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The Prediction of the Motor State of the Shore Bridge Based on the Generative Resistance Network GAN

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Abstract: In order to forecast the trend and the vibration characteristic parameters of the shore bridge driving system and find the internal faults. This paper analyze the trend by using a large number of bridge lifting motor historical data based on the theory of generative information against network GAN, introduce the base theory of the generative theory against network in detail, establish a prediction model based on GAN and use the model to predict crane driving system performance parameters. The experimental results show that the prediction model based on GAN can achieve satisfactory results in the prediction and realize the accurate prediction of the change trend of the bridge driving system.

1. Introduction

With the development of port and shipping, the monitoring of the state of the bridge is very necessary, especially the evaluation and trend analysis of the driving system. The traditional data analysis tools were based on the analysis and verification, however the data mining method were based on the use of discovery, applying algorithm to discover the important relationship between the data [1]. From the perspective of machine understanding data, the generative model usually needs Markov chain to train model, the computation complexity is high and the efficiency is low, which limits its application to some extent. In this paper, a lot of historical operation data of the shore crane are analyzed by the generation of counter network GAN to predict the trend of future vibration of the drive system of the shore crane. GAN (Generative adversarial networks) is a generative model proposed by Goodfellow et al. [2] in 2014, its basic idea is derived from the two game theory of zero sum game, consisting of a generator and a classifier, by the way of learning to fight the iterative training, approaching Nash equilibrium finally [3]. GAN as a generative model, it does not directly estimate the distribution of the sample data, but estimate the distribution of new sample data samples and generate the same distribution optimization model through training generator. The training process don't have to use the Markov chain methods [4] and do all kinds of approximate reasoning, no complex variational lower bound, reduce the difficulty of training greatly and improve training efficiency.

2. The basic theory and overview of GAN

2.1. The basic principle of GAN

The core idea of GAN is derived from Nash equilibrium of the game theory [5], it includes two neural networks: a neural network generator, a neural network discriminator [6]. The two neural networks optimize in the process of training, improve their ability to generate and discriminate, eventually reach a Nash equilibrium. Any differentiable function can be used to express the GAN's generator and discriminator, as shown in Figure 1 we can use differential function represent discriminator, its input is the real data *x*; use the differential function represent generator, its input is a random variable *z*, G (z) represent samples generated by the generator G as far as possible obey to real data.

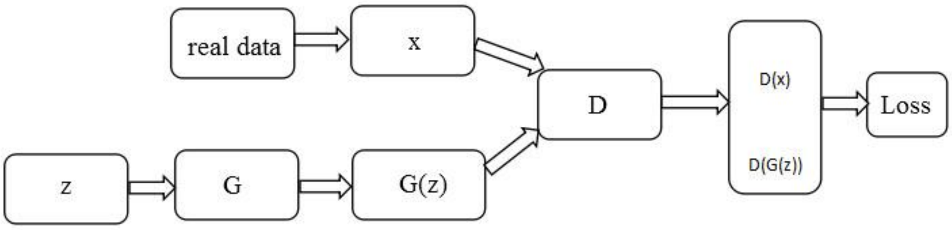

Figure1. The basic schematic diagram of the GAN

2.2. The learning method of GAN

For the learning process of the GAN [7], as shown in Figure 2, it adopts the alternating optimization method:

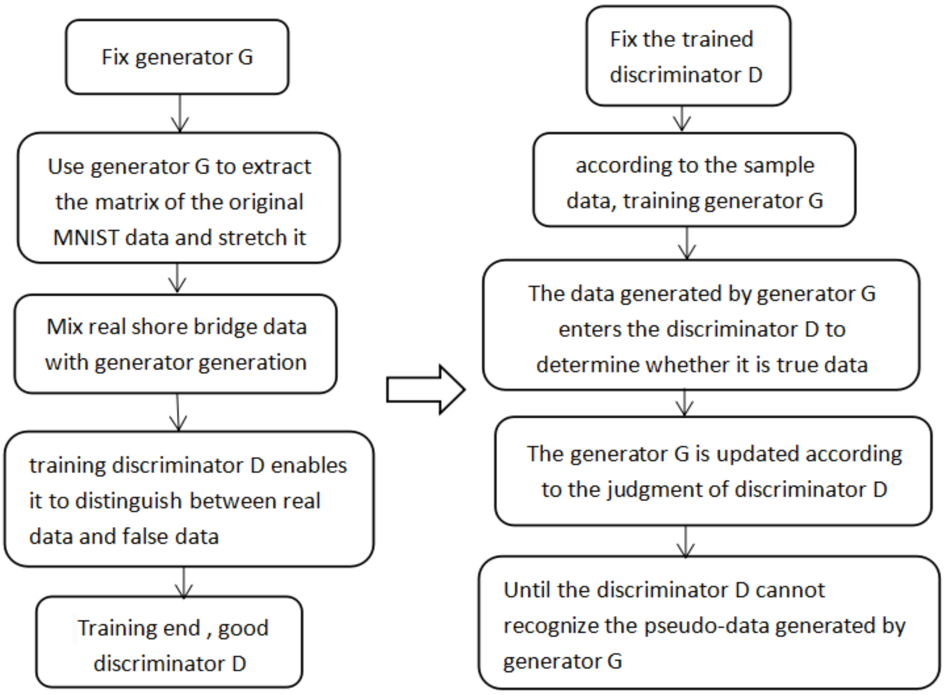

Figure2. The learning method of the GAN

Like two classification model training based on Sigmoid generally, training discriminator D is also a process of minimizing cross entropy, x sampling in real data distribution $P_{data}(x)$, z sampling in prior distribution $P_z(z)$, and its loss function is:

$$Obj^D(\theta_D,\theta_G) = -\frac{1}{2}E_{x\sim Pdata(x)}[\log D(x)] - \frac{1}{2}E_{z\sim Pz(z)}[\log(1-D(g(z)))] \tag{1}$$

The actual training is different from the conventional two valued classification model [8]. The training data set of the discriminator comes from two parts, the real data set distribution $P_{data}(x)$ and the generator data distribution $p_g(x)$. For given the generator G, we need to minimize (17) to get the optimal solution. In the continuous space, the formula (1) can be written as follows:

$$Obj^D(\theta_D+\theta_G)=-\frac{1}{2}\int_x p_{data}(x)\log(D(x))dx-\frac{1}{2}\int_z p_z(z)\log(1-D(g(z)))dz$$
$$=-\frac{1}{2}\int_x \left[p_{data}(x)\log(D(x))+p_g(x)\log(1-D(x))\right]dx \tag{2}$$

For any nonzero real number *a* and *b*, and the real value $y\in[0,1]$, the expression

$$-a\log(y)-b\log(1-y) \tag{3}$$

Get the minimum at the place $\frac{a}{a+b}$. Therefore, in the case of giving the generator G, the target function (2) obtain minimum value at the place

$$D_G^*(x)=\frac{p_{data}(x)}{p_{data}(x)+p_g(x)} \tag{4}$$

which is the optimal solution of the discriminator D. We can see that GAN estimates the ratio of two probability distributions density, which is also the key difference from other lower bound optimization or Markoff chain method [9].

3. State prediction of hoisting motor of shore crane based on GAN

3.1. Data preprocessing

Data this paper analyzed come from NetCMAS (network condition monitoring and assessment system) in 28 days of data sampling, take the front three weeks of data to establish prediction model, other data were used to compare and analyze the results according to prediction model. In order to improve the convergence speed of the model and the accuracy of the model, firstly normalize the data by using formula.

$$\hat{x}_i=\frac{x_i-\frac{1}{n}\sum_{i=1}^{n}x_i}{\max\limits_{1\le i\le n}\{x_i\}-\min\limits_{1\le i\le n}\{x_i\}} \tag{5}$$

Among: x_i is the value of the original data, $\hat{x}_i$ is the value of the normalized data

All the data are mapped to the [-1,1] interval for subsequent processing. The results of data preprocessing are show in Figure 3 and Figure 4.

