Anomaly Detection of Pantograph Based on Salient Segmentation and Generative Adversarial Networks

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Abstract. The pantograph is an important component of railway pantograph-catenary system, which can provide electric current for electrified railway electric locomotive. Since the pantograph is in an open roof environment, the defects of the pantograph are inevitable in the long run. In order to ensure the safe operation of trains, in this paper, we propose a new method for anomaly detection of pantograph based on salient segmentation and generative adversarial networks. First, an object location model is trained by U-Net which perform excellent properties for a small number of samples to accurately extract salient area of the pantograph. Second, a generative adversarial model is constructed to generate the reconstructed salient images of pantograph by vector mapping. Finally, the structural similarity algorithm is used to evaluate the similarity between the input salient image and the reconstructed salient image, so as to extract the image difference and realize the anomaly detection of the pantograph. Experimental results validate the effectiveness and accuracy of our approach.

1. Introduction

Pantograph is a kind of electrical equipment installed on the roof of the train through the underframe. The pantograph slide obtains electrical energy through directly contact with the wires of the catenary to supply power for the whole train. In order to ensure the safe operation of trains, it is significant to propose a new method to detect the abnormal state of pantograph in this paper, such as the missing horn, foreign objects (kites, birds, supports) invasion.

Nowadays, The non-contact detection methods based on image processing technologies are widely applied in the anomaly detection of pantograph. In[1], Hamey et al. used two CCD cameras to capture the top and side images of the pantograph, and then used morphological and closed operations to remove the image background and extract image features to obtain the abrasion of the pantograph slide. In[2], Ma et al. extracted the upper and lower edges of the pantograph slide to detect the pantograph. In[3], Chengdu Lead Science & Technology Co. Ltd. designed the SJ series pantograph condition detection system. In[4], Yao et al. proposed a new method based on interval type-2 fuzzy entropy and Hough transform for pantograph slide crack detection. In[5], Luo designed a model based on corner detection for pantograph offset fault detection, using SSD to obtain pantograph horn area, and then using wiener filtering, threshold segmentation, morphological gradient to obtain corner edges information to realize the pantograph offset detection. In[6], Zhang et al. proposed a method combining deep convolution network with handcrafted features to detect the pantograph-catenary.

In this paper, a new anomaly detection of pantograph is provided. The main contributions of this paper are that the salient segmentation model can quickly and accurately locate the overall outline of
the pantograph, and the generative adversarial networks can only use normal images to realize the reconstruction of abnormal images, which can effectively overcome the lack of abnormal samples.

2. Abnormal detection of pantograph
The architecture of our approach is illustrated in figure 1. To overcome the problem of imbalanced samples of pantograph, the U-Net and the GANs are proposed to detect abnormal images. As shown in figure 1, The framework is composed of three stages. First, The U-Net model is used to obtain the saliency map of pantograph. Afterwards, The generative adversarial networks is used to reconstruct the abnormal images into normal images. Finally, structural similarity algorithm is used to realize the anomaly detection of pantograph and visualize anomalous areas.

Figure 1. The framework of anomaly detection.

2.1. Salient segmentation model
As shown in figure 1, the first stage of our approach is to accurately locate the salient region of pantograph by salient segmentation. The aim of salient segmentation is to detect and separate the pantograph that people are interested in from the background, which can effectively suppress the background noise in the image and weaken the influence of unimportant information on the pantograph. The salient segmentation network is the standard architecture introduced in U-Net[7].

2.2. Generative adversarial networks model
GANs is an unsupervised machine learning algorithm originally proposed by Goodfellow et al. [8], which can be used to generate real images. DCGANs[9] is a typical and widely model to address training instability issues of GANs. The architecture of generative adversarial networks model based on positive salient samples[10] in this paper is illustrated in figure 2.

Figure 2. Architecture of generative adversarial networks model.
As shown in figure 2, At the training stage, G is a generator that learns the input $x$ representation and reconstructs the $x$ to the output $x'$ via $G_E$ and $G_D$. $G_D$ is a decoder, $G_E$ is an encoder that
consists of four 3x3 convolutions, a batch normalization layer and a rectified linear unit (ReLU). The G₀ network and D network are the standard generator and discriminator network introduced in DCGANs[9], respectively. At the test stage, the test image x is input into the network G, and the reconstructed x' is output. Then using the structural similarity(SSIM) algorithm to extract the features and evaluate the difference between x and x'.

