Deep Learning Based Arc Detection in Pantograph-Catenary Systems

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Abstract

Pantograph-catenary systems are the most important parts of electric trains. Faults that occur in pantograph-catenary systems seriously affect railway transportation. Arcs are the most important reporters of pantograph-catenary systems. Detection of arcs that give early signal of these faults is very important. In this paper, an approach using deep learning is proposed for the detection of arcs in pantograph-catenary systems. Arc detection is performed using CNN (Convolutional Neural Network). Deep learning have gained great importance in recent years. In this study, experimental results show that the proposed method is quite successful in detecting the arc.

Keywords—pantograph; catenary; deep learning; convulational neural network; CNN

1. Introduction

Pantograph-catenary systems provide the power to operate electric trains. For this reason, faults in these systems threaten the operation and safety of railway transportation. These systems must be continuously monitored, controlled and maintained for a healthy and continuous transport. The arcs formed in the pantograph and catenary systems indicate that the wires in the system are overheated. Overheating of the wires, it may be a sign that there is a fault or wear in the region. The long runs of the arcs in the pantograph-catenary system will damage these systems. Therefore, it is very important that the arches in the pantograph-catenary systems are detected early.

In recent years, the detection of arcs and faults in pantograph-catenary systems has gained great importance. Signal and image processing techniques are used for detection. Some literature studies on this area have been mentioned. Karakose et al. [1] have proposed an image processing based approach to diagnosis of pantograph-catenery systems. The approach has modeled the interaction between the pantograph and the catenary, and classifies the pantograph as dangerous, safe and defective by using image processing techniques. A block diagram of their study is given in Figure 1. Hao et al. [2] performed a dynamic analysis of the arc in the pantograph-catenary system during the pantograph lowering. According to the MHD theory, they developed a pantograph-catenary arc model. Mokrani et al. [3] performed a monitoring control for the pantograph-catenary system. They addressed the issue of regulating the contact force between the pantograph and the catenary. They proposed a linear time-varying model describing the evolution of contact force. The results obtained were satisfactory. Barmada and others [4] suggest a method of detecting arcs in pantograph-catenary systems using support vector based classification. They found out when an arc came out with the output of a phototype that they obtained using voltage and current information from the system.

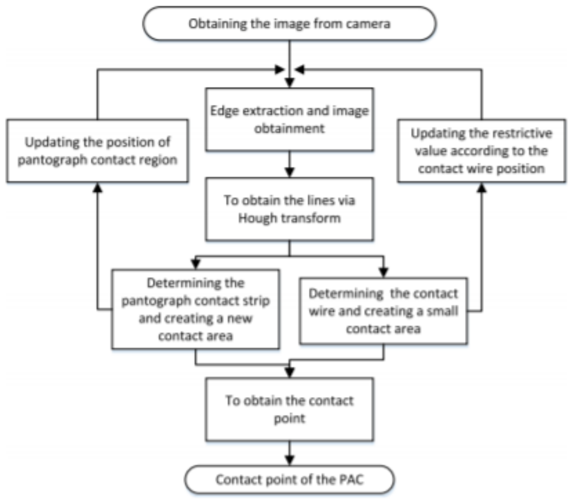

Fig. 1. Block diagram of a study in the literature [1]

