Learning for Tower Detection of Power Line Inspection

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ABSTRACT: Power line inspection is very important for electric company to keep good maintenance of power line infrastructure and ensure reliable electric power distribution. Research efforts focus on automating the inspection process by looking for strategies to satisfy all kinds of requirements. Following this direction, this paper proposes a learning approach for tower detecting problem where aggregate channel features are used to train the boost classifier. Adopting the sliding window paradigm, the electric tower can be located very fast. The main advantages of this approach are its efficiency and accuracy for processing huge quantity of image data. Obtaining highly encouraging results shows that it is really a promising technique.

Keywords: power line; inspection; aggregate channel features

1 INTRODUCTION

Electric power companies invest significantly for power line inspection to ensure reliable electric power distribution. In the past, workers tramped along power line with a telescope in their hands, tried to find any problems of power line above them. It is painfully laborious, they even went to everglades where cannot be easily entered into. The common strategy is aerial inspection by manned helicopter equipped with multiple sensors such as visual, infrared and ultra-violet cameras and so on. Data captured or recorded by expert crew with those above cameras are manually examined later to detect potential faults and damage on different power line components. This process is not only extremely time-consuming, but also very expensive and prone to human error. Moreover, the manned flights, which are carried out very close to the live power cables, are extremely dangerous to the crew. With these problems in mind, power industry is actively seeking solutions to automate different aspects of power line inspection.

In the last two decades, multiple complementary research directions have been investigated for automating the task of visual inspection. There are three main types of aerial platforms for power line inspection, such as Unmanned Aerial Vehicles (UAVs) [1-9], rolling on wire robot [10-15] and manned helicopter [16]. More recently, some authors have also proposed a hybrid climbing-flying robot which combines the advantages of UAVs and ROW robots into a single platform [17]. The robots (both UAVs and ROWs), which are currently put in use by Electric industry, require human intervention for navigation as well as data acquisition. After data acquisition, the main task of power line inspection is fault identification where computer vision can help. It involves automatic detection and localization of electric devices such as wires, towers, insulators and conductors and so on. The state of art has focused on tower detection. And the detection of tower can then be used to find various defects/faults of power line infrastructure.

This paper presents a learning based solution for tower detection and localization. Therefore, the background or other parts of image can be cropped quickly. Focus of Attention is concentrated on image region with tower. This process can also be used for images filtration. When millions of images were obtained by Unmanned Aerial Vehicle, lots of them may not include any power line devices. Those images that have no use for power line inspection should be deleted. And running this tower detection process as preprocessing stage can automatically delete those images without tower in them.

Some researchers have also focused on detection and segmentation of electric towers in the images[18-22]. Several authors apply straight line segment extraction for tower detection or localization[18, 19, 21, 22]. Other authors then apply different segmentation approaches to extract the complete tower from the image: e.g., a

template matching approach is used in [18]; graph-cut[23] based segmentation is used in [21]; a rule-based, as well as watershed segmentation [24] is used in [19]. Golightly and Jones [20] presented a different approach from the state of art where, instead of lines, the corners were considered the key identifying features of tower. They used a modified corner detector [25] to detect and track the tower tops. Although different approaches to tower detection and segmentation have reported promising results, most of the results have been reported on just one type of tower. However, the electric towers are extremely diverse in shape, appearance and size. Therefore, most the state of the art results cannot be generalized to several different tower types.

To achieve the goal of complete autonomy, researchers must aim towards developing more general approaches. This paper following this direction considers tower detection as a learning problem. Sliding window paradigm is adopted for tower detection with boosted detector which is based on boosted decision trees computed over multiple feature channels such as color, gradient magnitude and histogram of gradient oration. Our solution for tower detection can automatically get top performance with very fast speed no matter the image size is large or small since multi-scale pyramid strategy is considered and implemented well.

The rest of the paper is organized as follows: Section 2 states the problem addressed in this paper and describes several challenges which need to be addressed; Section 3 presents our approach to tower detection; the results are reported and discussed in Section 4; the final section is our conclusion and future research directions.

2 PROBLEM STATEMENT

Currently, different projects are looking for automating either the acquisition process or the analysis process, or both, with the main objective of being able to detect and diagnose different defects of the power line infrastructure by using new sensors or new inspection platforms (e.g., robots [3, 10, 15]; UAVs [4, 6, 7]). In all the new possible approaches, computer vision plays an important role for automatically moving the camera in order to maintain the electric tower inside the field of view of the camera, and for identifying and categorizing the different defects and failures of the power line infrastructure.

Nonetheless, in fact, computer vision is a very challenging task for this technique. There are different kinds of complicated situations the visual system has to deal with, such as viewpoint variation, illumination and background change. Because of the high variability of background, it is difficult to find a unique feature that can work in all the possible scenarios. Illumination changes also play an important role. It di-

rectly leads to power line segmentation from background algorithm not working for some low contrast images. Other problems such as constant viewpoint changes, (e.g., especially when cameras are manually moved) scale changes of the electric tower and its components add additional complexity to the idea of applying computer vision to solve this problem, in which, depending on the adopted strategy, could require a system that automatically defines which is the best frame to be used for detecting defects.

