Towards the Automatic Visual Monitoring of Electricity Pylons from Aerial Images

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Abstract: Visual inspection of electricity transmission and distribution networks relies on flying a helicopter around energized high voltage towers for image collection. The sensed data is taken offline and screened by skilled personnel for faults. This poses high risk to the pilot and crew and is highly expensive and inefficient. This paper reviews work targeted at detecting components of electricity transmission and distribution lines with attention to unmanned aerial vehicle (UAV) platforms. The potential of deep learning as the backbone of image data analysis was explored. For this, we used a new dataset of high resolution aerial images of medium-to-low voltage electricity towers. We demonstrated that reliable classification of towers is feasible using deep learning methods with very good results.

1 INTRODUCTION

Aerial surveillance of electricity network components is currently an active area of research. We review recent work on vision-based inspection of electricity network components from aerial images. We then demonstrate a novel application of deep learning for tower image classification. Specifically, we classify towers as being either suspension (S-type) or tension (T-type) towers. This classification, in terms of tower configuration, will be useful as a step in the inspection of other tower parameters, e.g., components around the cross-arm (insulators, clamps, shackles, etc.). Tower classification is achieved by first classifying each of the multiple images of a tower and then using voting to determine the tower class. Since many images do not contain the relevant part of the tower, we introduce a third unknown (U) image class, and train 3-class image classifiers. Identification of U images, which tend to be of the body and leg regions of a tower, is a useful step in the inspection of concrete muffs, warning signs, vegetation cover and anti-climbing devices, which are localized around these regions.

2 MOTIVATION

Globally, societies depend on continuity of service from critical systems such as electrical networks. Electrical networks support other critical services like transportation, telecommunications, food, water and healthcare. Electricity is generated and transmitted over a system of transmission and distribution network infrastructure. The networks are made up of high rising metal towers or pylons and span hundreds of thousands of kilometres (Andersson et al., 2005; Jones, 2005) along rivers, lakes, hills and lowlands and sometimes across dense vegetation (Liu et al., 2015). To ensure effective management , a set of standards is put in place and regulated. One such regulator is the Office of Gas and Electricity Markets (Ofgem) in the UK. The major role of this body is to ensure the enforcement of a uniform level of performance from all the distribution network operators (DNOs) within the industry (McGonigle, 2017).

To operate within these standards, DNOs make huge investment in asset acquisition and management. The United States alone requires about \$2 trillion investment for upgrades by 2030 (Bronski et al., 2015). There was over £16 billion of investment on electricity networks from 2010 and £34 billion needed up to 2020 (DECC, 2015). This trend is likely to continue in the coming decade as most of the transmission and distribution network infrastructure has served the better part of its lifespan. Disruptions reported in Europe, Asia and America within the last fifteen years (Bakshi, A., Velayutham, A., Srivastava, 2012; Schmidthaler & Reichl, 2016) point to the fact that electricity assets are aging and in need of constant monitoring. Making this situation worse is the increasing demand for energy. To mitigate the huge loss

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in finances and patronage associated with such failures, evolving new and effective management tools has become inevitable.

The current state-of-the-art for inspection of electricity transmission and distribution assets relies on visual aerial images. These are usually collected from helicopters (Matikainen et al., 2016). Other sensing alternatives like light detection and ranging (LiDAR) are in use. The deployment on helicopters has safety shortcomings and high operational costs. The current advancement in UAV technology for remote sensing offers advantages and has increasingly gained popularity in aerial photography and surveillance. The benefits of UAVs include their flexibility (Herwitz et al., 2004) and low cost of operation (Cai & Walker, 2010).

Given the large numbers of components and inspection parameters, a robust data management architecture is needed. Solutions should combine historical data, current conditions and energy demand to advise on a preferred course of action. There is an ongoing discussion towards Big Data architecture for smart grid (IEEE-Smart-Grid, 2017) and the role of machine learning and artificial intelligence is prominent.

