpretable geometric inference, the method exhibits robustness to unexpected changes in color and lighting in the environment. The low-cost and lack of requirement for precise knowledge of depth or camera intrinsic parameters makes it reliable and practical in power systems.

In experiments, segmented leaning electric poles were compared with the ground truth of actual leaning electric poles alongside roads, and the percentage of correctly classified pixels was evaluated. The results demonstrate that the proposed geometric inference method is capable of understanding leaning electric poles alongside roads, offering broad prospects for its application in power system early warning.

This work makes the following contributions: (1) a method for understanding leaning power poles in unstructured environments using a monocular camera; (2) faster and simpler detection of tilted power poles through geometric calculations; (3) the use of geometric reasoning to enable the proposed method to overcome complex environmental and lighting variations, making it more robust and reliable for application in real-world environments.

2 Overview

Fig. 2 shows an overview of the proposed method. The input is a monocular image, which undergoes preprocessing to extract lines. Based on proximity such as extendability and effective length, potential lines of boundaries of a utility pole are extracted, which can be refined through the relative orientation between potential lines and vanishing points. Based on merging lines, boundary lines of a utility pole can be approximated, and corresponding leaning angles estimated.

3 Understanding leaning utility poles

3.1 Preprocessing

First, lines and vanishing point (VP) are detected [19, 39] as follows:

$$line^i = [p_1^i, p_2^i] = [x_1^i, y_1^i, x_2^i, y_2^i]; \quad i \in [1, \mathbb{N}], \tag{1}$$

$$VP = [x^V, y^V] \tag{2}$$

where $\mathbb{N}$ is the number of lines.

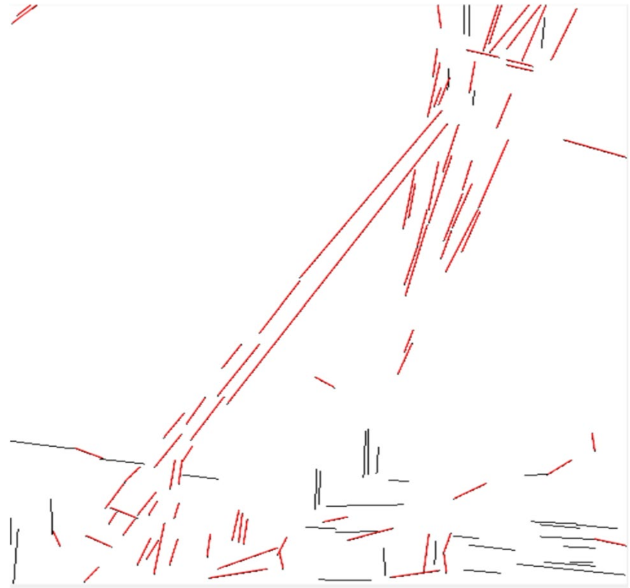

Fig. 3 Potential lines extracted by proximity. According to the normalized value for proximity, it is possible to extract the potential lines (in red) of a utility pole (color figure online)

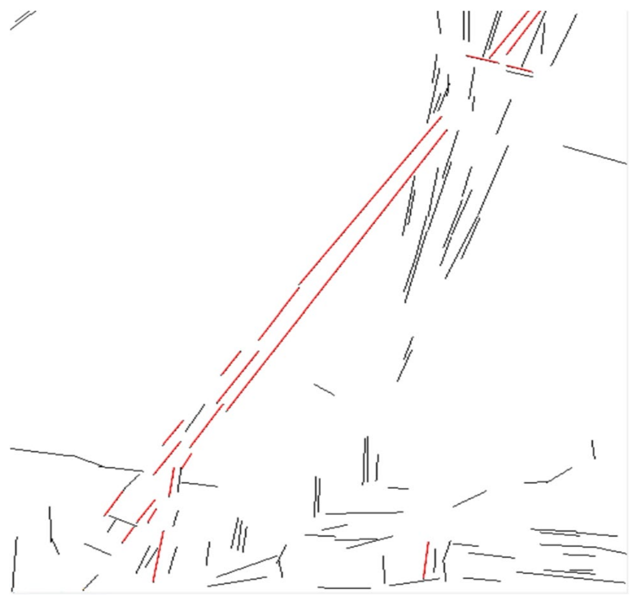

Fig. 4 Refining lines by orientation. According to the β^t value for orientation, it is possible to refine the lines (color in red) of a utility pole (color figure online)

