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Automatic Utility Pole Inclination Angle Measurement Using Unmanned Aerial Vehicle and Deep Learning

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Abstract

Measuring the inclination angles of utility poles of the electric power distribution lines is critical to maintain power distribution systems and minimize power outages, because the poles are very vulnerable to natural disasters. However, traditional human-based pole inspection methods are very costly and require heavy workloads. In this paper, we propose a novel pole monitoring system to measure the inclination angle of utility poles from images captured by unmanned aerial vehicle (UAV) automatically. A state-of-the-art deep learning neural network is used to detect and segment utility poles from UAV street view images, and computer vision techniques are used to calculate the inclination angles based on the segmented poles. The proposed method was evaluated using 64 images with 84 utility poles taken in different weather conditions. The pole segmentation accurcy is 93.74% and the average inclination angle error is 0.59 degrees, which demonstate the efficiency of the proposed utility pole monitoring system.

Keywords

Utility Pole Inclination Angle Measurement, Unmanned Aerial Vehicle, Deep Learning, Computer Vision

1. Introduction

The utility poles of the electric power distribution lines carrying power from local substations to customers are found to be very vulnerable to many natural disasters, such as wind gusts, storms, and hurricanes. Meanwhile, the power outages due to the failures of the poles can lead to severe consequences. For example, more than 5000 power utility poles were knocked down by the hurricane Harvey [1], and the resulting power outages caused a substantial economic loss in Texas in 2017. Therefore, monitoring the health condition of poles regularly is critical to maintain power distribution systems and minimize power outages. The inclination angle measurement of utility poles is particularly important, because inclination angles can be used to assess the healthy conditions of utility poles directly and are also essential for structural load strength related calculation in the civil engineering field. Combined with gravitational and wind forces applied on a pole, the inclination angle can be used to calculate the resilience condition of the pole, which can be further used to perform cost-benefit analysis to compare loss and savings during wind-related disasters for utility companies. Currently most utility pole detection systems are based on automotive laser scanning technology [2-4]. The mobile laser scanning (MLS) system can acquire massive point clouds of objects using vehicle mounted devices. However, the processing of the unstructured dataset that MLS system provides can be time consuming. Moreover, the utility poles in areas with the complex geographical environment also bring great difficulties for this vehicle-based method.

To address the issue above, we propose a novel system for utility pole inclination angle measurement using two innovative technologies: unmanned aerial vehicle (UAV) and deep learning neural network. Recently, UAV received intensive attention in many research areas because of its impressive data collection capability. UAV can provide high-resolution photos and videos in a much more convenient and flexible way compared to traditional methods. In our study, a UAV was used to collect street view images and videos that contain utility poles with varying inclination angles. As a breakthrough, deep learning has been widely used in machine learning, computer vision, artificial intelligence, and many other research areas and made significant progress since 2012. Convolutional neural network (CNN), a deep learning neural network structure with multiple convolutional layers, has achieved plausible performance in many challenging tasks, such as object detection and recognition, semantic segmentation, and image classification [5, 6]. In our study, CNN was used to detect and segment utility poles form UAV images for inclination angle calculation.

The main contirubtion of this research paper is that the development of a novel deep learning-based monitoring system to exam the health conditions of utility poles automatically by measuring inclination angles from UAV images. The rest of this paper is organized as follows: Section 2 introduces the proposed method; Section 3 discusses experiments and performance evaluation; and Section 4 presents the conclusions and future work.

2. Methodology

The proposed method consists of three major steps: (1) capture utility pole images using UAV; (2) segment poles from images using deep learning neural network; and (3) calculate the inclination angle of each utility pole using computer vision methods. The flowchart of our method is presented in Figure 1. Following is the detailed description of each step of the method.

