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Automatic Assessment and Prediction of the Resilience of Utility Poles Using Unmanned Aerial Vehicles and Computer Vision Techniques

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Abstract The utility poles of electric power distribution lines are very vulnerable to many natural hazards, while power outages due to pole failures can lead to adverse economic and social consequences. Utility companies, therefore, need to monitor the conditions of poles regularly and predict their future conditions accurately and promptly to operate the distribution system continuously and safely. This article presents a novel pole monitoring method that uses state-of-the-art deep learning and computer vision methods to meet the need. The proposed method automatically captures the current pole inclination angles using an unmanned aerial vehicle. The method calculates the bending moment exerted on the poles due to wind and gravitational forces, as well as cable weight, to compare it with the moment of rupture. The method also includes a machine learning-based model that is built by using a support vector machine to predict the resilience conditions of a pole after a wind event in a faster manner. The three modules of the proposed method are effective tools to classify pole conditions and are expected to enable utility companies to increase the resilience of their systems.

Keywords Angular deflection · Machine learning · Support vector machine · Texas · Utility pole resilience

1 Introduction

The frequency and intensity of extreme weather events have been gradually growing in the United States (U.S. Environmental Protection Agency 2016). The power distribution system, which is the final stage of electric power supply, is very prone to disruption from such events, and the utility poles of the power distribution system are particularly susceptible to damage from such events. It has been estimated that 80–90% of the power outages in the United States have occurred due to the failures of distribution systems caused by extreme weather (Executive Office of the President 2013; Gholami et al. 2016). Recent widespread power interruption statistics also show the growing importance of resilient distribution networks. Hurricane Harvey, for example, caused 5726 utility pole damages and kept approximately 219,000 customers nearly 14 days without power in 2017 (AEP Texas 2017). The Long Island Power Authority (LIPA) alone experienced 4500 utility pole damages during Hurricane Sandy in 2012 (U.S. Department of Energy 2013). According to Gholami et al. (2018), the power distribution system has to embrace lots of changes and complexities. Natvig et al. (2011) argued that the determination of component-level criticality with respect to the overall resilience of a system could help to prepare the repair list before a disaster event. Determining the health conditions of utility poles is thus critical where the poles are an important component of the power distribution network. However, the existing pole-by-

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pole inspection requires much time and effort and is error-prone.

Alam et al. (2019) proposed a photogrammetry-based methodology for measuring pole inclination angles to determine the health conditions of electric poles. The present study expands on Alam et al. (2019) to overcome the perceived limitations in terms of the collection and processing of pole image data. The objectives of the present research are:

- (1) To develop a neural network-based deep learning model to detect and segment utility poles from street view images and videos captured by an unmanned aerial vehicle (UAV);
- (2) To develop a computer vision-based method to calculate pole inclination angles using segmented pole images; and
- (3) To build a machine learning-based model based on a support vector machine (SVM) technique to predict the resilience of poles.

The primary contribution of the present study is the automation of the existing process of monitoring and inspecting the health conditions of utility poles and the assessment of the resilience of poles. Section 2 delineates the results of the literature review. Section 3 discusses the proposed method for the automation. Section 4 illustrates the data representation and experimental results of the proposed neural network-based deep learning model and the computer vision-based method. Section 5 discusses the calculation and representation of pole resilience with the SVM technique. Section 6 concludes with an outlook on future research directions.

2 Literature Review

The present study is concerned with the resilience of electric utility poles. The following subsections discuss the relevant previous studies on power distribution pole damages, the visualization of pole conditions using a convolutional neural network (CNN), and resilience quantification efforts.