3 LITERATURE REVIEW

Electricity assets are the valuable components (tangible and intangible) of the network, which are integral to the profitable delivery of the services that businesses depend upon (Clarke, 2011). These include transformers, high voltage towers, conductors, insulators, suspension clamps, connecting links, etc. For an asset to remain relevant, its health state should be inspected for signs of failure or degradation, so as to maximize availability, performance and reliability. Eyre-Walker et al. (2015) presented application of advanced condition assessment and asset management techniques for overhead electricity network asset monitoring to involve data acquisition and analysis.

Regular and effective inspection and management requires high financial commitment from owners and operators in the industry. This has triggered increased collaboration with researchers to find improved and cost-effective ways of conducting power-line inspection (Martinez et al., 2014). A major direction is improvement of alternative sensing platforms and the drive to automate the process (Matikainen et al., 2016).

Various events along power distribution lines may lead to power outages. The most common causes of outages are: (1) failure of power-line components (Larsson & Ek, 2004) and (2) interference with surrounding vegetation (Andersson et al., 2005). Causes of the 2003 major grid blackouts in North America and Europe included inadequate vegetation management (i.e. tree trimming). The use of line men for checking the encroachment of trees along power distribution lines is still practiced today. This is not only costly but inefficient. Remote alternatives have been introduced (Ahmad et al., 2015; Zhang et al., 017b).

The inspection of specific components accounts for the largest propotion of inspection tasks. These include conductors (Zhang et al., 017a; Chen et al., 2016; Sharma et al., 2014; Li et al., 2010), towers (Martinez et al., 2014) and insulators (Oberweger et al., 2014; Li et al., 2012; Salustiano et al., 2014).

3.1 UAV Navigation

Safe flight of a UAV along a power-line corridor is key to successful inspection. Although a pilot is dedicated to this task, there have been crashes due to system, human or environmental factors. System and human errors can be controlled but environmental impacts could come from several sources, e.g. gust wind. To solve the problem posed by gust wind, Liu et al. (2015) proposed the creation of a no-fly-zone along the distribution network corridor using GPS coordinates of the towers.

Sa et al. (2015) demonstrated the use of vertical take-off and landing of UAVs for the inspection of pole-like structures. They combined monocular, inertia and sonar data for navigation information and Extended Kalman Filters to maintain a safe distance from the pole even in the presence of environmental disturbances. Essentially, this is a detect and follow algorithm.

Golightly & Jones (2005) combined Hough transform and Kalman filters to guide a rotorcraft along detected powerlines. A follow-up study (Jones et al., 2006) used an air vehicle simulator (AVS) to demonstrate that visual data can be used to determine, and hence regulate vehicle position relative to the overhead lines. Cerón et al. (2018) developed a system that detects and follows powerlines from images.

3.2 Obstacle Detection and Avoidance

The detection of obstacles such as vegetation and buildings along powerlines has been investigated (Zhang et al., 2012, 017a,b). Low altitude photogrammetry has been explored in these studies to extract 3D point clouds of the power-line corridor. The distance between the powerlines and the 3D point cloud is taken as a criterion for automatically locating obstacles. Zhang et al. (2012) used monocular measurement and inertia to estimate the position of landmarks as well as the position and orientation of the UAVs.

3.3 Detection of Towers

Detection of electricity pylons was studied by (Dutta et al., 2015) and (Jiang et al., 2017). The main contribution of (Dutta et al., 2015) was to minimize clutter due to heterogeneous background using optimized mean shift-based segmentation. The resulting image was divided into a grid of rectangular patches called granules. The best granules were selected using gradient density and cluster density-based thresholding. The clusters corresponding to pylon regions within key granules were merged through shared boundary criterion. Finally, pylons were detected using context information. Results were encouraging. On the other hand, Jiang et al. (2017) explored the use of an unmanned aerial vehicle (UAV) for outdoor data acquisition. They achieved this using an oblique photogrammetric system integrated with a low-cost double-camera imaging system, an on-board dual-frequency Global Navigation Satellite System (GNSS) receiver and a ground master GNSS station in fixed position.

The use of UAVs in a cooperative way was proposed by (Pirbodaghi et al., 2015). This system used two robotic platforms that were heterogeneous and cooperative in executing tasks. While a rob-on-wire inspected the lines by moving on them, an octocopter served as a wireless relay node establishing data transfer between rob-on-wire and the ground station and carried out inspection at the same time on the towers.