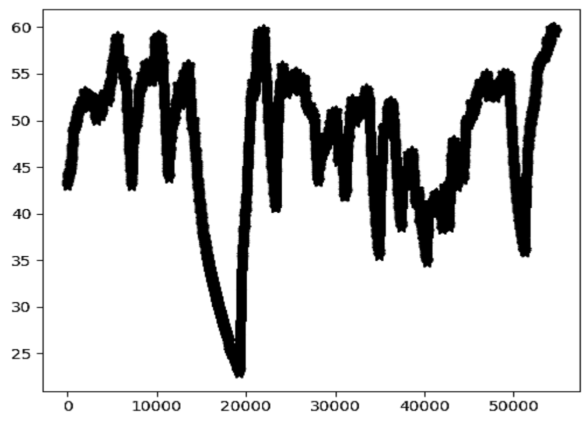

Figure.3 The original data map

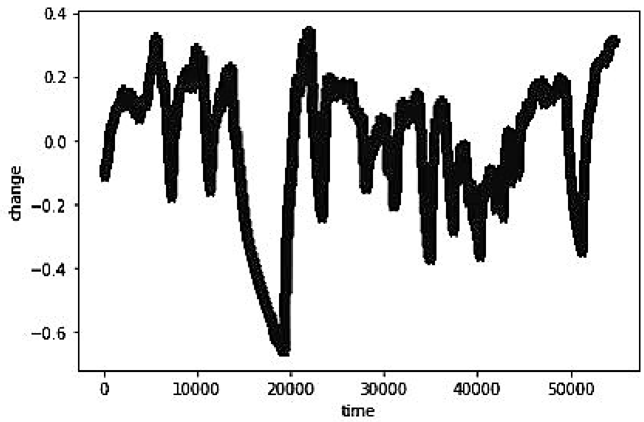

Figure.4 The processed data graphs

3.2. Establishment of data state prediction model for hoisting motor of shore bridge

The first three weeks of data are taken as training samples to establish a prediction model based on GAN, the flow chart of establishing model is shown in Figure 5.

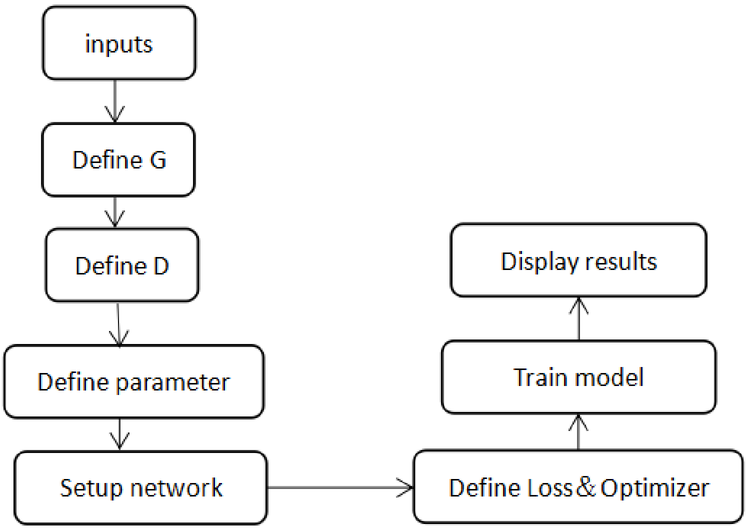

Figure 5 The flowchart based on GAN prediction model

Training model flow chart is show in Figure 6.

