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A Real-Time Monitoring and Diagnosis Method of Production Line Conveyor Chain for Digital Twin

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Abstract. Aiming at the widely used digital production line and facing the digital twinning technology, this paper proposes a real-time monitoring and diagnosis method of the transmission chain status of the production line based on the digital twinning. First of all, the failure and failure mechanism of the conveyor chain is studied, and then a real-time data monitoring method is proposed according to the failure mechanism. On this basis, a data processing and analysis model oriented to the digital twin model is constructed. Then, artificial intelligence algorithm is incorporated into the model to improve the ability of the twin model to independently judge the failure and failure of the conveyor chain. Finally, the feasibility and efficiency of the proposed method are verified by experiments. The accuracy rate of fault diagnosis reaches 98.02%.

Keywords: digital twin, conveyor chain, tension, neural network

1 Introduction

With the arrival of a new round of industrial revolution, the manufacturing industry is accelerating its transformation and upgrading. Automation and intelligence are the main development directions of current production. Therefore, the introduction of automatic production line can greatly improve the equipment utilization rate for enterprises, and play a role in improving productivity, improving quality and reducing labor costs.

Digital twinning technology can conduct real-time analysis and processing of production links, so as to obtain more comprehensive and valuable information, and provide fault prediction and health management services for production equipment. In the working process of the automatic production line, the conversion of the processing position of the processing object is realized through the conveyor chain, and the tension is the key factor to determine the transmission quality of the conveyor chain. During the transmission process, the tension of the transmission chain is constantly changing, which will lead to the situation that the chain is partially too tight or loose, and then affect the transmission accuracy of the workpiece. In serious cases, it will cause chain breaking and chain dropping accidents. Therefore, the realization of real-time monitoring and diagnosis of production line transmission chain status can maximize the production efficiency of enterprises. The improvements made to the current automatic production line status monitoring are as follows:

1) The failure and failure mechanism of the transmission chain are analyzed to provide the data monitoring basis for building the digital twin model;

2) Build the hardware environment for digital monitoring of the transmission chain, and process and analyze the collected signals to provide the data basis for the construction of the digital twin model;

3) The intelligent diagnosis algorithm is integrated to realize the independent diagnosis and analysis of the transmission chain status and improve the diagnosis accuracy.

In order to comprehensively discuss the method proposed in this paper, the main structure of this paper is as follows: Chapter 2 mainly collates the research results of relevant scholars on digital twins and transport chain, which has a good reference significance for the proposed method of this paper. Chapter 3 mainly carries out quantitative and qualitative analysis on the fault mechanism of the transport chain, and provides the basis for the construction of digital twin model. The fourth chapter mainly analyzes and processes the information collected by the signal acquisition equipment, and integrates the judgment method of deep learning data diagnosis to im-

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prove the accuracy of fault diagnosis. The sixth chapter is the conclusion part, which summarizes the process of this paper and puts forward new research directions.

2 Related Work

Relevant scholars have made certain achievements in the research of digital twinning technology of transmission chain and automatic production line. However, the combination of transmission chain monitoring and digital twins is rare, while the research results of digital twins in other directions can provide more references. Mahesh Kumbhar has developed a digital twin framework to detect, diagnose and improve bottleneck resources using utilization based diagnostic analysis. This method can directly use enterprise data from multiple levels to generate event logs and input them into the digital twin model for real-time monitoring of the production process [1]. Merino Jorge takes the fault detection and diagnosis process of building HVAC system as an example, and combines artificial intelligence technology to identify the information perception dimension of building specific faults, which is used as the basic framework of digital twins to realize building information diagnosis [2]. Talmaki Sanat A, has developed a scalable technical method to update the 3D equipment model in the graphic digital twin model, so as to carry out concurrent visualization of the monitored construction operations. Through simulation, we can find out the causes of the errors between models and objects [3]. Weixi Ren proposed a fault diagnosis method for wind turbine bearing based on digital twins to improve the accuracy and stability of fault diagnosis for wind turbine bearing, aiming at the problem of small number of bearing fault samples and low diagnostic accuracy [4]. Junzhen Xiong, based on the digital twin technology, realized the model simulation of the air compressor equipment in the cigarette factory on the cloud platform, and realized the functional design of the intelligent operation and maintenance platform of the air compressor equipment based on the digital twin technology through the research on the equipment management and fault maintenance of the air compressor equipment under the complex operation and support conditions [5]. Yuan Fang, aiming at the problems of the lack of effective human-computer interaction means in the production process of typical aviation product assembly line and the low degree of visual monitoring of the real-time operation status of equipment, proposed a method for monitoring the operation status of processing equipment based on digital twins, and verified the feasibility of the model through simulation analysis [6].