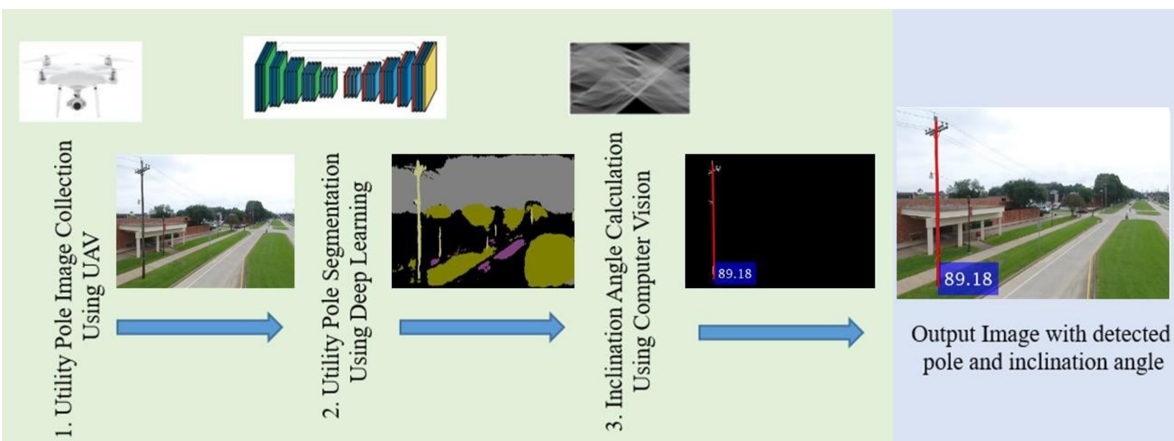


Figure 1: The flowchart of the proposed method

2.1 UAV-based Image collection

In this study, we applied UAV technology to collect utility pole images. The technology was selected for the following advantages. (1) The gimbal stabilizer of UAV is able to ensure that the UAV camera can capture high quality images and videos without vibration or shake, which is crucial for accurate measurement of utility pole angles. (2) UAV is equipped with Global Positioning System (GPS) that can record GPS information of unhealthy poles and be used to locate poles for timely repair. (3) UAV can capture utility pole images at heavy traffic roads and hard-to-access areas efficiently. (4) UAV can fly automatically according to a preset route and greatly save manpower and time.

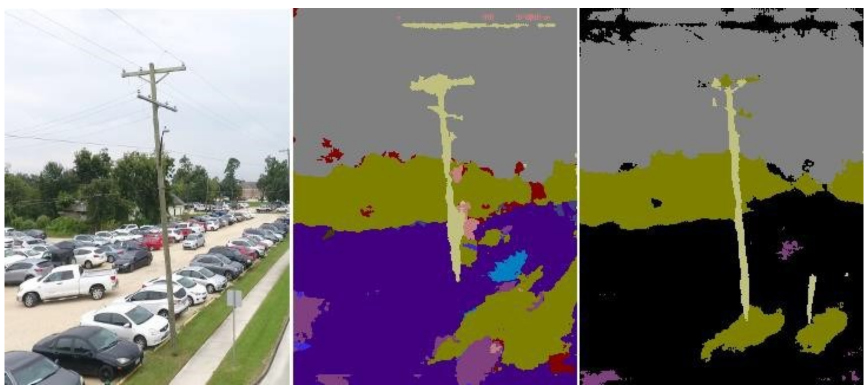
We used a DJI Phantom 4 drone to collect street view videos that contain utility poles with varying inclination angles. Moreover, the images were collected comprehensively under different weather conditions (e.g., sunny, cloudy, and rainy) and at different heights (from 5m to 20m) to enhance the robustness of the proposed monitoring system.

2.2 Deep Learning-based pole segmentation

Utility pole segmentation from UAV images plays the most important role in the presented monitoring system. Widely used CNN architectures for pixel-wise image segmentation includes SegNet, FCN, DeconvNet, CRFASRNN, Decoupled, etc. [7-11]. These network models have similar encoder-decoder structures. The encoder network generates low-resolution image representations, while the decoder network maps these low resolution representations to pixel-wise predictions. The main difference among these segmentation networks lies in the decoder part.

After comparing several popular CNN architectures for pixel-wise segmentation, we adopted SegNet [7] model in this study for pole segmentation due to its efficiency regarding memory and computation time. SegNet has a very similar convolutional encoder-decoder architecture as DeconvNet without fully connected layers of VGG16 encoder network, which consists of 90% of the trainable parameters of the entire network. This helps to reduce memory consumption and improve inference time without sacrificing performance as we aim to design an efficient monitoring system.

