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A New Fault Detection Algorithm for EMUs based on Deep Learning

Zhi Liu [a], Yanru Sun
North China University of Technology, Beijing, 100144, China
[a]lzliu@126.com

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Abstract. Health monitoring is an important task for high-speed railway EMUs. Traditional methods for detection have the problem of low detection rate or high false alarm. In this paper, a new fault detection algorithm is proposed based on deep learning. A region proposal network is applied and a network is trained based on EMU images. Initial experiments show that the proposed network can achieve 95.67% accuracy in detection, which the speed of 0.1-0.2 second per image.

1. Introduction

With the rapid development of high-speed railway in China, monitoring of high-speed EMU's health status becomes an increasingly problem. To monitor the health status of moving EMUs, some Trouble of moving EMU Detection System (TEDS) have been deployed in important railway stations during the latest years. However, Most of the systems rely on traditional image processing technology to detect fault. Due to the complex structure of the EMU body and various unpredictable faults may occur, the performance of such systems is less than satisfactory.

Deep learning is a new emerging technology in machine learning. By constructing an artificial neural network with deep layers, system can learn complicated features from data automatically, and describe the object more precisely and insightfully. Deep networks have been applied in various fields, including object detection and recognition, natural language understanding, and so on, and show prominent performance improvement in these field. Although deep learning network is powerful, there are very few researches on applying it to fault detection. In this paper, we try to utilize deep learning network to monitor the health status of EMU and propose a new fault detection algorithm.

There are several kinds of deep learning networks, including Auto Encoder, Deep Belief, and Convolutional Neural Networks (CNN), and so on[1]. Compared with the other two, Convolutional Neural Network [2] has more advantages in image processing and recognition. Therefore, in this work, CNN is chosen to perform the task of fault detection in this paper.

A typical CNN network is composed of number of convolution layers and pooling layers. Figure 1 shows a simplified structure of CNN [3]. In the figure, C_x is a convolution layer, and S_{x+1} is a pooling layer. f_x and W_x are multiplicative bias, and b_x is an additive bias, and σ is a Sigmoid function.

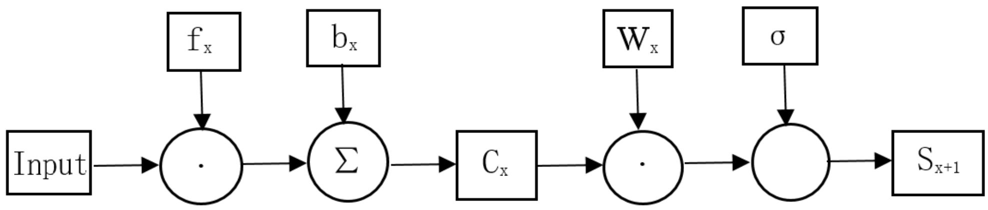

Fig.1 Structure of CNN

2. Algorithm design

To simplify the task of health monitoring, we formulate it to be the problem of fault detection. That is, for each interested area of the EMU surface, try to detect the kind of fault may occur. If no fault can be found in the area, it is a health area. Popular CNN networks designed for object detection include

SPPnet [4], Fast R-CNN [5], Faster R-CNN [6], etc. Among them, Faster R-CNN has the best performance, both in detection time and accuracy. Therefore, our algorithm is based on Faster R-CNN.

Using classifier to design an algorithm for fault detection, the first problem is to build candidate area. There are two popular ways to generate candidate area. One is Selective Search (SS) [8], and the other is Region Proposal Network (RPN). Compared with SS, RPN network adds 2 extra convolution layers (Full convolution classification layer and Full convolution regression layer), and use CNN to generate Region Proposal, which makes RPN superior to SS in speed.

2.1 Region Proposal Network.

The Region Proposal Network [6] is illustrated in figure 2.