The reconstruction loss \( L_{\text{rec}} \) between x and x' is defined as[11]:

\[
L_{\text{rec}} = \mathbb{E}_{x \sim P_{\text{data}}(x)} \| x - x' \| = \mathbb{E}_{x \sim P_{\text{data}}(x)} \| x - G(x) \|
\]

(1)

To avoid the issue of loss of image details using only reconstruction loss, in addition, the adversarial generation loss \( L_{\text{GAN}}(G, D) \) [8][9] is defined as follows:

\[
L_{\text{GAN}}(G, D) = \mathbb{E}_{x \sim P_{\text{data}}(x)} [\log D(x) + \log(1 - D(G(x)))]
\]

(2)

So, the overall objective function for the model becomes the following:

\[
L = \arg \min_G \max_D (w_{\text{rec}} L_{\text{rec}}(G) + w_{\text{GAN}} L_{\text{GAN}}(G, D))
\]

(3)

Where \( w_{\text{rec}} \) and \( w_{\text{GAN}} \) are the weighting parameters to adjust the adversarial generation loss and the reconstruction loss.

2.3. Structural similarity and anomaly detection

In the paper, the structure similarity algorithm SSIM[12] is used to extract the feature differences between the input image and the reconstructed image. SSIM is a calculation method based on the local differences between the image samples x and y. SSIM is defined as follows:

\[
\text{SSIM}(x, y) = \frac{(2u_x u_y + C_1)(2\delta_{xy} + C_2)}{(u_x^2 + u_y^2 + C_1)(\delta_x^2 + \delta_y^2 + C_2)}
\]

(4)

Where \( u_x \) and \( u_y \) are the mean of samples x and y, \( \delta_x^2 \) and \( \delta_y^2 \) are the variances of the samples x and y, respectively. \( \delta_{xy} \) is the co-variance. \( C_1 = (K_1L)^2 \), \( C_2 = (K_2L) \), \( K_1 \) and \( K_2 \) are constants, with values of 0.01 and 0.03, respectively, and \( L \) is the pixel value range of the image.

Through the SSIM algorithm, we obtain the structural similarity score and the difference image of the two input images, and then visualize the differences on the input image. The difference visualization steps are as follows: First, finding the contours of the difference image. Then, spreading the contours pixel by pixel to calculate the area of each contour containing area, and select the largest area area as the difference area between the input images. After that, calculating the area around the outline of bounding box and store the relevant coordinate. Finally, the difference area is drawn on the input image according to the saved bounding box coordinates.

3. Experiments and results

The experimental environment in this paper is described as follows: Ubuntu 16.04.14 operation system, GPU: NVIDIA RTX 2080Ti with 11GB memory, python 3.6.4, deep learning open-source software library PyTorch.

3.1. Salient segmentation experiment and result

In this paper, 100 labeled images of pantograph are chosen to train U-Net model, and 400 unlabeled images as the test data set. We trained the U-Net using Adam algorithm with a batch size of 10, the momentum parameters are 0.5 and 0.999, the learning rate is 0.005[7]. After 100 epochs, the salient images of the pantograph which met the experimental requirements of this paper were obtained. Figure 3 and figure 4 show the original images and salient pantograph images, respectively.
3.2. Generative adversarial networks experiment and result

In the generative adversarial networks experiment, 300 salient normal images were used as the training set and 100 (50 normal images and 50 abnormal images) images were used as the test set. We trained the model using Adam algorithm with a batch size 10, the initial learning rate is 0.0002, the momentum parameters are 0.5 and 0.009. The optimization of the model is based on the loss function in Equation (3), using the weight $w_{rec}$ value is 1, and the $w_{GAN}$ value is 50, which were empirically chosen to based on the empirical value of [11] to yield optimum results. Figure 5 and figure 6 show the result of generative adversarial networks.

3.3. Structural similarity and anomaly detection experiment and result

In this paper, SSIM algorithm is used to calculate the difference between the original salient image and the reconstructed salient image from three aspects of image brightness, contrast, and structure, and visualize the difference image. The value of SSIM is within $[-1, 1]$. The larger the value of SSIM, the greater the similarity of the image. In order to obtain a higher accuracy rate, the SSIM threshold is set as 0.9 in this paper. Table 1 shows the accuracy of the test image with different threshold of SSIM.

| SSIM | 0.50 | 0.55 | 0.60 | 0.65 | 0.70 | 0.80 | 0.85 | 0.90 | 0.95 |
|------|------|------|------|------|------|------|------|------|------|
| Accuracy/% | 32.00 | 32.00 | 34.00 | 34.00 | 36.00 | 60.00 | 78.00 | 90.00 | 68.00 |
In this paper, we chose several typical anomalous states such as missing horn, foreign objects (kites, birds, supports) invasion. Some experimental results are shown in figure 7.

Figure 8 provides the histogram distribution of abnormal images in the test stage, where the abnormal items in the figure represent the original images of the input, and the normal items represent the abnormal image reconstructed as normal.

4. Conclusion

This paper proposed a novel anomaly detection method of pantograph. Salient segmentation model is introduced to obtain salient pantograph at first stage. Generative and adversarial networks is introduced to construct the abnormal images to normal images at second stage. Structural similarity algorithm is used to extract the difference between the input salient image and the reconstructed salient image, and visualize the difference area at three stage. Experiments confirm the effectiveness of our method. Future research can focus on improving the resolution of reconstructed images and increasing the diversity of samples of pantograph.

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