In addition to the detection of towers, there is a need to identify defects in its components. A method for estimating corrosion on towers was presented in (Tsutsumi et al., 2009). It was based on a support vector machine using the radial basis function kernel. Some synthetic images using colour temperature and brightness were added to augment the training data. This was evaluated using 1,427 images of 8 towers. Detection of other defects on towers has not been adequately explored.

3.4 Detection of Insulators

Detection of insulators and insulator defects has been studied (Oberweger et al., 2014; Zhai et al., 2017; Liu et al., 2017). Saliency and adaptive morphology were the bases for insulator fault detection. Liu et al. (2017) detected insulators and hammers using a multi-layer perceptron. Jabid & Ahsan (2018) detected insulators using rotation invariant local directional pattern (RI-LDP) features. These features were used by an SVM to classify regions of insulator and predict their faults.

3.5 Detection of Conductors

The detection of conductors has been addressed in several studies. In (Yang et al., 2012), video frames were binarised through an adaptive thresholding approach and a Hough transform was used to detect line candidates. This was followed by a fuzzy C-means clustering algorithm to discriminate the conductor lines from other detected line patterns like roads, river banks and vegetation. Li et al. (2008) used a pulse coupled neural network filter to remove background noise from images prior to Hough transform being employed to detect straight lines. Thereafter, knowledge-based line clustering was applied to refine the detection results. Bhujade (2013) and Sharma et al. (2014) suppressed the natural surroundings (regions of sky and vegetation) and used a Hough transform. In (Tian et al., 2015), conductors were extracted based on directional constraints using a double-side filter, and an improved Hough transform with parallel constraint was used for conductor recognition. Their results show significant improvement because of the addition of direction and parallelism constraints. Similarly, Zhu et al. (2013) presented a double-side filter-based conductor recognition method for a UAV vision system. This method was based on linear object enhancement and parallel lines constraints as in (Tian et al., 2015). A Radon transform was used to find the parallel lines. Real-time detection of conductors from video was presented in (Liu & Mejias, 2012). Ippolito et al. (2016) also showed a real-time method but with 3D scanning using LiDAR. This utilized a voxel-based method with a series of classifiers to identify and reconstruct conductors. A mini UAV mounted with LiDAR was proposed in (Santos et al., 2017) for sensing the powerline corridor.

Most studies reviewed in this section focus on detecting conductors without considering defect detection or analysis. Zhang, F. et al. (2016) presented a technique to detect and remove fog from an image to enhance detection. Zhai et al. (2017) compared the capability of three edge detection algorithms using images of towers. Xie et al. (2017) suggested the use of multiple sensors from a large UAV. Qin et al. (2018) based their approach on a cable inspection robot to improve the payload and power capabilities of their inspection platform. Menendez et al. (2016) presented a simulation of a UAV-based line tracking system and mounted a visual sensor on a robotic arm

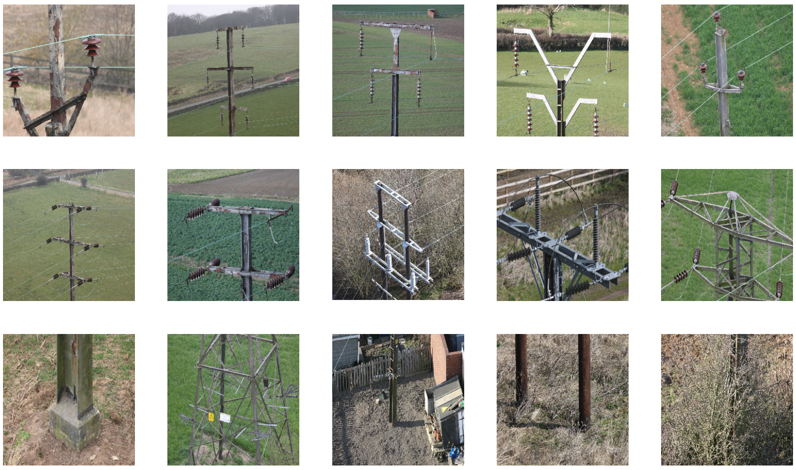


Figure 1: Top: images of S-type towers. Middle: images of T-type towers. Bottom: images from which tower type is not apparent.

that detected and tracked lines.