2.1 Utility Pole Damages

Electric utility poles are damaged by various causes, including wind, flooding, decay, trees or branches falling on lines or poles, and wind-borne debris. Among those, this study focused on the extreme wind force induced by wind-related hazards such as hurricanes. The Caribbean Disaster Mitigation Project (1996) conducted research to estimate pole damages during a hurricane. The research examined the impact of bending stress on the failure of a pole

without, however, taking into consideration the influence of the gravitational load affected by the pole's inclination angle. Han et al. (2014) estimated the expected flexural failure of a pole and the foundation failure during hurricanes. For the flexural failure, they assumed the prior condition using structural reliability, in which all parameters other than wind speed are taken as deterministic. For the foundation failure model, they assumed the stress distribution of the soil to be linear. Bhat et al. (2018) investigated the resilience of the power distribution system that included 7051 wood poles located in the southeast of the United States. They used an integrated hurricane hazard model with a component fragility model to predict the probability of failure of the system. The probability of the failure of a wood pole was calculated by the difference between the moment capacity (R) of the wooden pole and the wind-induced moment demand (S). Bjarnadottir et al. (2013) proposed a framework to analyze the risk of impact of a hurricane on utility poles and assessed the potential impact of climate change on the annual pole failure. They addressed the degradation of pole strength over time in their failure model and used the fragility curve to predict the pole failure. Gustavsen and Rolfseng (2000) created a simulation-based method to investigate the rate of wooden pole replacement due to decaying pole strength over time and climatic loads from wind and ice. They found that pole damage due to climatic loads may incur high costs for repair work and the loss of power. Potvin and Short (2016) conducted a resilience test of overhead distribution components under dynamic loads instead of static loads.

2.2 Application of a Convolutional Neural Network (CNN) to Visualize Utility Pole Conditions

Most of the existing automatic systems for monitoring utility poles are built based on the automotive laser scanning technology. The mobile laser scanning (MLS) system can acquire massive point clouds of objects using vehicle-mounted devices. The basic idea of the method is to detect pole-like structures from the point clouds data using different algorithms. Yokoyama et al. (2013) proposed a method for pole detection by classifying each point. After removing ground points and performing smoothing to the input point clouds, each point is classified into different categories based on the analysis of its neighborhood. The disadvantages of this approach are the need for manual elimination of ground points and the usage of a predefined height as a feature during the classification. These limitations make the method less robust. Liberge et al. (2010) proposed an approach that could create a minimal height image and a maximal height image from 3D laser point clouds. The approach assumes that the ground points correspond to the points in the minimal height image, and the

points in the maximal height image belong to pole-like objects. The significant limitation of this approach is that it requires the pre-removal of buildings from the point clouds.

Landa and Ondroušek (2016) developed a method for detecting pole-like structures based on the directional vector. The drawback of this method is that a big number of false positives are generated due to the failure to separate trees and pole-like structures. Although an algorithm was introduced to reduce false positives, the algorithm removed many utility poles as well. Ordóñez et al. (2017) developed a methodology for recognizing pole-like objects by using a heuristic segmentation algorithm. Although the algorithm assumes that poles are isolated and almost plumb, the detection of poles that are leaning or bent with large inclination angles is much more crucial for the resilience analysis. Lehtomäki et al. (2010) introduced a method based on scan-lines. Each scan-line is segmented separately, and the segments that are directly on top of each other are considered to belong to one cluster. If a candidate cluster fulfills several criteria—height, shape, direction, and so on—it is recognized as a pole. The authors claimed over 80% correctness for pole detection. In general, however, it is very time-consuming to process the unstructured dataset provided by the MLS system using laser scans.

Utility poles in areas with a complex geographical environment also present great difficulties to vehicle-based methods. Some other methods detect utility poles from images by finding certain patterns or shapes related to poles. Hazelhoff et al. (2014), for example, designed a method for detecting both lighting fixtures and poles. This method restricts the detection of lighting poles with specific fixture shapes and utility poles with very small inclination angles, which limits the applications of the method. The methods proposed by Golightly and Jones (2003) and Cheng and Song (2008) recognize utility poles by detecting the pole-top cross-arm region. Such methods are also limited due to the reliance on particular shapes. In practice, the shape of the pole-top of a utility pole varies and is usually occluded or mingled with other objects in images. Cetin et al. (2009) proposed a method to locate utility poles from aerial images by detecting the shadow of a pole. The method is limited due to its requirement of a clear shadow falling on a plain terrain. Sharma et al. (2015) developed a method that extracts 2-dimensional geometric shapes of utility poles to detect poles. The method uses a shape-based template whose long rectangular trapezium is perpendicularly intersected by at least one trapezium representing a pole crossarm. This method, however, does not apply to cases where the poles have no crossarm or pole crossarms are occluded by trees or buildings.

