An Improved Defect Detection Method of Water Walls Using the WGAN

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Abstract. This paper proposes an improved water wall defect detection method using Wasserstein generation adversarial network (WGAN). The method aims to improve the problems of poor safety and high level of maintenance personnel required by traditional inspection methods, and improve the accuracy and safety of water wall defect detection through automated inspection. The WGAN is used to expand the water wall defect data. Then the extended data set and the original data set are loaded into a convolutional neural network for training, respectively. The results show that the accuracy of the expanded data set is significantly improved, which can achieve the industrial requirement of the thermal power generation.

Keywords: WGAN; Water wall; Convolutional neural network; Defect detection; Thermal power generation.

1. Introduction

With the development of China's society and economy, China's electricity consumption has also increased year by year. At the end of 2014, the total domestic electricity production capacity reached 1.36 billion kilowatts [1]. During this period, the installed capacity of power generation generated a total of 150 million kilowatts of increase, and 70% of these increases were generated by the thermal power. The thermal power generation in China's total power generation remains at about 80% [1]. The main energy source of the thermal power generation is the coal combustion. Therefore, the boiler is one of the most important and basic energy source equipment for thermal power plants. According to statistics, the accidents of four tubes including water wall tubes, reheater tubes, superheater tubes and economizer tube in thermal power boilers account for about two-thirds of domestic boiler accidents [2]. Due to the complex environment inside the boiler, there are various types of defects on the inside and outside walls of water wall tubes. The inner wall defects of the water wall are mainly corrosion, while the outer wall includes wear, corrosion and tear [3].

At present, the main detection method of water-cooled walls in China is non-destructive testing of water walls, that is, water walls can be effectively inspected without damaging water walls. Non-destructive testing methods for water walls are mainly magnetic particle testing[4], radiographic testing, eddy current testing[5], and ultrasonic testing. The magnetic particle detection has high requirements for the smoothness of the surface of the water wall and is not good at detecting small cracks[6]. Conventional single-channel eddy current testing is inefficient [7]. And ultrasonic testing has the disadvantages such as poor signal defects and high distance requirements [3]. Therefore single non-destructive testing method cannot meet the needs of water wall defect detection.
2. Generative Adversarial Networks

The generative adversarial network (GAN) was proposed by Goodfellow et al\[8\]. The GAN is widely used in the computer vision. Wu et al. used the GAN for human pose recognition[9]. Jin et al. used a GAN integrating the neural network to implement a bobbin yarn grasping method[10]. Chen et al. used the GAN to realize facial expression recognition[11]. And some fault diagnosis in industrial process can be achieved effectively based on the GAN.

And the structure of the GAN is shown in figure1.

![Figure 1. The structure of the generator network.](image)

The GAN uses a two-person zero-sum game, that is, the sum of the interests of the two parties in the game is a constant. The generation adversarial model is mainly composed of a discriminator (D) and a generator (G). G generates a picture G (z) by receiving a random noise z, D receives the picture x, and judges whether x is a real picture, and outputs the predicted probability D(x)..

During the training process, G and D have a clear division of the labor. The goal of G is to generate a sufficiently real picture to deceive D. The goal of D is to distinguish the picture generated by G from the real picture. The ideal situation of the entire GAN is that whether it is a real dataset or a generated dataset, D (G (z)) = 0.5. The training process can be obtained by equation (1).

\[
\min_{G} \max_{D} V(D, G) = \mathbb{E}_{x \sim P_{\text{data}}} \left[ \log D(x) \right] + \mathbb{E}_{z \sim P_{\text{z}}} \left[ \log(1 - D(G(z))) \right]
\]

Where, \( P_{\text{z}} \) is the true sample distribution, and \( P_{\text{g}} \) is the sample distribution produced by the generator. For the generator G, Goodfellow proposed two parameters is proposed as shown in equation (2) and equation (3).

\[
\mathbb{E}_{x \sim P_{\text{data}}} \left[ \log(1 - D(x)) \right]
\]

\[
\mathbb{E}_{z \sim P_{\text{z}}} \left[ - \log D(x) \right]
\]

For a given generator G, the corresponding optimal discriminator D can be obtained by equation (4).

\[
V(D, G) = \int_{x} P_{\text{data}}(x) \log D(x) dx + \int_{z} P_{\text{z}}(z) \log(1 - D(G(z))) dz
\]

Differentiating D(x) can be given as follow:

\[
D^*(x) = \frac{P_{\text{r}}(x)}{P_{\text{r}}(x) + P_{\text{g}}(x)}
\]

That is, if \( P_{\text{r}}(x) = 0 \) and \( P_{\text{g}}(x) \neq 0 \), the optimal discriminator outputs 0. If \( P_{\text{r}}(x) = P_{\text{g}}(x) \), the optimal discriminator outputs 0.5, which is the most ideal case.

Generally, the better the effect of the discriminator, the more serious the gradient disappearance of the generator[12]. Under the (approximate) optimal discriminator, the ultimate goal is to minimize the JS divergence between \( P_{\text{r}} \) and \( P_{\text{g}} \). In experiments, in order to optimize the results, the discriminator is trained as many times as possible, which also leads to the minimum loss of the generator. However, since the overlap of \( P_{\text{r}} \) and \( P_{\text{g}} \) is almost negligible under normal circumstances, the JS divergence becomes almost constant, which in turn causes the gradient of the generator to disappear.