3.2 Proximity

The edge lines of boundaries of a utility pole always appear fragmentary due to diverse disturbance from varying changes in illumination and color with unexpected weather conditions. However, there still exist traceable visual clues in which those scatter lines have geometric features including proximity and orientation, which can help us to infer the boundaries of a utility pole.

3.2.1 Extendability

Among the extracted fragmentary short lines, those following extendable constraints are more likely to be a part of a real utility pole. For each two lines, the extendable constraint can be defined as follows:

$$\tau^{i,j} = [p_m^i, p_m^j],\ i,j \in [1, \mathbb{N}] \tag{3}$$

$$\alpha^{i,j} = \Theta(\tau^{i,j}, line^i) + \Theta(\tau^{i,j}, line^j) \tag{4}$$

where Θ is a function to compute the angle between two lines. p_m^i and p_m^j are midpoints of $line^i$ and $line^j$, respectively. $\alpha^{i,j}$ is the value to measure the extendability between $line^i$ and $line^j$. A smaller $\alpha^{i,j}$ means two lines ($line^i$ and $line^j$) are more likely to compose a boundary line of a real utility pole.

3.2.2 Effective length

For two lines satisfying extensibility, the effective length responds to the relative geometric relationship between them. Two extendable lines having a good effective length are more likely to be components of a utility pole. For each two lines $line^i$ and $line^j$, the effective length can be described as follows:

$$P_j^{i,1} = \Delta(p_1^i, line^j) \tag{5}$$

$$P_j^{i,2} = \Delta(p_2^i, line^j) \tag{6}$$

where $P_j^{i,1}$ is a projected point of p_1^i on $line^j$. $P_j^{i,2}$ is another projected point. Δ is a function that computes a projected point between a point and a line.

Then the following can be found:

$$\phi^{i,j} = MAX(D(P_j^{i,2}, P_1^j), D(P_j^{i,2}, P_2^j)) \tag{7}$$

$$\varphi^{i,j} = MAX(D(P_j^{i,1}, P_1^j), D(P_j^{i,1}, P_2^j)) \tag{8}$$

where $\phi^{i,j}$ and $\varphi^{i,j}$ are two length, and the effective length can be defined as follows:

$$\mathbb{L}^{i,j} = \begin{cases} L^i + L^j,\ if(P_j^{i,1} \notin [x_1^j, x_2^j]), (P_j^{i,2} \notin [x_1^j, x_2^j]) \\ \phi^{i,j},\ if(P_j^{i,1} \in [x_1^j, x_2^j]), (P_j^{i,2} \notin [x_1^j, x_2^j]) \\ \varphi^{i,j},\ if(P_j^{i,1} \notin [x_1^j, x_2^j]), (P_j^{i,2} \in [x_1^j, x_2^j]) \\ L^j,\ if(P_j^{i,1} \in [x_1^j, x_2^j]), (P_j^{i,2} \in [x_1^j, x_2^j]) \end{cases} \tag{9}$$

where $\mathbb{L}^{i,j}$ is the effective length between $line^i$ and $line^j$. A larger $\mathbb{L}^{i,j}$ means two lines ($line^i$ and $line^j$) are more possibly partial lines of a utility pole. D is a function that compute Euclidean distance between two points.