In summary, some components of the power-line corridor including towers, insulators and conductors have been studied in the literature. The use of computer vision techniques is popular and several machine learning algorithms (e.g. multi-layer perceptron, pulse coupled neural network) have been used. The potential of deep learning as the backbone for analyzing the sensed data has not been sufficiently covered partly due to lack of suitably labelled data. Nguyen et al. (2018) and Zhang et al. (2018) have highlighted the huge potential of this approach. Recent success of deep learning for the detection and classification of objects directly from images presents an exciting opportunity for real-time inspection of components of electricity transmission and distribution networks.

4 CLASSIFICATION OF TOWERS FROM AERIAL IMAGES

4.1 Data Formation

The dataset used for this study was collected using helicopters mounted with high resolution cameras. Each image has 5616x3744 pixels. The images are of towers from low-to-medium voltage lines. Each line is identified by a unique line number (e.g. A54, A74). Along each line are multiple towers (e.g. A54(002), A54(003), etc).

Images are taken of each tower from different views (e.g. right and left circuit) across the crossarm, body and foot regions. All the images of a tower are grouped into a tower 'bag' with a unique identifier (tower number). Each tower bag has been inspected and labelled by an expert. It is important to emphasize that although multiple images of each tower were acquired, a single label has been assigned to the entire bag. Some suspension (S-type) towers are shown in Figure 1 (row 1), i.e., different tower structures with suspended cables. Row 2 of Figure 1 shows some T-type (tension) towers. These towers also have different structures with cables pulling on the structure. With respect to how the data is formed, most image-based classification and detection problems (datasets) have one label per image. Here, tower images were captured to have good representation of the components and conditions but labelled as a bag. This bulk labelling presents the following challenges: (1) In each tower bag there are a mix of cross-arm images (rows 1 and 2 of Figure 1) and images of body and leg regions (row 3 of Figure 1); (2) Images of tower body or leg regions (row 3 of Figure 1) have no features identifying them as S-type or T-type. Therefore, attempting to classify such images independently as being of S-type or T-type towers will cause errors.

To address the problem of bulk label assignment, all images of tower body/leg regions were labelled as U images (unknown). At image level, there are thus three class labels: S, T, and U.

It is required that images found in the training set are not present in the testing set. Considering that in our dataset each tower has several images (bag of examples), training and testing sets have been assigned tower-wise.

There are 28231 images for training, 4593 for validation and 4240 images for testing. The breakdown of towers and images across class labels is presented in Table 1.

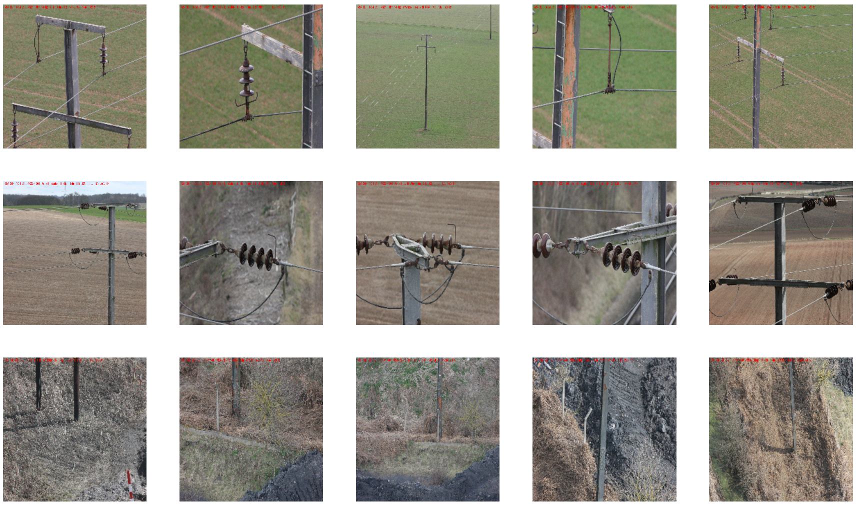


Figure 2: Examples of test images that were correctly classified. Top: S class. Middle: T class. Bottom: U class.