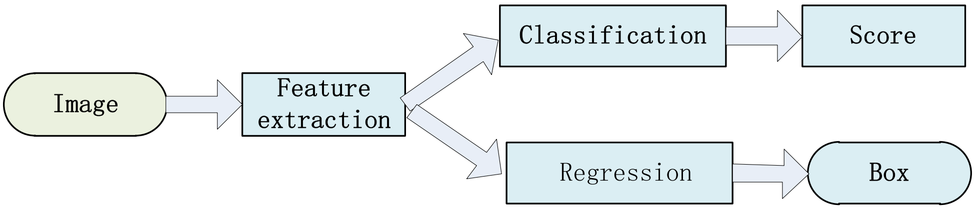

Fig.2 Region Proposal Network (Faster R-CNN [6])

Firstly, use a small network to slide over the output of the shared convolution layer to generate a low dimensional feature vector.

Secondly, input the low dimensional vector to the box regression layer (reg) and box classification layer (cls). At every point predict the border of the object and the score of the objectness.

The cost function of the region proposal is given by:

$$L(\{\mathrm{p}_i\},\{\mathrm{t}_i\}) = \frac{w_1}{N_{cls}}\sum_i L_{cls}(p_i,\mathrm{p}_i^*) + \frac{w_2}{N_{reg}}\sum_i p_i^* L_{reg}(t_i,t_i^*) \tag{1}$$

Where i is the index of anchor in a mini-batch, and p_i is the prediction probability of anchor i. If anchor is positive, $p_i^* = 1$, otherwise $p_i^* = 0$. t_i is a vector, representing the four coordinates of the bounding box. t_i^* is the vector of the coordinates of the ground-truth bounding box. L_{cls} is the loss function:

$$L_{cls}(p_i, p_i^*) = -\log(p_i p_i^* + (1-p_i^*)(1-p_i)] \tag{2}$$

Regression loss function L_{reg} is given by:

$$L_{reg}(t_i,t_i^*) = \begin{cases} (t_i - t_i^*)^2 & \left|t_i - t_i^*\right| < 1 \\ |t_i - t_i^*| - 1 & otherwise \end{cases} \tag{3}$$

Where $p_i^* L_{reg}$ indicates that the regression loss only exists when anchor is positive ($p_i^* = 1$), and w_1, w_2 are balance weights.

2.2 Structure of the fault detection network.

The model of EMU monitoring network is shown in figure 3.

3. Experiments

3.1 Experiment setup

All experiments are carried out based on CAFFE framework.

To train a deep learning network, large scale data is required, to ensure that the network can learn good representation of the data. However, for high-speed railway EMUs, it's difficult to find so many fault images. Therefore, in this paper, 4 typical kinds of fault images are focused on, including nut missing, crack, hollow, and apron missing. Each fault has eight different forms of images, with different affine transformation and noise. Totally there are 400 thousands images.

3.2 Experiment results

1500 images are used in the detection stage, each with resolution of 256x256.

When the number of iteration is 30000, of all the 1500 test images, 1414 is detected to be correct, accuracy is 95.67%. The time for one image processing is 0.1-0.2 second. The detection result is shown in table 1.

Table 1. Detection accuracy for each fault

Fault	Hollow	Crack	Nut missing	Apron missing	Average
Accuracy	98.41%	91.27%	96.96%	93.29%	95.67%

From table 1, we can find that, the detection accuracy of different faults varies. The reason is that, in the training stage, the number of images with fault hollow is much larger than that of images with fault crack. Therefore, the network can learn better representation of the fault hollow than the fault crack. Figure 4 shows part of the visualized detection result:

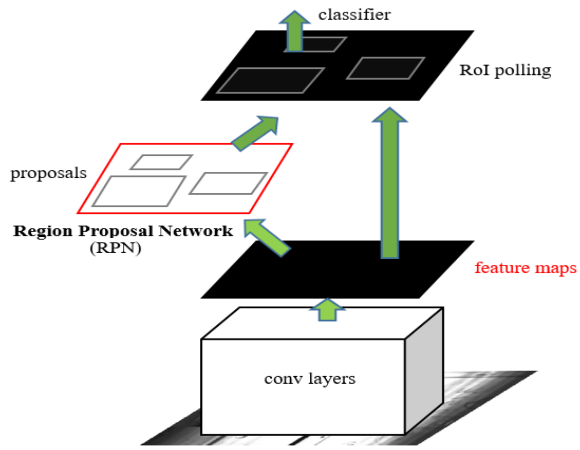

Fig.3 Model of the network [6]

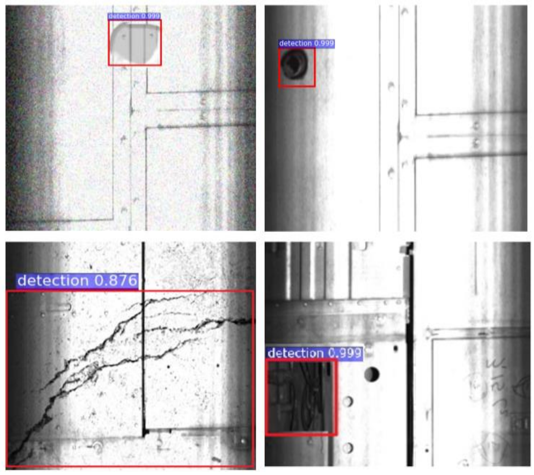

Fig.4 Visualization of the detection result

And figure 5 shows the influence of the number of iterations to detection accuracy. It can be found from the figure that, when the number of iterations is about 30000, the detection network performs the best.

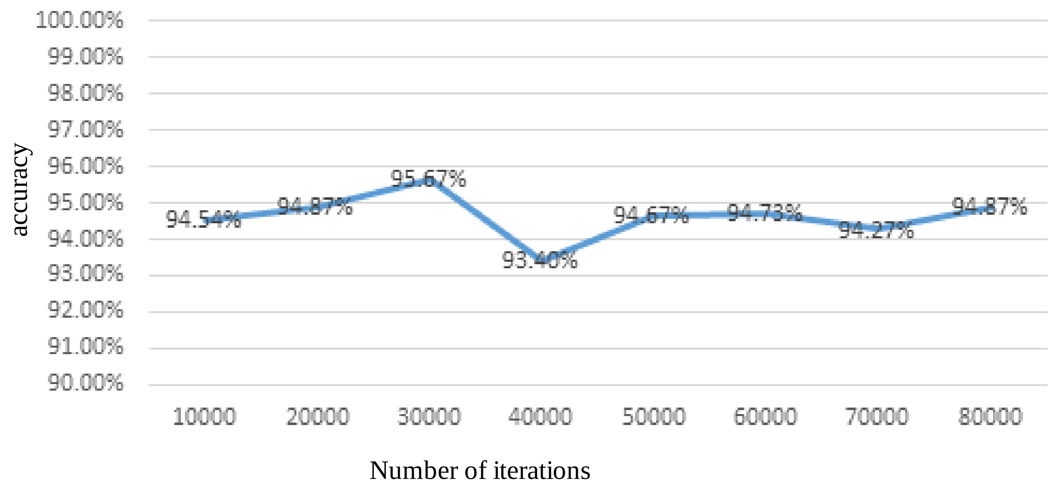

Fig.5 Number of iterations vs. accuracy

4. Conclusion

Health monitoring is an important job for high-speed railway EMUs. In this paper, a new health monitoring algorithm is proposed to detect four typical faults may occur in EMU system. The proposed algorithm is based on Raster R-CNN, using a modified region proposal network, and a network is trained based on the fault images. Initial experiments showed that the proposed algorithm can get accuracy about 95.67%. And the detection time is 0.1-0.2 second per image, which meet the requirement of the TEDS system. Further study is still in progress.

Acknowledgements

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