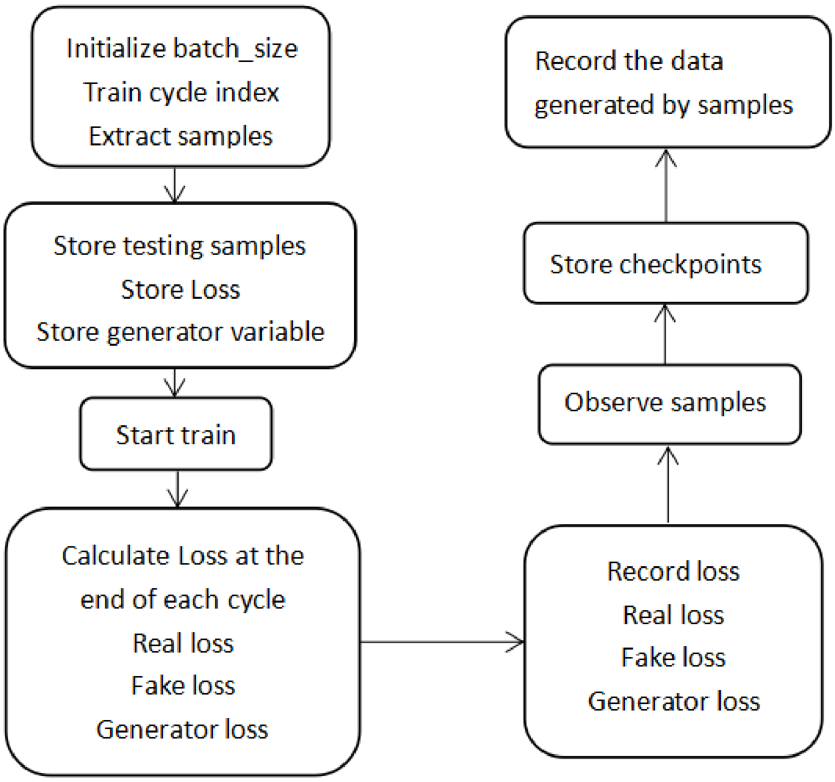

Figure 6 The training model flow chart

3.3. Test for data state prediction model for hoisting motor of shore bridge

The data are brought into the prediction model, and the prediction results are shown in Figure 7.

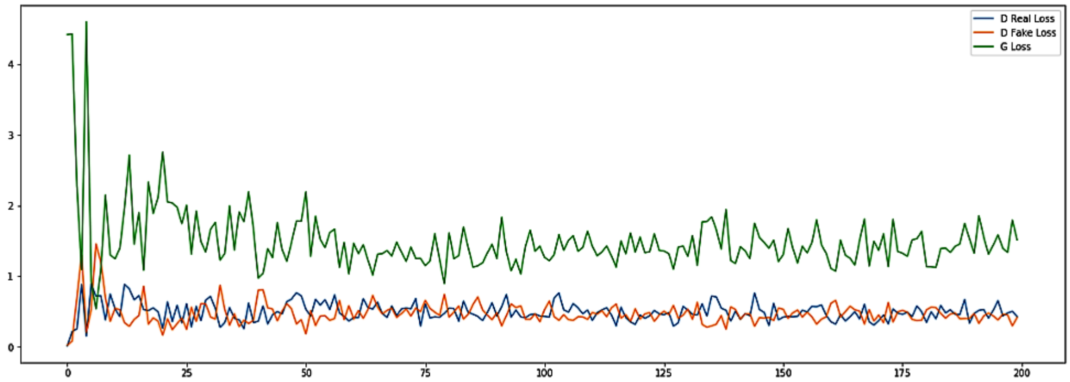

Figure.7 the test diagram of the data state prediction model of shore bridge hoisting motor

From Figure 7, we can see that the final discriminator overall loss fluctuates around 1, while real loss and fake loss fluctuate almost on a horizontal line. This indicates that the discriminator has no ability to distinguish true or false data at last, but to make judgement randomly. That is, the prediction results of the prediction model based on GAN are all satisfactory. Therefore, the prediction model based on the GAN model has high accuracy and reliability in the long term prediction of the running performance characteristic parameters of the hoisting motor.

4. Conclusion

Generative adversarial networks (GAN) is introduced to predict the performance parameters of motor of shore crane, first introduce the generative adversarial networks (GAN) theory, and then establish the prediction model of the shore bridge drive system based on GAN, forecast the crane hoisting motor trend by using this model. The experimental results show that the prediction model based on GAN can achieve satisfactory results in prediction, and can provide scientific prediction results for condition monitoring, maintenance and maintenance of shore crane.

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