Another important factor that must be taken into consideration when automating the power line inspection is the quality of the images. The image quality changes depending on the kind of inspection that is conducted and on the vehicle used for inspection. When an exhaustive inspection is conducted, details are perceived much better, and therefore it would be more feasible for a computer vision algorithm to detect defects on those images. Nevertheless, this kind of inspection requires the helicopter to go slow and also to stop in every tower, something that with manned helicopters implies a considerable increase of the inspection price. In general, for accurate inspections, the quality of the images should be good. But this, on the other hand, is currently difficult to ensure, especially at low prices.

Currently, there is not a complete solution that satisfies the different requirements of automated power line inspection: simultaneously detect electric towers, check for defects and analyze security distances. Therefore, in terms of cost-benefits, it is important for energy companies to solve this problem and try to find a system that can deal with the different requirements of the inspections at high speed. In this paper, we explore the electric tower detection problem applying a machine learning approach, using low quality images. Therefore, the system will help in reducing the maintenance cost of the electric system by being able to cope with one of the problems of increasing the vehicle speed (reducing the quality of the images).

3 TOWER DETECTION STRATEGY

The objective of the proposed strategy is to determine the position of the electric tower in single images. Due to the difficulty of the task (e.g., wide variety of backgrounds), a learning-based approach is used. A boosted detector based on boosted decision trees is trained for tower localization and segmentation from background with very fast speed. Aggregate channel features are used to train boosted decision trees. Once the boosted decision trees have been trained, they can be applied to tower detection of power line inspection. In the following paragraphs, the boosted decision trees and aggregate channel features are described.

Boosting is a simple but powerful tool for classification and can model complex non-linear functions[26, 27]. The general idea is to train and combine a number

of weak learners into a more powerful strong classifier. Decision trees are frequently used as the weak learner in conjunction with boosting, and in particular orthogonal decision trees, that is, trees in which every split is a threshold on a single feature, are especially popular due to their speed and simplicity [28-30]. Decision trees with oblique splits can more effectively model data with correlated features as the topology of the resulting classifier can better match the natural topology of the data [31].

For training and detecting, the channel features are used. Given an input image, Aggregate Channel Features (ACF) computes several feature channels, where each channel is a per-pixel feature map such that output pixels are computed from corresponding patches of input pixels (thus preserving image layout). We use the same channels as [29]: normalized gradient magnitude (1 channel), histogram of oriented gradients (6 channels), and LUV color channels (3 channels), for a total of 10 channels. We down sample the channels by 2x and features are single pixel lookups in the aggregated channels. Thus, given a h×w detection window, there are h/2×w/2×10 candidate features (channel pixel lookups). We use RealBoost [27] with multiple rounds of bootstrapping to train and combine 2048 depth-3 decision trees over these features to distinguish object from background. Soft-cascades [32] and an efficient multiscale sliding-window approach are employed. And we uses slightly altered parameters from [29] (RealBoost, deeper trees, and less downsampling); it increases model capacity and benefits our final approach.

The boosting algorithm for learning can be described as follows:

- Given example images$(x_1, y_1), \ldots, (x_n, y_n)$ where y_i=0, 1 for negative and positive examples respectively.

- Initialize weights $w_{1,i} = \dfrac{1}{2m}, \dfrac{1}{2l}$ for $y_i = 0,1$ respectively, where m and l are respectively the number of negatives and positives.

- For $t = 1, \ldots, T$:

1. Normalize the weights, $w_{t,i} \leftarrow \dfrac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$

2. Select the best weak classifier with respect to the weighted error:

$$\varepsilon_t = \min_{f,p,\theta} \sum_i w_i |h(x_i, f, p, \theta) - y_i|$$

3. Define $h_t(x) = h(x, f_t, p_t, \theta_t)$ where f_t, p_t and θ_t are the minimums of ε_t

4. Update the weights:

$$w_{t+1,i} = w_{t,i} \beta_t^{1-e_i}$$

Where $e_i = 0$ if example x_i is correctly classified, otherwise $e_i = 1$, and $\beta_t = \dfrac{\varepsilon_t}{1 - \varepsilon_t}$.

- The final strong classifier is :

$$C(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq \dfrac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 & otherwise \end{cases}$$

Where $\alpha_t = \log \dfrac{1}{\beta_t}$

The algorithm described above [35n] is used to select key weak classifiers from the set of possible weak classifiers. While the AdaBoost process is quite efficient, the set of weak classifier is extraordinarily large. Since there is a weak classifier for each distinct feature/threshold combination, there are effectively KN weak classifiers, where K is the number of features and N is the number of examples. In order to appreciate the dependency on N, suppose that the examples are sorted by a given feature value. With respect to the training process, any two thresholds that lie between the same pair of sorted examples are equivalent. Therefore, the total number of distinct thresholds is N.