We trained the adopted SegNet model using the Cambridge-driving Labeled Video Database (CamVid) road scene image dataset that consists of 367 training images and 101 validation images with resolution 480×360. Moreover, instead of segmenting input images into 11 classes (i.e., sky, building, pole, road, pavement, tree, sign symbol, fence, vehicle, pedestrian, and bike) used by the original SegNet, we separated the images into five classes, pole, sky, road, vegetation, and others (all other objects except previous four) because our study focuses on particularly on utility pole detection. Sky and road classes were used to verify the inclination angles, and vegetation class was used to check the visibility of utility poles. Figure 2 illustrates the segmentation results of an example image given by the original SegNet and our retrained SegNet. We can see that our network with 4 classes yielded better segmentation results.



(a) (b) (c)

Figure 2: Utility pole segmentation. (a) Input UAV image, (b) Segmentation results using original 12-class SegNet, and (c) Segmentation results using 4-class SegNet.

2.3 Computer vision-based inclination angle calculation

After deep learning-based UAV image segmentation, we applied the following computer vision methods to refine detected utility poles and calculate the inclination angle of each pole.

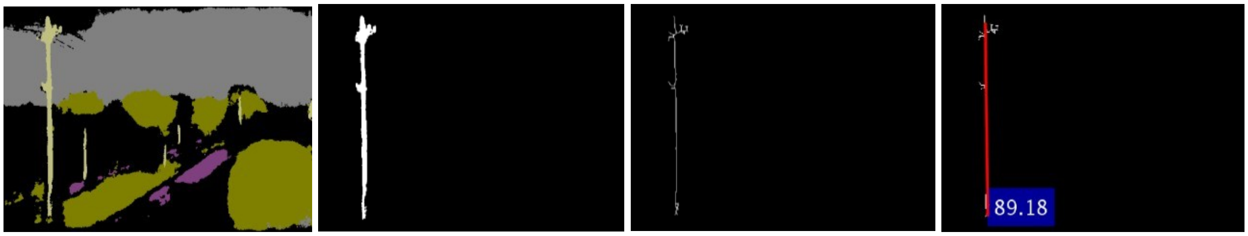
(1) Although the network can achieve decent segmentation, it still produces some noisy regions. The connected component method is applied to label each candidate region classified as utility pole by SegNet with a unique ID.

(2) All labeled candidate pole regions are filtered using a predefined area threshold. The regions that are too small to be utility poles are considered as noisy pole regions (i.e., false alarms) and are removed by area thresholding. The remaining pole regions are marked as true pole regions (i.e., true positive) for inclination angle calculation.

(3) The skeleton of each utility pole can be extracted using morphological image operations. The extraction is achieved by performing multiple erosion operations of the pole regions. For each pixel in the pole superimposing the origin of a predefined erosion kernel, if the kernel is completely contained by the region the pole pixel is retained. Otherwise the pole pixel is deleted. Ultimately, the skeleton extraction removes the pixels on the boundaries of the pole region without allowing the region to break apart and generates a one-pixel thickness skeleton of each utility pole.

(4) After that, Hough Transform [8] is applied to find the best line segment fitting the pole skeleton and calculate the inclination angle of a utility pole. Hough transform is a feature extraction technique for detecting lines and other geometric shapes in an image in parameter space. In our study, the Hough Transform is used to find the longest line segment that has the largest number of co-line skeleton pixels. To avoid unbounded slope values, Hough Transform is performed in a polar coordinate system. The output line function, therefore, can represent the detected utility pole and its slope is used to calculate the corresponding declination angle of the pole in the image.

Because the UAV takes consecutive photos or videos during its flight, multiple photos are captured for each utility pole from different viewpoints, the biggest declination angle of a pole is selected as the final system output. Figure 3 illustrates the intermediate results of the steps discussed above.



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

Figure 3: Detected pole region refine and inclination angle calculation. (a) the segmented UAV image given by SegNet; (b) extracted pole region from (a) after the area thresholding; (c) the skeleton of the pole; and (d) the output of Hough Transform (red line segment) and the calculated inclination angle (white number in the blue box).

3. Experiments

In this section, we will introduce our UAV pole image dataset and experiment setting and demonstrate experimental results of the proposed utility pole monitoring system.