Therefore, potential lines can be extracted by a smaller $\alpha^{i,j}$ and a larger $\mathbb{L}^{i,j}$, and these two geometric constraints can be described as follows:

$$\mathbb{C}^{i,j} = \|\alpha^{i,j}\| + \|1/\mathbb{L}^{i,j}\| \tag{10}$$

where $\mathbb{C}^{i,j}$ is a normalized value for proximity. A smaller $\mathbb{C}^{i,j}$ represents lines ($line^i$ and $line^j$) are more likely to be a utility pole. Here, we rank the line combinations according to $\mathbb{C}^{i,j}$ value. The top-ranked line combinations of smaller $\mathbb{C}^{i,j}$ are selected, which can be defined as following:

Fig. 5 Identify a leaning utility pole. First: merged long lines are extracted. Second: boundary lines. Third: understanding. Through extracting pairs of merged long lines, it is possible to identify a utility pole with a leaning angle

$$line^t = [x_1^t, y_1^t, x_2^t, y_2^t];\ t \in [1, \mathbb{N}^t], \tag{11}$$

$$St.\ Min\ \mathbb{C}^{i,j} \tag{12}$$

Here $Min\ \mathbb{C}^{i,j}$ represents the constraints that the equations should satisfy. $line^t$ represent the potential line and $\mathbb{N}^t$ is the number of potential lines, as the red lines shown in Fig. 3.

3.3 Orientation - VP

Since projected lines of a leaning utility pole do not converge to the VP, it is possible to establish another orientation constraint for extracting potential lines, which can be defined as follows:

$$\zeta^t = [p_m^t, VP],\ t \in [1, \mathbb{N}^t] \tag{13}$$

$$\beta^t = \Theta(\zeta^t, line^t) \tag{14}$$

where ζ^t is virtual line. p_m^t is the midpoint of $line^t$. β^t represents the geometric relationship between a potential line $line^t$ and VP. A larger β^t means the potential $line^t$ is more possibly a part of a utility pole.

Then, potential lines of utility poles can be refined as follows:

$$line^R = [x_1^R, y_1^R, x_2^R, y_2^R];\ R \in [1, \mathbb{N}^R], \tag{15}$$

$$St.\ Max\ \beta^t \tag{16}$$

where $line^R$ represent the refined lines. The top-ranked lines of larger β^t can be selected, as shown in Fig. 4.

3.4 Understanding

3.4.1 Merging

Since the boundaries of a utility pole are fragmentary lines, it is important to merge the scattered lines into a long line. For each two lines in the refined lines $\{line^R\}$, a merged line can be defined as follows:

$$\mathbb{M} = Max(\Gamma(line^g, line^h));\ g, h \in [1, \mathbb{N}^R], \tag{17}$$

$$St.\ Min\ \alpha^{g,h} \tag{18}$$

where $\mathbb{M}$ is a long line merged by two refined lines $line^g$ and $line^h$. Γ is a function obtaining two points that have the farthest distance. $\alpha^{g,h}$ is the angle condition. A smaller value $\alpha^{g,h}$ means two refined lines $line^g$ and $line^h$ are more likely to merge to a long line. The extracted long lines can be described as in Fig. 5.

3.4.2 Boundary lines

The boundary lines of a utility pole are seen as a pair of merged long lines, which can be defined as follows:

$$\mathbb{B} = (\mathbb{M}^m, \mathbb{M}^s);\ m, s \in [1, \mathbb{N}^{\mathbb{M}}], \tag{19}$$

$$St.\ Min\ \Theta(\mathbb{M}^m, \mathbb{M}^s), Min\ \Pi(\mathbb{M}^m, \mathbb{M}^s) \tag{20}$$

where $\mathbb{B}$ is a pair of two merged long lines $\mathbb{M}^m$ and $\mathbb{M}^s$. $\mathbb{N}^{\mathbb{M}}$ is the number of merged long lines. $\Theta(\mathbb{M}^m, \mathbb{M}^s)$ and $\Pi(\mathbb{M}^m, \mathbb{M}^s)$ are the angle and distance of two merged long lines, respectively.