2.3 Efforts to Quantify Utility Pole Resilience

Several methods have already been developed to measure overall system resilience. Bruneau et al. (2003, p. 736) defined resilience as “the ability of the system to reduce the chances of shock, to absorb the shock if it occurs and to recover quickly after a shock.” They introduced a resilience triangle to measure the percentage of lost quality or the functionality of the infrastructure over time. Zobel (2011) adapted this resilience triangle and developed a deterministic approach to quantify resilience as the total possible loss over a certain long term. The approach considered one parameter for the percentage of functionality loss $X \in [0, 1]$ and another parameter for the time required for full recovery $T \in [0, T^*]$. The approach used the resilience triangle for a single event loss to calculate the total possible loss as the triangular area $(XT/2)$. Zobel and Khansa (2012) further extended this approach to the recovery from multiple sequential disruptive events.

The resilience of utility poles significantly affects the stability of power distribution systems. Similarly, the system-level resilience is dependent on the resilience of the components (Mitchell and Beyeler 2015). Han et al. (2014) studied the probability of direct damage in a power distribution system at the component-level by using combinations of structural reliability and physical damage models updated with the Bayesian approach. However, their model suffers from lack of confidence because the structural reliability models and failure data have not been used effectively at the component level. Thus, their model can potentially produce inaccurate damage estimates. Even though our proposed SVM model is also at the component level, the SVM model helps portrait future damage more effectively. The recent advancement in machine learning (ML) provides many effective solutions for complex problems in power systems. Eskandarpour et al. (2017) proposed a three-dimensional SVM model to predict the states of the components of a power grid system. They classified the outcomes of the model into two categories: outage and operational. Hink et al. (2014) evaluated machine learning classification techniques, such as SVM, OneR, Random Forests, NNge, and Adaboost, for discriminating power system disturbances and cyberattacks. Guikema (2009) investigated the risk of natural disasters to critical infrastructure systems based on statistical learning theory. The study concluded that SVM is a promising machine learning technique for classification problems in infrastructure risk and reliability analysis. The support vector machine technique was also regarded as a member of a large family of linear classifiers that can help find the maximum separation between the classes. Thukaram et al. (2005) used an artificial neural network (ANN) and SVM to locate the faults in distribution systems. The ANN was

used to build a relationship between measurements and the fault distance. The support vector machine technique was also used to perform multiclass classification, adopting four types of faults and seven classes.

3 The Proposed Method for Automatic Resilience Assessment of Utility Poles

Figure 1 illustrates the framework of the proposed method to automate the existing process of monitoring and inspecting the health conditions of utility poles and the assessment of the resilience of poles. The method is comprised of three modules:

- (1) Automatic determination of the inclination of each utility pole by applying unmanned aerial vehicle (UAV) technology, computer vision technique, and machine learning;
- (2) Prediction of the failure of utility poles based on bending moment theory; and
- (3) Resilience representation with support vector machine (SVM) for a simpler and faster determination of the resilience of poles.

3.1 Determination of Pole Inclination Angle

The proposed pole inclination angle measurement method consists of three steps: (1) capture utility pole images using UAV; (2) segment poles from images using a deep learning neural network; and (3) calculate the inclination angle of each utility pole using computer vision methods (Fig. 2).

3.1.1 Unmanned Aerial Vehicle-Based Image Collection

In the present study, the UAV technology was adopted to collect utility pole images, which was intended to overcome the shortcomings of the manual or vehicle-based collection methods used in the previous work (Alam et al. 2019). The adoption of the UAV technology has the following advantages: (1) The gimbal stabilizer of the UAV is able to ensure that the UAV camera can capture high-quality images and videos without vibration or shaking, which is crucial for accurate measurement of utility pole angles. (2) Unmanned aerial vehicles are equipped with Global Positioning Systems (GPS) that can record the GPS information of unhealthy poles and be used to locate poles for timely repair. (3) UAVs can capture utility pole images near heavily trafficked roads and in hard-to-access areas efficiently. (4) UAVs can fly automatically according to preset routes and greatly save manpower and time. In our study, a DJI Phantom 4 drone was used to collect street view images with utility poles.

