Power Line Segmentation and Detection of Broken Strands

Subjects: Automation & Control Systems

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Power lines are critical infrastructure components in power grid systems. Strand breakage is a kind of serious defect of power lines that can directly impact the reliability and safety of power supply. Due to the slender morphology of power lines and the difficulty in acquiring sufficient sample data, strand breakage detection remains a challenging task. Moreover, power grid corporations prefer to detect these defects on-site during power line inspection using unmanned aerial vehicles (UAVs), rather than transmitting all of the inspection data to the central server for offline processing which causes sluggish response and huge communication burden.

power line inspection strand breakage detection power line segmentation unmanned aerial vehicle CNNs handcrafted models

1. Introduction

Electric power lines are critical infrastructure components that transport electrical energy from power generation plants to users. Since most power lines are implemented in an outdoor environments, they are vulnerable to various types of damage that can impact the reliability and safety of the electricity supply. One typical type of damage is the breakage of strands, which can lead to electrical faults and power outages if they are not eliminated in a timely manner. Thus, detecting broken strands on power lines is essential for ensuring uninterrupted power supply and preventing accidents.

In recent years, due to the high maneuverability, good economic property, and capability of high-quality image acquisition of unmanned aerial vehicles (UAVs), they have been more and more widely applied in power line inspection [1][2]. They have significantly eased the process of capturing high-resolution images of power lines from different angles. However, finding the defects in power lines and other components in the obtained images still relies on manual interpretation or centralized processing on the cloud server with large deep learning models. Due to the rise in labor costs and the rapid growth of data volume, inefficient manual interpretation is gradually being phased out. The centralized processing manner suffers from a huge communication and computational burden, and the delay of offline processing [3]. Therefore, detecting the power line defects in real-time on site with algorithms and computational resources carried by UAVs is a preferable method. There are already many researchers developing online image processing systems for UAV-based power line inspection [3][4]. However, the existing technology cannot meet the requirements of practical applications in terms of accuracy and efficiency.

Furthermore, developing an accurate and robust strand breakage detection method is challenging. On the one hand, the power lines and broken strands are thin objects; their features become indistinct in images captured by UAVs from a distance. On the other hand, obtaining sufficient sample data for training a deep learning model is extremely hard since strand breakage occurs rarely and, once discovered, it is immediately eliminated to prevent serious consequences.

As intelligent inspection and defect detection technologies show great potential to significantly reduce the cost and risk of manual operation in power system inspection, related research has been conducted for more than a decade. In the following sections, related works that cover both traditional computer vision methods and deep learning-based approaches for power line segmentation and detection of broken strands will be presented.

2. Power Line Segmentation

In the past, power line segmentation tasks often relied on purely hand-crafted models. These hand-crafted models were typically constructed based on low-level local features such as gradients, brightness, texture, and other prior information from wire images. Chen et al. [5] developed the Cluster Radon Transform to extract linear features of power lines from remote sensing imagery and devised a set of rules to distinguish power lines from other linear features like roads. Zhou et al. [6] developed an edge detection method for power line detection, which selects optimal parameters for changing backgrounds and, hence, overcomes the threshold problem in other methods. Du et al. [7] used Hough Transform (HT) butterflies to prove that the HT is not only effective for detecting and locating linear-shaped targets but also for curved wire objects. In the aforementioned works, it has been demonstrated that hand-crafted models constructed using traditional computer vision methods are feasible for power line segmentation tasks. However, these methods still suffer from issues such as low detection accuracy and limited generalizability.

In comparison, significant progress has been made with convolutional neural networks (CNNs) [8][9]. Building upon these advancements, CNNs have also been applied on power line segmentation. However, power line segmentation tasks based on neural networks often face challenges in achieving high-quality feature extraction due to the slender morphology of power lines. The network architecture proposed by Chang et al. [10] suggests fusing shallow and deep features within the neural network. They introduced a compact neural network composed of a generator and a discriminator within the conditional generative adversarial network (cGAN) framework [11]. Additionally, skip connections were incorporated between each encoder and decoder in the network architecture. In the work of Zhang et al. [12], a method of multi-level feature map fusion was introduced. They proposed a convolutional neural network based on the VGG16 architecture [13], which is capable of obtaining hierarchical predictions from different convolutional layers. By leveraging multiple levels of information, the network can automatically learn how to combine them and generate satisfactory fused outputs. In recent work, Choi et al. [14] attempted to generate the location information of power lines in input images by introducing attention into a two-stage semi-supervised learning framework. In the first stage of their method, they utilized the information from various layers of the VGG network to form an Attention Localization Mask (ALM); in the second stage, the mask and sub-network were used to generate the contour information of the power lines. However, their proposed method exhibits a significant increase in computational complexity compared to conventional one-stage semantic segmentation networks, making it challenging to deploy in practical applications. On the other hand, He et al. [15] explored the use of a more powerful baseline and network light-weight design in power line segmentation tasks. They employed a light-weight backbone structure (DFC-GhostNet [16]) for feature extraction and combined it with contextual information features to enhance the U-Net algorithm [17]. Furthermore, they designed a hybrid feature extraction module based on convolution and transformers to optimize deep semantic features, improving the model's ability to locate towers and transmission lines in complex environments.

3. Strand Breakage Detection

Similar to power line segmentation tasks, early methods for detecting broken strands in power lines often relied on handcrafted models. Researchers modeled the presence or absence of defects in power lines by utilizing low-level local features such as gradients, brightness, texture, and other prior information derived from power line images. These handcrafted models were then used for defect detection tasks related to power lines. Ishino et al. [18] constructed handcrafted models for defect-free power line images using statistical information such as brightness, texture, and morphology. They utilized this model to perform simple classification of broken strand power lines. On the other hand, Mao et al. [19] employed the Histogram of Oriented Gradients (HOG) algorithm to extract gradient features from power line images and used a hybrid classifier composed of the Support Vector Machine (SVM) algorithm to classify normal power lines, broken strand power lines, and obstacles. In the study conducted by Jalil et al. [20], the Canny edge detector and HT were exploited for power line detection. Then, within the corresponding IR image, they computed the histogram of the image, and performed Otsu's thresholding to identify the faults or hot spots.

In recent studies, deep learning-based object detectors have been widely applied in industrial scenarios related to the power system [21][22]. Existing methods usually exploit a two-stage process to locate the regions of power line strand breakage. These detectors typically employ a sliding window approach in the first stage to capture candidate regions that may contain faults and, in the second stage, they discriminate the regions where actual faults occur. In the study by Wang et al. [23], a CNN-based power line fault detection method was proposed. In the first step, a CNN is used in conjunction with the sliding window method to predict all parts of the input image and generate an output map. In the second step, the output map is preprocessed to enhance its localization characteristics. Finally, the target detection is completed based on the preprocessed output map information. On the other hand, Xu et al. [24] applied Faster R-CNN [25] to detect fracture areas in power lines. However, what distinguishes their work is the introduction of an attention mechanism into the feature extraction network of Faster R-CNN. This mechanism guides the network to focus specifically on the parts of the input image directly relevant to fractured regions, thereby enhancing the model's training effectiveness and robustness.

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