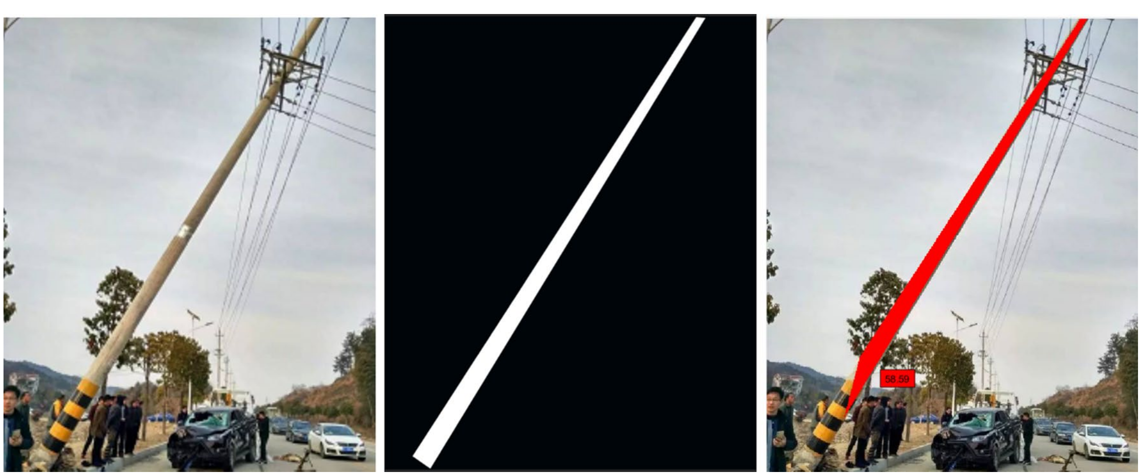

Fig. 6 Understanding a leaning utility pole. Left: input image [19]. Middle: ground truth. Right: understanding of a leaning utility pole (leaning angle is 58.59 in right). Compared to the ground truth, a utility pole (e.g., red areas) can be understood with leaning angle (color figure online)

Fig. 7 Robustness experiment. First column: original environment. From second column to right column: changes in color, illumination and image noise, respectively. The proposed method is robust against changes in color, illumination, and image noise (color figure online)