Fig. 1 The framework of the method proposed to determine the resilience of utility poles—three modules

Fig. 2 Flowchart of the proposed method to determine the inclination angle of utility poles

3.1.2 Deep Learning-Based Utility Pole Segmentation

Segmenting utility poles from UAV images is critical in the presented monitoring system. Widely used CNN models for pixel-wise image segmentation 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. After comparing several popular CNN architectures for pixel-wise segmentation, a SegNet model was modified in this study for pole segmentation (Golightly and Jones 2003). The SegNet model has a convolutional encoder-decoder architecture for robust semantic pixel-wise labeling. It has 13 convolutional layers without fully connected layers, which helps to reduce memory consumption and improve inference time without sacrificing performance. The modified network separates each image into five classes (pole, vegetation, sky, road, and others) and can detect the utility poles more accurately than the original SegNet that segments input images into 11 classes (sky, building, pole, road, pavement, tree, sign symbol, fence, vehicle, pedestrian, and bike). The manually marked ground truth images and a transfer learning strategy were applied to optimize the model weights that were pre-trained using Cambridge-driving Labeled Video Database (CamVid).

Five-fold cross-validation (training images 20% and test images 80%) was used to evaluate the SegNet model. Training image augmentation and local contrast normalization were performed before training. The weights of VGG16 trained on an 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. The batch size was set to 4 according to our GPU (Nvidia GTX 1080Ti) 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.

3.1.3 Computer Vision-Based Inclination Angle Calculation

After deep learning-based UAV image segmentation, the following computer vision techniques were applied to refine detected utility poles and to 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 a utility pole by the 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 (that is, false alarms) and are removed by area thresholding. The remaining pole regions are marked as true pole regions (that is, true positive) for inclination angle calculation.
- (3) The skeleton of each utility pole can be extracted using morphological image operations. The extraction is done by performing multiple erosion operations of the pole regions. A pole pixel is retained if the predefined erosion kernel is completely contained by the pole region when the kernel origin is at the pixel. Otherwise, this 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) The Hough Transform technique (Cheng and Song 2008) is applied to find the best line segment fitting the pole skeleton and calculate the 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, the 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 pole angle, which is the angle between the pole skeleton and the positive x -axis direction with the coordinate origin at the lower-left corner of the image.
- (5) A pole may be captured several times from multiple view directions in different images and have different pole angles. Assume a pole was captured T times, its maximum inclination angle is the angle that maximizes the angle between the pole and 90° direction (Inclination Angle = $\arg\max_{1 \leq i \leq T} |\text{poleangle}_i - 90^\circ|$).

In this study, the area threshold value was set to 150 experimentally. Therefore, any regions with areas smaller than 150 pixels were removed as noisy regions. The top 30% longest line segments were extracted from each image by Hough transform with distance and angle intervals setting to 1 pixel and 0.1° , respectively. Two 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 a length smaller than 30 pixels were removed. The parameters used in the experiments were decided by a trial and error preliminary computation to ensure numerical stability. Figure 3 illustrates the intermediate results of the steps described above.

3.2 Determination of Utility Pole Failure Based on the Bending Moment

The second part of the proposed method is concerned with the determination of the failure of utility poles based on the moment exerting in the body of a pole that is induced by wind and gravitation forces.

3.2.1 Representative Utility Poles and Wind Events

The National Electrical Safety Code (NESC 2017) specifies the design loads and the required material properties of the wooden poles used for electric power distribution systems. Basically, the grade of a pole determines the strength and allowable load for the pole. A pole is classified by its height, class, and species of the wood. According to the code, the NESC grade C wooden poles are used for overhead distribution lines in the United States (Quanta Technology 2009). This research considered a southern yellow pine (SYP) pole with a 13.716 m (45 ft) height and class 5, which is used the most for power distribution lines in the United States. The American National Standards Institute (ANSI 2017) also sets the specifications and dimensions of wood poles.