The wrapper method can be used to learn a perceptron which utilizes M weak classifiers. The wrapper method also incrementally proceeds by adding one weak classifier to the perceptron in each round. The weak classifier added is the one when added to the current set yields a perceptron with lowest error. Each round takes at least O(NKN), and the time to enumerate all binary features and evaluate each example use that feature. This neglects the time to learn the perceptron weights. Even so, the final work to learn a 200 feature classifier would be something like O(MNKN).

The key advantage of AdaBoost over the wrapper method is the speed of learning. Using AdaBoost, a feature classifier, can be learned in O(MNK). In each round, the entire dependence on previously selected features is efficiently and compactly encoded through using the example weights. These weights can then be used to evaluate a given weak classifier in constant time.

We use AdaBoost for the learning and training with ACF for feature computing. Furthermore, we add multi-scale mechanism in our implementation. Given an image, ten channel features in original scale are computed as Figure 1.

4 EXPERIMENTS AND RESULTS

In order to train and evaluate the ACF boosted detector for detection, 1,400 images have been divided into 3 sets: training, cross validation and the test set. 300 images (tower and background) have been used for training, while 200 images are used for the cross validation and 200 for the test set. A total test error of
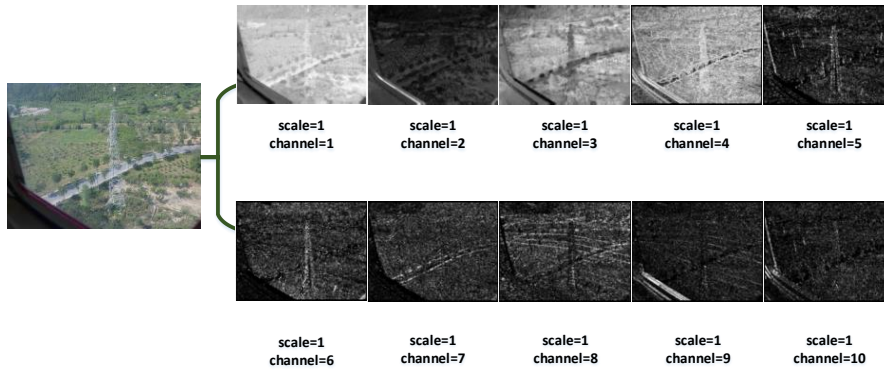
Figure 1. Ten aggregate channel features of an image.

3.25% is attained. A false positive rate of 1.5% was achieved, which means that only 3 of the 200 background test images were incorrectly classified as tower. On the other hand, we obtain a false negative rate of 2%, which indicates that 4 tower images out of 200 used for testing were predicted as background. These results suggest that, although overall performance of the classifier is good, tower images are more often predicted as background than background images as tower.
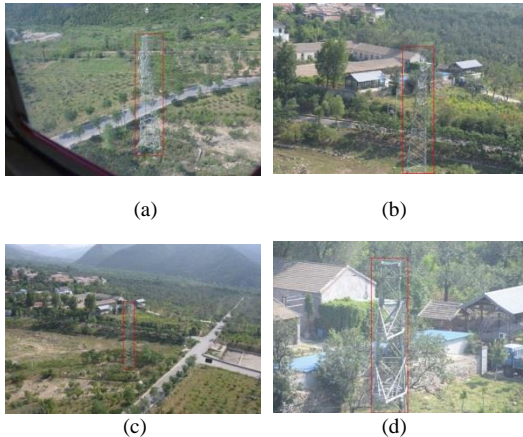

Figure 2. Tower detection results.

5 CONCLUSIONS

Power line infrastructures are heterogeneous and complex, making automatic power line inspection a difficult problem. Therefore, the research in this field is attractive. To achieve the goal of autonomous inspection, research efforts must aim towards developing general approaches that satisfy several requirements such as simultaneous detection of power lines and electric towers, check for defects in several power line components and the security distances analysis among others. Current paper usually focuses on this direction, with emphasis on electric tower detection in aerial inspection data. And we believe that it is a key stage to conduct more complex tasks such as defects analysis, especially when the main source of information comes from poor quality images.

The key innovation of this paper is the investigation of a learning framework for providing a complete solution for tower detection which may be the fastest paradigm since we have used boosted detector. Another main reason for the good performance is that we use aggregate channel features, including color, normalized gradient magnitude and histogram of gradients. However, such features may not be an ideal representation for all types of towers. This problem was more visible during the evaluation of the complete system, especially with higher number of misclassifications. Therefore, exploring other feature spaces is our work in the future. And finally, we hope to significantly promote the results of tower detection.

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