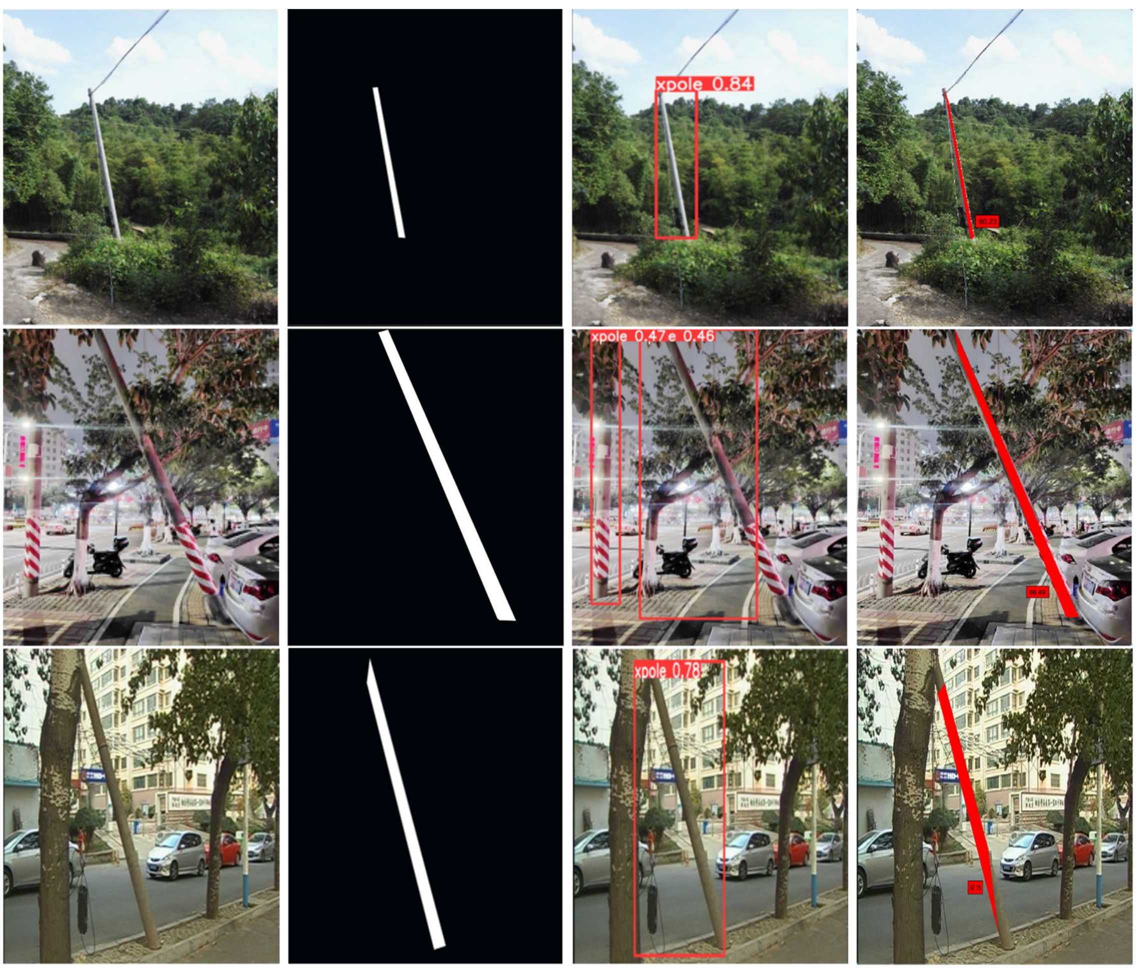

Fig. 8 Experimental comparisons with YOLOv5 [40]. First column: leaning utility poles. Second: ground truth. Third: YOLOv5 [40]. Fourth: our understanding. Our algorithm can understand leaning utility poles in various unstructured environments with leaning angles

Table 1 Evaluation on understanding utility poles

Method	Resolution(H*W)	IoU(%)
HRNet-OCR [38]	640*360	59.32%
Deeplabv3+ [41]	512*512	79.67%
Our method	1500*459	79.85%

3.4.3 Leaning angles

To evaluate the risk of structural failure of a leaning utility pole, it is important to estimate its leaning angle, which can be defined as follows:

$$\Psi = (\theta^{\mathbb{M}^m} + \theta^{\mathbb{M}^s})/2; m, s \in [1, \mathbb{N}^{\mathbb{M}}] \tag{21}$$

where Ψ is the estimated leaning angle of segmented utility pole. $\theta^{\mathbb{M}^m}$ and $\theta^{\mathbb{M}^s}$ is the slope angle of boundary lines in $\mathbb{B}$, as shown in Fig. 5.

4 Experimental results

4.1 Experimental Architecture

We proposed a geometric model to understand various inclined electric poles using a low-cost monocular camera. Since precise depth data or pretraining is not required, experiments were conducted on a computer with an Intel Core i5-10200H 2.40 GHz CPU with 16 GB of RAM, without a high-performance GPU.

4.2 Datasets

As the proposed algorithm is designed to identify leaning utility poles based on road cameras, the focus is on the identification and leaning angle of tilted utility poles in unstructured environments. Datasets such as Google Street View [38] could not meet the requirements of leaning utility poles. The FDWW dataset [19] includes diverse leaning utility

Fig. 9 Experimental comparisons with DeepLabv3+ [41]. First column: leaning utility poles. Second: ground truth. Third: DeepLabv3+ [41]. Fourth: our understanding. Our algorithm can segment leaning utility poles and understand corresponding leaning angles, without any prior training

Fig. 10 More experimental comparisons. First column: leaning utility poles [42]. Second: YOLOv5 [40]. Third: Deeplab V3+ [41]. Fourth: our understanding. Our method has better performance on understanding utility poles (e.g., 3rd row)

poles in various unstructured environments, helping us to evaluate the effectiveness of the method.