According to ANSI, the pole considered in the present study has top and ground circumferences of 0.483 m (19 in.) and 0.825 m (32.5 in.), respectively (ANSI 2017). Figure 4 illustrates a single-phase line pole. For the simplicity of calculation, the mean diameter of the pole is considered as 0.208 m (8.2 in.). The pole setting depth is determined as 10% of the pole height plus 0.610 m (2 ft). Thus, the pole is to be installed 1.981 m (6.5 ft = 4.5 ft + 2 ft) underground and 11.735 m (38.5 ft) above the ground surface. The mean ultimate tensile stress for a SYP wood pole is 10,190 psi, which is $70.26 \times 10^6 \text{ N/m}^2$ (NESC 2017). Tensile stress (σ_t) on a pole is derived from the moment at the baseline of a pole. A moment-based

Fig. 3 Detected utility pole region refine and angle calculation. **a** The pole regions segmented from an unmanned aerial vehicle (UAV) image by SegNet; **b** the extracted pole region from (a) after the area

thresholding; **c** the skeleton of the pole; and **d** the output of the Hough Transform (red line segment) and the calculated pole angle (white number in the blue box)

Fig. 4 Layout of a single-phase line utility pole

resilience is determined based on the three conditions: resilient ($\sigma_t \leq 8000 \text{ psi}$), moderately resilient ($8000 \leq \sigma_t \leq 10,190 \text{ psi}$), and non-resilient ($10,190 \text{ psi} \leq \sigma_t$). According to Quanta Technology (2009), the grade C construction can withstand a moderate tropical storm that corresponds to an extreme wind speed of 85 mph. The level of utility structure damage and power outage by wind events, which is specific to the pole structures, are determined by the Saffir-Simpson hurricane wind scale shown in Table 1 (NOAA 2019a).

3.2.2 Representation of Forces on a Utility Pole

The wind pressure acts on the pole and cables and causes a bending moment in the pole (Han et al. 2014). If a pole is already in an inclined position (θ , degree of an inclination angle), two forces—wind and gravitational forces—will act on the pole to incur bending moment (Eren Tokgoz et al. 2017). Thus, the total induced force on the pole is equal to the summation of the wind forces on the pole and cables and the gravitational force. The component of gravitational

Table 2 Parameters for the calculation of wind loads per National Electrical Safety Code (NESC) Rule 250. Source NESC (2017)

Pole	Cable
$K_z = 1.0$	$K_z = 1.1$
$G_{RF} = 0.97$	$G_{RF} = 0.88$
$I = 1.0$	$I = 1.0$
$C_f = 1.0$	$C_f = 1.0$

force perpendicular to the ground is defined as $F_{g\perp} = F_g \sin \theta = mg \sin \theta$ (Eren Tokgoz et al. 2017). The mass of the pole is determined by $m = \frac{\pi d^2 h \gamma}{4}$, where d is the mean diameter of the pole, h is the height of the pole, γ is the specific weight of the pole, g is the gravitational constant, and θ is the pole inclination angle. The wind force component on the bare pole surface acts perpendicular to the pole which is also adopted from Eren Tokgoz et al. (2017), and can be expressed as $F_{w\perp} = F_w \cos \theta$, where, $F_w = CPA$, with P = wind pressure, A = cross-sectional area, and C = constant. The force due to extreme wind pressure can be calculated using the NESC suggested formula $P = 0.00256 K_z G_{RF} I C_f V^2$, where V is the 3-second peak gust wind speed in the region where the pole is located, K_z is the velocity pressure exposure coefficient, G_{RF} is the gust response factor, I is the important factor, and C_f is the shape factor. The wind force on cables can also be computed using the same formula for the wind force on the pole by changing the value of different factors, as shown in Table 2. The length of a cable between two poles and its diameter are considered to be 43.89 m (144 ft) and 0.017 m (0.057 ft), respectively (Caribbean Disaster Mitigation Project 1996).

3.2.3 Determination of Bending Moment and Modulus of Rupture

The present study expands on the flexural pole failure model developed by Han et al. (2014) by additionally involving the pole inclination angle and gravitational force.