Vazquez and others [5] suggest a contactless sensor to monitor the catenary-pantograph effect. This sensor measures the height changes of the contact wire when the pantograph passes. With the measurements obtained, the deterioration between the pantograph and catenary is detected. The sensor consists of a line-scanner camera focusing on an infrared screen. The mathematical model of the sensor system developed in the study and its practical results are given. Ma et al. [6] have developed a new method to calculate the radiation originating from the back of the pantograph on the high-speed railway. They combine numerical modeling with laboratory experiments. Capece and others [7] developed an automatic image based inspection system for locomotive pantographs. They are capable of capturing and analyzing images at a speed of 300 km/h in spite of various environmental conditions. They succeeded in analyzing over 10000 pantographs. Wei et al. [8] studied high-speed photography and pantograph arc in a laboratory simulation system. Tang and others [9] propose a method to detect the visual anomaly by combining the appearance, scale and location of the view with the probabilistic Bayesian approach for the observation of the pantograph head. Experimental results show that the Bayesian detector gives better results in complex environments than the classical object detector. Östlund et al. [10] suggest a method for maintaining the contact strip in the pantograph depending on the condition of the contact strip. They predict the contact strip wear by monitoring the working distance of the DC component of the locomotive current. Hamey and others [11] developed an in-service monitoring system for detecting wear and damage at pantographs in electric locomotives. Yang et al. [13] set up a signal and image processing based experimental setup for pantograph inspection. In another study, the vibrational signals of the catenary system were measured by a pantograph mounted device [14]. In this method, good results were obtained when the defective region was large. But it cannot detect the fault early.

In this paper, an approach using deep learning is proposed for the detection of arcs in pantograph-catenary systems as well as signal and image processing methods in the literature. In the proposed study, arc detection is performed using CNN (Convolutional Neural Network). Research in recent years shows that CNN is very successful in complex machine vision problems [15]. CNN provides very successful results in operations such as classification, segmentation and object detection. In this article, as seen from the application results, CNN produced quite successful results in detecting the arc.

2. Monitoring Pantograph-Catenary Systems

Pantograph-catenary systems provide a power source for the transport of electric trains. While the pantograph-catenary systems provide a power source, the pantograph collector strips contact the catenary as shown in Figure 2.

Fig. 2. Pantograph-catenary image [16]

Since the pantograph and catenary contact each other, over time contact areas can be worn away. Worn areas can heat up more due to electrical conduction, and the amount of wear can increase when heated. These probable situations are affecting the continuation and safety of railway transportation. Defects occurring in these systems can be detected at an early stage and measures can be taken to prevent major accidents and high maintenance costs [12].

The monitoring of pantograph-catenary systems and the diagnosis of failures in these systems have become an important issue in recent years. Particularly as the train speed increases, the prevention of failures that can occur in pantograph-catenary systems has become even more critical. Many railway companies provide periodic maintenance to railway equipment to replace the existing defective part and prevent possible failures. Periodic maintenance refers to unnecessary workload for equipment that has not been damaged. In addition to this, it is necessary to stop the transportation service for periodical maintenance. This is not a desired situation. For this reason, the status monitoring and automatic detection systems of pantograph-catenary systems have been studied in recent years. Faults in the monitored system can be detected at an early stage. Early detection allows for maintenance planning. Thus, the interruption of service in railway transportation can be reduced to a minimum. In addition, maintenance costs will also be reduced because only equipment that has failed or is likely to fail is to be serviced.

Signal and image processing techniques are used for state monitoring and automatic detection in pantograph-catenary systems. Vibration signal from the pantograph-catenary system can be analyzed related to the health condition [17]. Or you can get information about the pantograph status with an accelerometer. Condition monitoring techniques with signal processing use the current and voltage signals obtained from the pantograph. Therefore, sensors must be installed on the train to obtain current and voltage [18]. Normal or thermal cameras are used for image processing or computer vision techniques based status monitoring and automatic detection. Especially with thermal cameras, monitoring has become very popular in recent years. Because thermal cameras use infrared rays and pantograph-catenary systems emit heat when they touch each other. In this way, even in the dark, the system can be perceived. In the literature, the block diagram of the systems that monitor the situation with image processing and computer vision techniques is as in Figure 3 in general. As can be seen in Figure 3, these systems consist of three basic parts: image acquisition, computer vision and object detection.