4.3 Evaluation

4.3.1 Metrics

We adopted intersection over union (IoU) as the evaluation metric. IoU is commonly used to assess performance in computer vision tasks such as object detection and image segmentation. It measures the accuracy of predicted bounding boxes by calculating the ratio between the intersection and union of the predicted and ground truth bounding boxes. The specific formula is as follows:

$$IoU = \frac{TP}{TP + FN + FP} \tag{22}$$

In the formula, TP is the number of true positive samples, which are correctly predicted as positive samples. FN is the number of false negative samples, which are negative samples incorrectly predicted as positive samples. FP is the number of false positive samples, which are positive samples incorrectly predicted as negative samples.

4.3.2 Data evaluation

In an unstructured environment, with disturbances such as cars, trees, and changing illumination (e.g., day and night), as shown in Fig. 6, our approach can successfully understand utility poles with leaning angles. Estimated electric poles were compared to ground truth, and the percentage of correctly classified pixels was evaluated, as shown in Table 1. Compared to other data-driven methods (HRNet-OCR [38] and Deeplabv3+ [41]), our algorithm shows a state-of-the-art performance at understanding diverse leaning utility poles, which is practical and feasible in the visual inspection of power distribution infrastructures.

Furthermore, an experiment on robustness was performed on leaning utility poles within diverse unstructured environments of different color, illumination and noise. Because the presented algorithm uses geometric inferences, as shown in Fig. 7, the approach can successfully understand leaning utility poles, which is robust against changes in illumination, color and image noise.

4.4 Comparison

Firstly, the proposed method was compared with the deep learning model YOLOv5 [40], with results shown in Fig. 8. Although YOLOv5 is capable of bounding the utility poles, it also includes some other clutter and it fails to interpret the orientation of tilted utility poles. In contrast, our method can understand and explain the posture of tilted utility poles in diverse unstructured environments, which is more useful to make risk-informed decisions to make power distribution infrastructures resilient.

Fig. 11 More experimental examples. First/Third row: leaning utility poles in diverse unstructured environments. Second/Fourth row: our understanding

Next, we compare our algorithm with the DeepLabv3+ semantic segmentation method, which utilizes a residual network (ResNet) as the backbone, and combines atrous convolution and multi-scale fusion strategies to achieve high-precision image segmentation [41]. Although it can segment tilted utility poles, the shapes of the segmented utility poles are irregular and incomplete, with many redundant areas. In comparison, as shown in Fig. 9, our algorithm can accurately segment the contours of utility poles using their geometric properties, without prior training, which improves the efficiency of the safety inspection of power distribution system.

More comparisons were performed on the Alam's dataset [42], as shown in Fig. 10. It is difficult to detect and segment utility poles through YOLOv5 [40] and Deeplab V3+ [41]. By contrast, our method can understand utility poles with leaning angles without any prior training.

In additional experiments, as shown in Fig. 11, the results confirmed the accuracy and robustness of the proposed algorithm in terms of both detection accuracy and resistance in such environments, enabling the enhanced reliability of power distribution infrastructure systems.

5 Conclusion

We proposed an algorithm that can effectively understand leaning utility poles in unstructured environments using a low-cost monocular camera without prior training. The image information is preprocessed to effectively extract straight lines. Subsequently, a combination strategy is employed for the initial selection of the extracted straight lines. Utilizing the geometric properties of interfering line segments, vanishing point constraints are applied for further refinement, resulting in preliminary straight lines, which can be integrated and segmented to obtain slanted power line poles. Unlike deep learning methods, the proposed algorithm is interpretable and does not require prior training. Its interpretable geometric reasoning makes it robust to changes in illumination and color. Furthermore, due to the absence of external devices, the method consumes less energy and requires less investment, enhancing its practicality and feasibility. Experimental results demonstrate that our method can effectively understand leaning utility poles in both structured and unstructured environments, meeting the requirements of power system safety inspection.

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Data availability Data will be made available on reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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