Table 1 Saffir-Simpson hurricane wind scale. Source NOAA (2019a)

Category	Wind speed	Type of damage and outage
1	74–95 mph	Extensive damage to power lines and poles likely will result in power outages that could last a few to several days
2	96–110 mph	Near-total power loss is expected with outages that could last from several days to weeks
3	111–129 mph	Devastating damage to the structure will occur with power outages for several days to weeks after the storm passes
4	130–156 mph	Catastrophic damage will occur, and power poles will isolate residential areas. The outages will last weeks to possibly months
5	157 or higher mph	Catastrophic damage will occur, and power poles will isolate residential areas. The outages will last weeks to possibly months. Most of the area will be uninhabitable

If the total force exerted on a pole exceeds the pole's maximum capacity, then the pole will fail to withstand. That means, a pole will fail when the tensile stress becomes greater than the modulus of rupture, which can be expressed mathematically as $f(x) = R - F = \sigma_R - \sigma_t = \sigma_R - \frac{M_{pole}}{Z} = \sigma_R - \frac{32M_{pole}}{\pi d^3}$, where $f(x)$ = limit state function, R = resistance capacity of a pole, F = total force on the pole, σ_R = modulus of rupture, σ_t = tensile stress, M_{pole} = induced moment on pole at ground line, Z = modulus of section ($\frac{\pi D^3}{32}$), and d = mean diameter of a pole (Han et al. 2014). The moment generated by the gravitational force $M_{g\perp}$ is calculated as $M_{g\perp} = F_{g\perp} * d_g$, where $F_{g\perp}$ = gravitational force and d_g = distance of the force. The moment generated by the wind force on the pole $M_{w\perp}$ is determined as $M_{w\perp} = F_{w\perp} * d_w$, where $F_{w\perp}$ = wind force on the pole and d_w = distance between the point of force and the ground line of a pole. The moment on a pole due to the wind force on cables M_c is calculated by $M_c = F_c * d_c$, where F_c = wind force and d_c = distance from the ground line to the cable. The total moment on a pole is the summation of the moment due to the gravitational force, the moment due to the wind force on a pole, and the moment due to the wind force on the cable. Thus, the moment on the baseline of the pole is computed as $M_{pole} = \{(F_{g\perp} * d_g) + (F_{w\perp} * d_w) + (F_c * d_c)\}$. Given the total moment, the tensile stress σ_t exerted on a pole is calculated as noted earlier. According to the NESC standard, SYP wood poles are considered to permanently fail when the tensile stress exceeds the mean modulus of rupture, $\sigma_t = 70.26 \times 10^6 \text{ N/m}^2$ (NESC 2017).

4 A Case Study

This section discusses the results of the application of two parts of the proposed method (Fig. 1): the automatic determination of the inclination of each utility pole (module 1), and the bending moment-based prediction of the failure of poles (module 2). A case study in which the proposed method was applied is also presented. Figure 5 shows the site selected for the case study, which is located in Beaumont, Texas, United States. The UAV images were collected in June and October 2018 as well as March 2019.

4.1 Existing Condition

There are 173 utility poles with variant inclination angles within the selected site. The drone photos of the poles were first inspected manually to determine the maximum inclination angle of each pole. Figure 6 shows the distribution of the pole inclination angles of the 173 poles in a histogram. The resilience conditions of a pole based on the

inclination angle (θ) were classified as: healthy ($0^\circ \leq \theta \leq 5^\circ$); critical ($5^\circ < \theta \leq 10^\circ$); and unhealthy ($10^\circ < \theta$). The histogram shows that about 80% of the 173 poles were in healthy condition, while about 18% and 2% were in critical and unhealthy condition, respectively.

4.2 Results of the Automatic Measurement of the Utility Pole Inclination Angles

The proposed method was evaluated by measuring the difference of angle between the manually marked ground truth and the inclination angle detected by the method. Multiple photos were taken for each utility pole from different directions to ensure the capture of the biggest inclination angle. Using a DJI Phantom 4 drone, 333 images were collected from the site under different weather conditions—for example, sunny, cloudy, and rainy—and at different heights from 5 to 20 m, with a resolution of 3360×2100 pixels. Figure 7 illustrates some output images of the detected poles (red lines) and their inclination angles (white numbers in blue boxes).