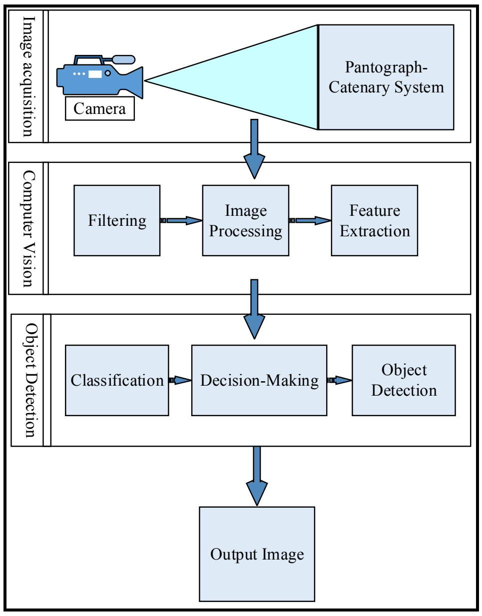

Fig. 3. General block diagram of studies in literature

In the image acquisition section, pantograph-catenary videos are taken from a thermal or normal camera mounted on the train. In the computer vision section, this video is framed. By applying the necessary filters to the frames, noise is removed from the images. Feature extraction is performed by applying appropriate image processing techniques to the processing to be performed on the filtered images. In the third part, classifications are made according to the obtained properties. Classified images are taken as an input to a decision mechanism and object detection is performed. Finally, detected objects are applied to the video display.

The work that uses image processing and computer vision techniques does not damage the pantograph-catenary systems because it is contactless. It is very useful in this face.

3. Proposed Method

In the pantograph-catenary systems, the arcs can come to the foreground due to the contact between the pantograph and the catenary. In this study, the arcs are detected using deep learning. A block diagram of this study is given Figure 4.

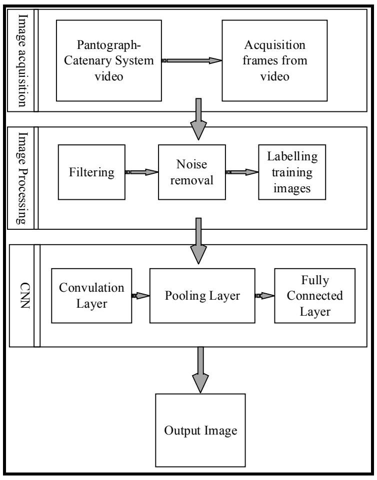

Fig. 4. Block diagram of the proposed method

A pantograph video was divided into frames and 811 images were obtained. 700 of these images were used as training data. 111 of these images were used for testing purposes. 700 of the obtained pantograph images were prepared as training data. The arcs in the image were prepared as training data by taking bounding boxes

In this study, the detection of the arcs in the pantograph images is done with Convolutional Neural Network (CNN), a deep learning architecture. The block diagram of the work is as shown in Figure 5.

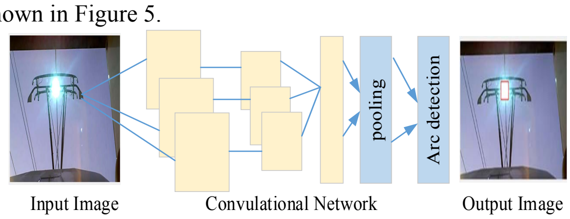

Fig. 5. Block diagram of the work

A feature map is extracted from training data with a CNN. The proposed CNN includes 5 convolution layers as shown in Figure 6, and each convolution layer is followed by a pooling layer. The kernel of all of the convolutional layers are the same size 3x3. There are 3 fully connected layers in the network.

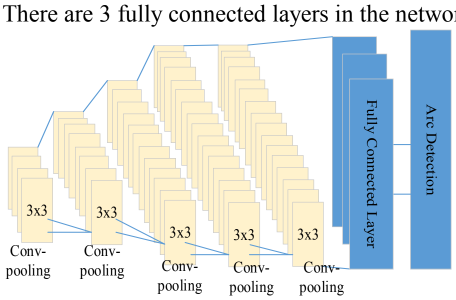

Fig. 6. Architecture of the CNN

Convolution Layer

In this layer, the output value is calculated by multiplying the weight value of the neuron related to the input data as shown in Figure 7. Filters are used in this layer can learn. These filters are randomly generated at the beginning and the optimum filter values are calculated during the training process. The feature maps of the image region that are convolved with the filter are removed. With the help of filters, curves, squares and patterns in an image can be extracted. The main purpose in this layer is to extract the feature from the input image. The output of the layer can be named as activation map or feature map.