3.1 UAV Pole Image Dataset

The UAV pole image dataset used in our study has 64 images containing 84 utility poles with varying inclination angles. All pole images were captured by a DJI Phantom 4 drone from the campus of Lamar University, Beaumont, Texas under different weather conditions (e.g., sunny, cloudy, and rainy) and at a different height (from 5m to 20m). The original resolution is 3360×2100.

3.2 Experiment Settings

For SegNet segmentation, the original high-resolution images were resized to 480×360 to fit the input image size of the SegNet neural network. Local contrast normalization was performed to all the images before training. The weights of VGG16 trained on ImageNet Large Scale Visual Recognition Challenge dataset were used to initialize the encoder parameters of SegNet. Stochastic gradient descent (SGD) was applied to train SegNet with a base learning rate of 0.001 and momentum of 0.9 using Caffe implementation. Batch size was set to 4 according to our GPU capability. Cross-entropy loss was used as the loss function to train the network. Median frequency balancing was performed to balance the number of pixels from each class by setting the weight of each class in the loss function to the ratio of the median of all class frequencies divided by the class frequency.

For pole region refine and inclination angle calculation, the area threshold value was set to 200. Therefore, any regions with area size smaller than 200 pixels were removed as noisy regions. Top 30% longest line segments were extracted for each image by Hough transform with distance and angle intervals setting to 1 pixel and 0.1 degree, respectively. Two line segments were merged if they were associated with the same Hough transform bin and the distance between them was less than 30 pixels and line segments with length smaller than 30 pixels were removed. The parameters used in the experiments were decided by a trial and error preliminary computation to ensure the numerical stability.

3.3 Performance Evaluation

The proposed system was evaluated using 84 utility poles by measuring the angle differences in degree between the manually calculated ground truth and the inclination angles yielded by the system. The experimental results demonstrate that the utility poles in UAV images can be accurately segmented. SegNet achieved an accuracy of 93.74% after 40,000 iterations of training. The average angle difference is 0.59 degrees with the variance of the error distribution 0.77. Figure 4 illustrates some output images with the detected utility poles (red lines) and their inclination angles (blue boxes). The last example has the largest angle difference, 5.57 degrees, among 84 poles. It was caused by an inaccurate pole segmentation that failed to separate a utility pole and a short pole partially overlapped with it.

Table 1 lists the numbers of poles with angle difference smaller than 1 degree, bigger than 1 degree and smaller than 2 degrees, and bigger than 2 degree, as well as their means. Figure 5 shows the angle difference of each utility pole with ID from 1 to 84.