The 173 utility poles were segmented 665 times from 333 images because one pole appears multiple times in different images. Among the 665 inclination angles automatically detected for the 173 poles, the maximum angle of each pole is used as its inclination angle. The performance is evaluated using the difference ($\Delta\theta$) between the automatically detected inclination angle and the manually determined one. Table 3 lists the number of poles for $\Delta\theta \leq 1^\circ$, $1^\circ < \Delta\theta \leq 2^\circ$, and $2^\circ < \Delta\theta$, as well as their means for the 173 utility poles. Figure 8 shows the detected inclination angles of 38 poles with $1^\circ < \Delta\theta \leq 2^\circ$ (blue circles) and 13 poles with $2^\circ < \Delta\theta$ (red circles). The vertical error bars indicate their angle differences. The range of angle difference is from 0° to 5.5° . The average angle difference is 0.72° with the variance of the error distribution 0.688° . The results demonstrate that the utility poles in UAV images can be segmented accurately and inclination angles can be measured precisely.

4.3 Results of the Utility Pole Failure Determination Based on the Bending Moment

The failure determination method was applied to determine the impact of extreme wind speeds of 70 mph, 80 mph, 90 mph, 100 mph, and 110 mph. These speeds were selected to examine the conditions of poles both in tropical storms and hurricane events. According to NOAA (2019a), “a tropical storm is a tropical cyclone that has maximum sustained surface winds ranging from 39 to 73 mph and a hurricane is a tropical cyclone that has maximum sustained surface winds of 74 mph or greater”.

Fig. 5 The selected Beaumont, Texas, case study site and the existing utility poles (labeled as 1–173). *Source:* Google Maps, Google, Inc., February 2020

If the tensile stress induced by the total moment at the bottom line of a pole exceeds the modulus of rupture, the pole fails permanently. Figure 9a shows the conditions of the poles at 70 mph wind speed, the tensile stress of all poles, and the modulus of rupture. The tensile stress of every pole is under the modulus of rupture, and thus all poles are sustained. At 80 mph wind speed, the one pole with an inclination angle of 14° experiences the tensile stress greater than the modulus of rupture and thus fails (Fig. 9b). The pole with an angle larger than 14° will fail at 80 mph. At 90 mph, there are four poles that pass the modulus of rupture (Fig. 9c)—poles with an angle greater than 11° will fail at 90 mph. At 100 mph, 26 of the 173 poles are expected to fail (Fig. 9d)—any pole with an angle greater than 6° will fail at 100 mph. At 110 mph, all poles cross the modulus of rupture, and thus will fail (Fig. 9e),

which coincides with the prediction based on the Saffir-Simpson wind scale.

5 Resilience Representation with Support Vector Machine (SVM) for a Future Wind Event

A machine learning-based classification model is proposed to classify the utility pole conditions after a wind event to demonstrate the usefulness of our moment-based methodology for the future prediction of the pole conditions. Specifically, SVM is used to classify the three conditions—resilient, moderately resilient, and non-resilient—of the poles in this study. The support vector machine technique has already proved its well-established advantages over other classification methods. Despite many possible applications and usefulness, SVM is not widely used in the

Fig. 6 Distribution of the pole inclination angles of the 173 utility poles in the Beaumont, Texas, case study site

Fig. 7 Example output images of utility poles with calculated inclination angles

resilience analysis. Previously, the decision boundaries about the condition of a utility pole were drawn around three conditions based on only the pole inclination angle, θ : resilient (green, $0^\circ \leq \theta < 15^\circ$), moderately resilient (yellow, $15^\circ \leq \theta < 25^\circ$), and non-resilient (red, $25^\circ \leq \theta$), without considering cable effect (Alam et al. 2019). However, in this study, the inclination angle is combined with four types of moments to provide a more comprehensive utility pole condition classification to calculate the overall tensile stress on a pole. These four moments are: moment due to wind force on pole surface, moment due to gravitational force on pole, moment on pole due to the wind force on cables, and total moment on pole. New ranges of inclination angle have been introduced (healthy $0^\circ \leq \theta \leq 5^\circ$; critical $5^\circ < \theta \leq 10^\circ$; unhealthy $10^\circ > \theta$). These ranges have been slightly reduced in this study since cable weight can add additional stress on the pole. It should be noted that the choice of inclination angle ranges can be changed easily based on the choice of decision makers. The tensile

Table 3 Distribution of angle differences of the 173 utility poles in the Beaumont, Texas, case study site