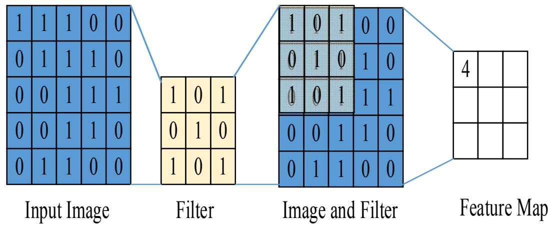

Fig. 7. Convolution Layer

Pooling Layer

As shown in Figure 8, the dimensions of feature maps received as input are reduced.

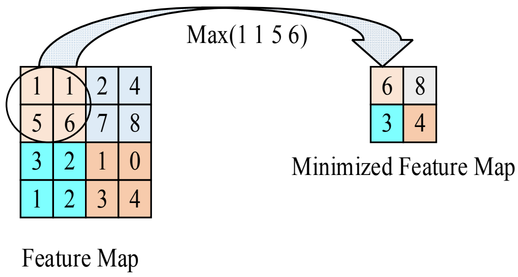

Fig. 8. Pooling Layer

In the proposed study, max pooling is used to reduce the size of the feature map in the pooling layer.

Fully Connected Layer

This layer forms the final layer of the convolutional network. Featured maps are given as input to this layer and it is determined whether they are within the boundaries specified in the training data. Three fully connected layers are designed. It is determined by these layers that the feature maps do not overlap with the arc regions within bounding boxes given in the training data.

4. Experimental Results

In this paper, Convolutional Neural Network (CNN) architecture is proposed for arc detection in pantograph-catenary systems. For this, a video belonging to the pantograph-catenary system was used. 811 images were obtained by separating the video frames. Most of the images contain arc. A frame of the video is as shown in Figure 9.

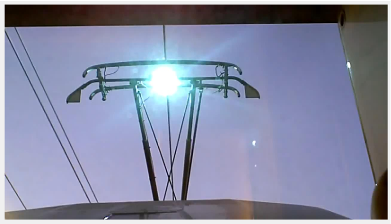

Fig. 9. Pantograph image with arc

700 of the obtained pantograph images were prepared as training data. The arcs in the image were prepared as training data by taking bounding boxes with Matlab 2017a. some images prepared as training data are as shown in Figure 10. The network was first trained at 80000 iterations with a learning rate of 0.001. The application was developed in parallel for each color layer using the parallel programming feature of Matlab 2017a. The network is trained with 700 labeled pantograph data. CNN has reached the desired learning rate in 1359 iterations. Training error rate is given in Figure 11.

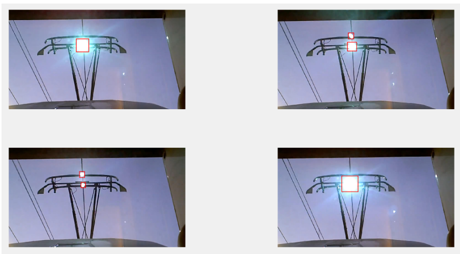

Fig. 10. Labeled training images

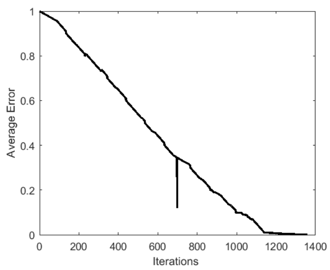

Fig. 11. Network training performance

The remaining 111 pantograph images were used for the test. In the images used for the test, the application detected 97% of the arc area correctly. Figure 12 shows the output of a given image for the test. Traced filters are applied to the input images in the network and the arcs in the pantograph are placed in bounding boxes.