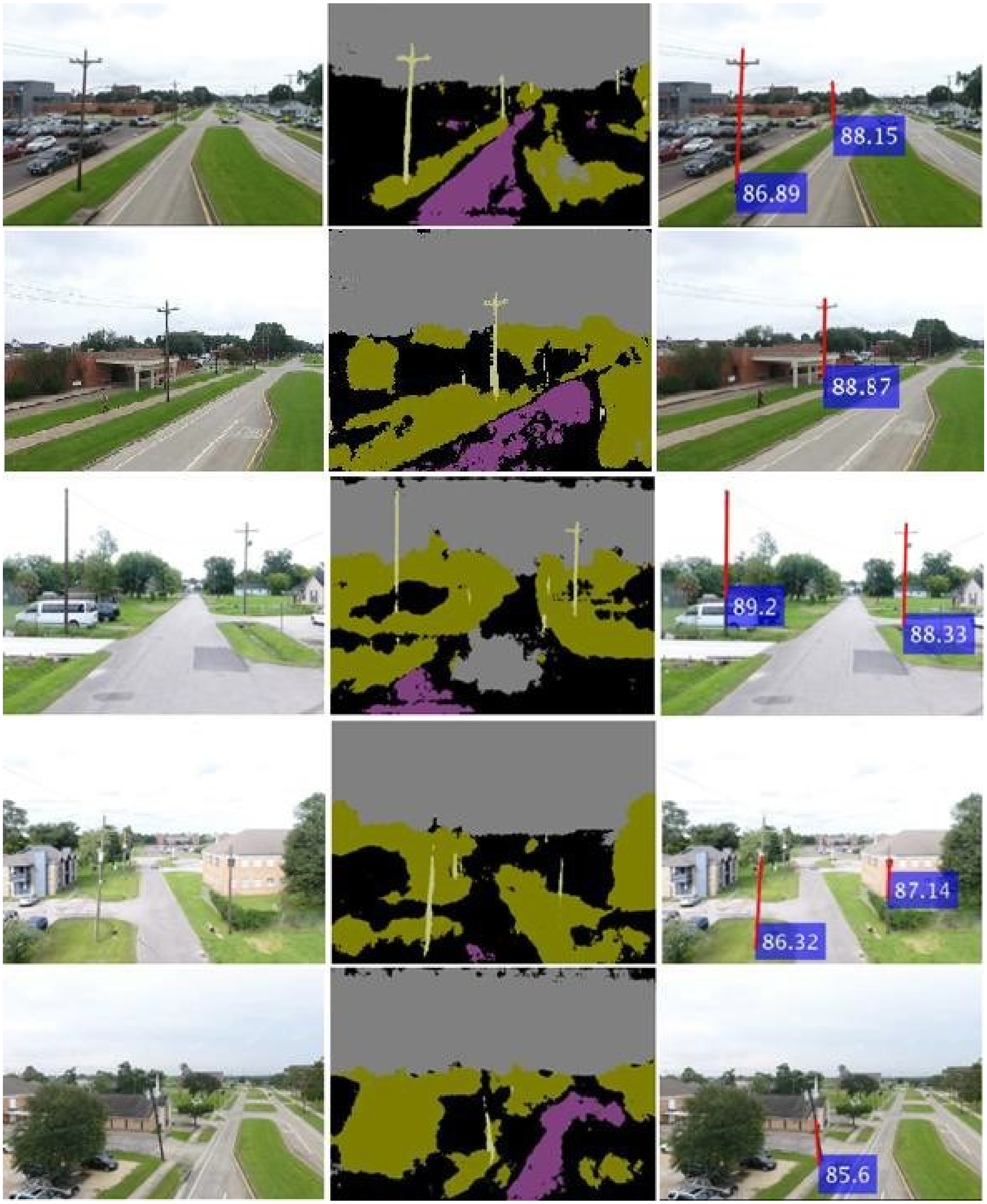


Figure 4: Example output images with calculated inclination angles

Table 1: Distribution of angle difference of 84 poles

Angle Error (degree)	Mean Error (degree)	Number of Poles
< 1 degree	0.286	68 (80.95%)
1< and < 2 degrees	1.235	12 (14.28%)
2 degrees <	3.848	4 (4.77%)

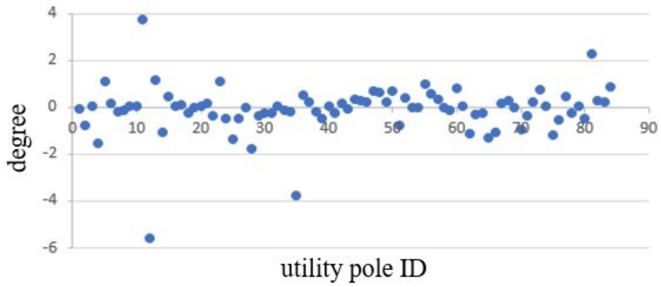


Figure 5: Angle differences of 84 utility poles with IDs 1 to 84.

4. Conclusions

Monitoring the health condition of utility poles of the electric power distribution lines is critical to maintain power distribution systems and minimize power outages. A low-cost and reliable utility pole monitoring system that can measure utility pole inclination angless automatically is proposed in this paper. The system applies state-of-the-art deep learning neural network to segment utility poles from UAV images and uses computer vision techniques to calculate the inclination angle of each detected utility pole. The proposed method was evaluated using total 84 utility poles and the average difference between manually measured inclination angles and calculated inclination angle was 0.59 degrees, which demonstrated that the proposed method could segment utility poles efficiently and calculate inclination angles accurately. In the future work, we will continue to improve the accuracies of pole segmentation and inclination angle calculation and extend our system to examine the clearance between poles and vegetation.

Acknowledgements

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