Angle error (°)	Mean error (°)	Number of poles
$\leq 1^\circ$	0.428	122 (70.5%)
$1^\circ < \text{and} \leq 2^\circ$	1.468	38 (22%)
$2^\circ <$	2.923	13 (7.5%)

stress on a pole was calculated based on these new ranges. In that case, the pole conditions were assumed to be divided into three resilient classes based on the tensile stress σ_t : resilient (green, $\sigma_t \leq 55.16 \times 10^6 \text{ n/m}^2$), moderately resilient (yellow, $55.16 \times 10^6 \text{ n/m}^2 < \sigma_t < 70.26 \times 10^6 \text{ n/m}^2$), and non-resilient (red, $70.26 \times 10^6 \text{ n/m}^2 \leq \sigma_t$).

An SVM model with a Gaussian kernel was used as the classifier in the experiment. The performance was evaluated by a fourfold cross validation that randomly selected 75% samples from each class for training, and the remaining 25% samples for testing. The inclination angles measured in Sect. 3.1.3 and four moments calculated at 90 mph wind speed were used as the input features. Only 90 mph wind speed was used for the following reasons:

- (1) The 90 mph wind speed is within the range of a Category 1 hurricane, which is much more likely to occur than other hurricane categories. From 1851 to 2018, there were 122 category 1, 80 category 2, 64 category 3, 24 category 4, and 4 category 5 hurricanes in the United States (NOAA 2019b).
- (2) The induced moments for different wind speeds are linearly correlated, and the moments calculated at 90 mph wind speed can completely represent the

moments calculated at other wind speeds—the performance of the SVM cannot be improved by adding more moment features.

- (3) Based on the resilient conditions of the collected utility poles, 90 mph wind speed can provide a good class distribution, so that each class has an appropriate number of poles for SVM training and testing. Note that decision makers can select another wind speed based on their pole collections without changing the system for resilience prediction.

Of the 173 utility poles at our study site, 123 poles were in the green class (Class 1), 46 poles in the yellow class (Class 2), and 4 poles in the red class (Class 3). The confusion matrix of the SVM classification results are shown in Fig. 10. All samples in Class 1 and Class 3 were classified correctly and 3 samples in Class 2 were misclassified as Class 1. The overall classification accuracy is 98.266%. This experimental result can be used for future wind event prediction.

6 Conclusion

Continuous monitoring of the health condition of utility poles can play a vital role in minimizing power outages during and after a major wind event. To supply power continuously and safely, utility companies must examine and make critical decisions for maintenance or replacement of poles based on the current conditions of poles. To this end, the proposed method for measuring the resilience of utility poles can effectively contribute to increasing the capacity of utility companies. The method proposed in this study significantly advances the previously proposed

Fig. 8 The automatically detected utility pole angles and the angle differences between them and ground truth. The blue circles are 38 poles with angle differences between 1° and 2° and the red circles are 13 poles with angle differences larger than 2° . The vertical error bars indicate the angle differences between the automatically detected pole angles and the manually calculated pole angles

Fig. 9 Utility pole conditions at **a** 70 mph, **b** 80 mph, **c** 90 mph, **d** 100 mph, and **e** 110 mph

Fig. 10 Confusion matrix of the utility pole condition classification result of the 173 utility poles at the Beaumont Texas case study site

approach by automating the processes of data collection and calculation, which is realized by using advanced techniques and technologies, including UAV, neural network, machine learning, and SVM. Pole images can be

captured automatically by a UAV, which is followed by the automatic analysis of the utility pole angles by a CNN network to determine the resilience of the poles. This automation allows utility companies to reduce the amount of time and the workforce needed for an inspection significantly, compared to the conventional manner of manual inspection. It also increases the accuracy of the inspection results. The prediction of the resilience based on SVM allows utility companies to make decisions for preventive maintenance more promptly.

The present study is an ongoing research endeavor. A few limitations of the outcomes of the study will be further addressed in future study. The loading factors considered were limited to wind forces and gravitational forces. Other factors, such as soil conditions, as well as aging and deterioration of materials, are significant and need to be looked into in the future. Additional experiments can be conducted to determine the optimal positions of a UAV to capture image data more effectively. Lastly, the present study will be extended to automate the assessment of the effect of vegetation growing near cables and poles on the resilience of the power distribution system.

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