Table 1: Distribution of data for training, validation and testing sets.

	Towers (Number)	Images (Number)
Training	S-type (519)	S (12621) U (3102)
	T-type (270)	T (9166) U (3343)
Validation	S-type (79)	S (1963) U (709)
	T-type (41)	T (1469) U (452)
Testing	S-type (80)	S (1829) U (551)
	T-type (39)	T (1215) U (645)

4.2 Training

We fine-tuned a VGG16 network (Simonyan & Zisserman, 2015) using ImageNet weight initialization. We replace the fully connected layers with a new fully connected output layer with 3 nodes (3 classes). We also trained from scratch, a ResNet with 86 layers and based on pre-activation of residual modules (He et al., 2016).

The images are 5616x3744x3 in size (colour). They were resized to 244x244x3 to fit our target input shape. The input images were randomly augmented and fed into the model. To ensure that the model sees different sets of images each time they were sampled, we applied width and height shifts, zooming and flipping. The model was optimized using Stochastic Gradient Descent (SGD) with learning rate of 1e-3.

4.3 Evaluation

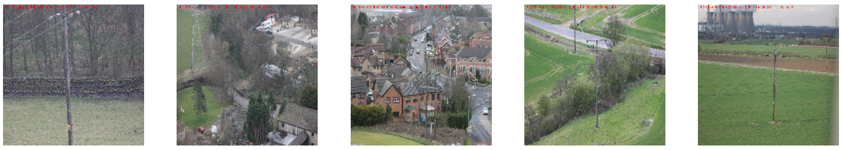
There are 118 towers comprising of 4240 images in the test set. The distribution of towers and images for testing is shown in Table 1. The VGG-based classifier predicted 97.04%, 97.69% and 96.32% of S, T and U test images correctly. The ResNet classified 96.99%, 96.54% and 95.65% of S, T and U test images correctly.

Figure 2 shows some examples of S, T, and U images that were correctly classified. Figure 3 shows examples of incorrect classifications. Comparing the results, one notices that close-range images with relatively clean backgrounds are correctly classified. Some characteristics of the incorrectly classified images are (1) long-range images, (2) heavy background clutter, e.g. houses, trees, (3) instances of multiple objects e.g., Figure 3, row 1, image 3, and (4) cases of wrong labels e.g., Figure 3, row 3, images 3, 4 and 5.

4.4 Voting Mechanism for Tower Level Classification

An aim of this study is to classify towers as suspension (S-type) or tension (T-type). Each tower is presented as a bag of images. Within each bag are 20-30 instances. We use a majority voting mechanism. This samples all the image predictions for each bag and counts the number of occurrences of S and T labels. The label with the highest count is returned as the final prediction for the bag (i.e. tower level classification). We envisaged a situation in which there is a tie (equal predictions of targets). However, there was no tie in our experiments. As shown in Table 2, the VGG-based model misclassified one S-type tower as

(a) S images misclassified as T



(b) T images misclassified as S

(c) U images misclassified as T

Figure 3: Examples of test images incorrectly classified.

T-type. On the other hand, ResNet predicted all the towers correctly as shown in Table 3.

Table 2: Fine-tuned VGG model: Confusion matrix with majority voting for tower level classification.

		Predictions	
		S-type	T-type
Actual	S-type	79	1
	T-type	0	38

Table 3: ResNet: Confusion matrix with majority voting for tower level classification.

		Predictions	
		S-type	T-type
Actual	S-type	80	0
	T-type	0	38

5 CONCLUSION

We reviewed methods for electricity network asset inspection. This included the use of machine learning, computer vision and the potential of deep learning. We presented the classification of electricity towers based on their configuration. To the best of our knowledge, there is no previous report of a deep learning-based classification of tower images. Our method of electricity tower and image classification is a precursor for the inspection of other power-line components and condition parameters: (1) inspection of components around the cross-arm (insulators, clamps, shackles, conductors, etc.), (2) inspection of concrete muffs, DODs, tower name plates, etc.

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