Based on the JS divergence problem mentioned above, Arjovsky uses a new method—Wasserstein distance to replace the JS divergence in traditional GAN networks [13], as shown in equation (6).
Where $\gamma$ represents the set of all possible joint distributions of the combination of $P_r$ and $P_g$. For each possible joint distribution $\gamma$, sample $(x, y) \sim \gamma$ can get a generated sample $y$ and a real sample $x$, and calculate the distance $||x - y||$ between the pairs. And the lower bound on this expected value in all possible joint distributions is defined as the Wasserstein distance. So Kantorovich-Rubinstein duality theory is used to convert the problem into the following equation (7).

$$\max_{w \in \mathcal{W}} E_{x \sim P_r} [f_w(x)] - E_{x \sim P_g} [f(x)]$$

Then the neural network method is used to solve the above problem as the following:

$$\max_{w \in \mathcal{W}} E_{x \sim P_r} [f_w(x)] - E_{x \sim P_g} [f(x)]$$

3. Convolutional Neural Network

Convolutional neural network is a feed-forward neural network, which excels in image classification and target detection. The structure of such a network usually includes an input layer, a hidden layer, and an output layer, where its hidden layer generally includes a convolutional layer, a pooling layer, and a fully connected layer[14].

3.1. Input Layer

The input layer can process multi-dimensional data. Because the convolutional neural network uses a gradient descent algorithm, the input features must be standardized, which is conducive to the learning efficiency of the convolutional neural network.

3.2. Convolutional Layer

The convolutional layer is responsible for the feature extraction, Convolution layer contains multiple convolution kernels.

3.3. Pooling Layer

The pooling layer is responsible for information filtering and feature extraction of the feature map output by the convolutional layer.

3.4. Full Connected layer

The fully connected layer is like a classifier and usually appears in the last layers of the network. It can integrate the distinguished information extracted in the previous part.

3.5. Output Layer

For the image problem studied in this paper, the output layer is responsible for outputting the classification labels predicted by the network for pictures.

4. Experimental

4.1. Data Set Preparation

The data set is composed of 200 samples with 64 * 64 water wall defect data and 200 samples with 64 * 64 water wall defect-free data from the actual thermal power generation. The data set is divided into a training set and a test set with a ratio of 4:1.

4.2. Experimental Procedure

The Autokeras framework is used to train the original data set to obtain a network structure with excellent experimental results under the original data set. The defect data in the original data set is input into WGAN to obtain new generated defect data, which
4.3. Experimental Results

The relatively good network structure obtained by training the original dataset. And the WGAN is used to train the original dataset, and epoch = 100000. At epoch=3000, The WGAN initially generated data with defect characteristics of the water wall. At epoch=7000, the defect characteristics are more obvious. And at epoch=100000, the defect data with relatively good effects could be generated. The comparison between the original data and the generated data is shown in figure 2 and figure 3.

![Figure 2. The original data.](image)

![Figure 3. The generated data.](image)

In order to verify the feasibility of this expansion method, this experiment uses the following three data sets for experiment: 1) original data set, 160 defect data sets, 160 normal data sets; 2) conventional way extended data set, 184 defect data sets, 184 normal data sets, compared with the original data set, each increased by 24 conventional extended data; 3) WGAN extended data set, 184 defect data sets, 184 normal data sets, Compared with the original data set, there are 24 additional data extended by WGAN. We use convolutional neural networks to predict new data sets that add generated images. Since the Autokeras 0.3.5 used in this experiment cannot fix the random seed, this experiment trains the original data set and the conventional way expand data se and the WGAN extended data set 10 times each, and the results on test set are shown in table 1.

| Table 1 The Accuracy In The Test Set. |
|--------------------------------------|
|                                | ACCURACY  |                                |                                |                                |
|                                | original data | 86.08% | 88.99% | 91.14% | 89.87% |
|                                | 82.23% | 93.67% | 91.14% | 87.34% |
|                                | 91.14% | 92.41% |                                |                                |
| Conventional way extended data set | 89.87% | 89.87% | 89.87% | 91.14% |
|                                | 91.14% | 89.87% | 86.08% | 91.14% |
|                                | 89.87% | 91.14% |                                |                                |
| WGAN extended data set          | 89.87% | 92.41% | 89.87% | 93.67% |
|                                | 92.41% | 96.20% | 93.67% | 92.41% |
|                                | 93.67% | 97.47% |                                |                                |

The average accuracy of the WGAN extended data set is 93.17%, the average accuracy of the original data set is 89.37%, and the average accuracy of the conventional way expand data set is 90.00%, which prove the effective of the proposed defect detection method of the water wall.
5. Conclusion
This paper presents an improved defect detection method of the water wall using the Wasserstein Generative Adversarial Networks. The WGAN is used to expand the water wall defect data, which increases the diversity of the water wall defect data. Then the extended data set and the original data set are loaded into a convolutional neural network to build the defect detection model of the water wall, respectively. The results show that the accuracy of the expanded data set based on the proposed method can achieve is 93.17%, which can achieve the industrial requirement of the thermal power generation. In the future work, more deep learning and virtual sample generation methods will be used in the defect detection of the water wall. In the current water-wall automatic defect detection experiment, the biggest problem we encountered was that in the past, power plants lacked the collection and classification of defect data, resulting in the inability to further generate more and more detailed multi-category defect pictures through the WGAN network. This is The reason why this method cannot be used on a large scale. Therefore, the future development direction of this experiment is to deploy this water-wall automatic defect detection system to further effectively collect multiple types of defect data, and re-use the WGAN network to train the data set to obtain more effective high-quality data and improve the model quality. This can make the method more widely used.

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