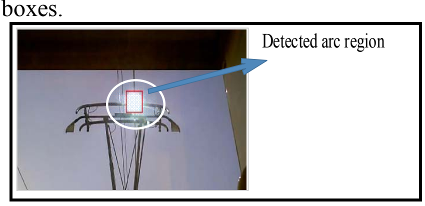

Fig. 12. Detected arc region

Some of the results images used for the test are shown in Figure 13. In Figure 13, the input image, the CNN output image and the precision value of the image is given. Precision value is ideally equal to 1. Precision values of given images should be close to 1, showing how successful the study is in detecting the pantograph. Table 1 gives the average Precision value of 111 test images. The average Precision value was found to be 0.9752. This value is very close to 1. This demonstrates how the improved CNN architecture is the right method for arc detection.

Pixel values containing the areas within the bounding boxes obtained from the output images that are the results of the test and the pixel values containing the areas within the bounding boxes, which are labelled, were compared for each test image. This comparison how much greater the number of pixels results in conflicting accuracy of the study is so high. Figure 14 shows the overlap ratio of these pixels as a percentage. The overlap ratio of the pixels is also the accuracy rate. As can be seen from the graph, in the majority of test images, the overlap between the pixels in the bounding boxes of the test images and the pixels in the bounding boxes of the resulting image is over 90%.

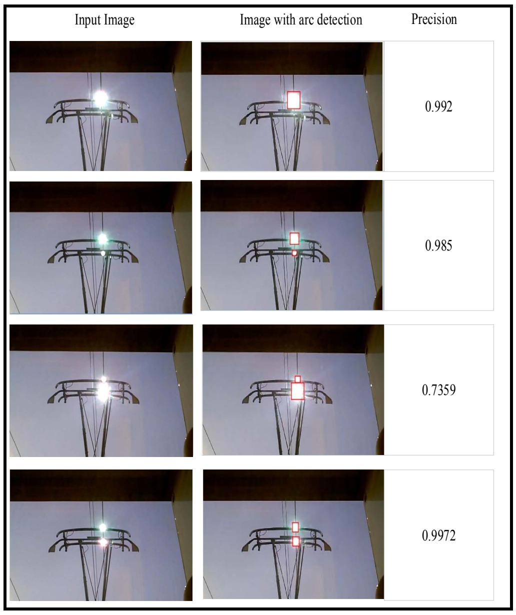

Fig. 13. Detection of arc fields in pantograph images tested

Table 1. Average precision value for test images

Test Image Number	Average Precision
111	0.9752

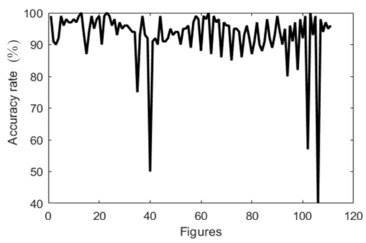

Fig. 14. The overlap rate between the pixels in the labeled bounding boxes in the test image and the pixels in the bounding boxes of the resulting images

5. Conclusions

Pantograph-catenary systems provide the power to provide transportation to electric trains. While providing power, the pantograph is in contact with the catenary. This contact can cause erosion and deterioration of the catenary or pantograph collector strips over time. Arcs are the most important reporters of wear and tear that are occurring or are about to occur in pantographs and catenary. Therefore, monitoring of pantograph-catenary systems and detection of arcs are very important. Early detection of arcs will allow railway companies to plan maintenance. This will reduce the maintenance cost and the workload. It will also provide safe transportation.

In this study, a deep learning approach is proposed for the detection of arcs in pantograph-catenary systems. Convolutional Neural Network is the most popular Deep Learning architecture, especially in the field of computer vision. 700 of the pantograph images taken from a video are used as training data for this architecture. 111 of the images were used for the test. As will be seen in the experimental results, the average precision value of the test images is 0.9752. This value is very close to 1. This shows how successful our work is in detecting the arcs.

7. References

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