3 Data Mechanism Analysis of Digital Twin Model

The conveyor chain is a commonly used dragging and conveying device in the automatic production line. Whether the conveyor chain runs well or not directly affects the production accuracy of the production line. The content of this chapter is to establish the digital twin model of condition monitoring through the study of the failure mechanism of the conveyor chain. Common conveyor chains are shown in Fig. 1.

Fig. 1. Common conveyor chain

3.1 Conveyor Chain Failure Mechanism

During the transportation of the workpiece, the chain tension will change with the influence of the load, and the instantaneous load change may make the tightness of the part or the whole chain exceed the design limit, thus causing serious consequences such as chain breaking and chain dropping. If the chain is too loose, the chain is easy to drop at the turning point. In addition, the loose chain will also have a great impact and vibration load on the sprocket, exacerbating the occurrence of chain fracture, chain seizure and other failures [7]. If the transmission chain is too tight, the friction resistance between the transmission modules will increase significantly, the energy consumption will increase, and the wear degree of relevant parts will increase, which will aggravate the aging of the chain [8]. Therefore, the tension is an important factor to determine the tightness of the conveyor chain. When analyzing the tension of the conveyor chain, first simplify the conveyor chain to an ideal elastomer, as shown in Fig. 2. The area enclosed by the dotted line in the figure represents the tension of the conveyor chain when it is stationary, the area enclosed by the solid line represents the tension of the conveyor chain when it is in motion, S_1 represents the tension of the chain and sprocket under the rated load, S_2 represents the tension of the conveyor chain at the separation position of the chain and sprocket under the rated load, and S_3 represents the tension of the conveyor chain at the meshing position of the chain and sprocket under the rated load, S_4 represents the tension at the separation position of the chain and sprocket of the scraper conveyor under the rated load.

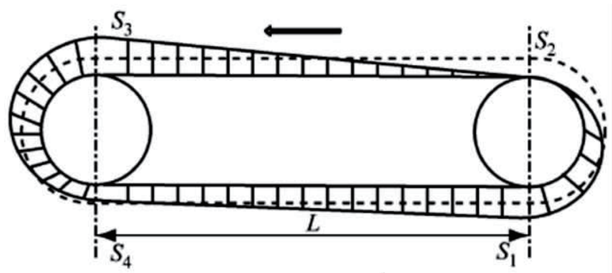


Fig. 2. Schematic diagram of tension

3.2 Monitoring Method of Tension

In order to control the tension of the transmission chain in a good state range, it is necessary to automatically monitor the tension of the transmission chain in real time. In order to obtain the tension data of the conveyor chain, the micro-strain monitoring sensing technology is used to monitor the pre-tension of the conveyor belt. The micro-strain monitoring sensing technology is to use the small deformation of the strain gauge to obtain the tension change. The monitoring process is shown in Fig. 3. The strain gauge is added to the chain link connected to the transmission chain, and the data processing circuit, wireless data receiving and transmitting module and power supply module are installed at the appropriate position of the frame around the transmission chain. During the production and operation of the entire automatic production line, the pre-tension of the transmission chain can be measured according to the deformation of the strain gauge.

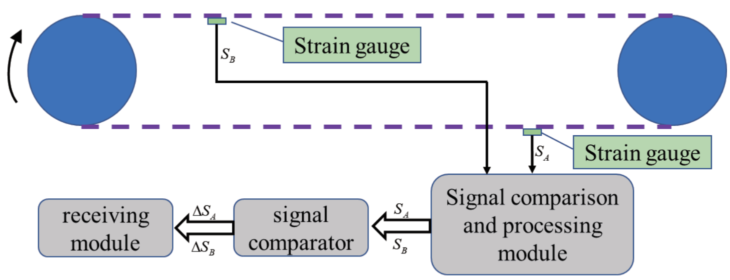


Fig. 3. Schematic diagram of data monitoring

The strain gauge used in this paper is made of semiconductor or metal conductor material. Under the action of external force, the length of the strain gauge changes. According to physical knowledge, the relationship between the resistance value R of the strain gauge and the length l of the strain gauge can be obtained:

$$R = \rho \cdot L / S . \tag{1}$$

Where R is the resistance value, ρ is the resistivity, L is the length, and S is the cross-sectional area. The change value of tension is mainly obtained by measuring the resistance value of strain gauge. The advantages of using micro-strain to automatically monitor the chain tension are as follows: first, install strain gauges on the chain link, which has high monitoring accuracy and small space; Secondly, as long as the chain is deformed, the chain tension change value can be measured immediately, which is sensitive and real-time.

4 Construction of Digital Twin Model Monitoring System

Real-time monitoring of conveyor chain fault is an important link in the manufacturing workshop processing process. The conveyor chain is affected by the transmission object. The tension of the entire transmission system has strong nonlinearity and uncertainty, and changes dynamically in real time. To this end, the built real-time monitoring system of transmission chain status should include status monitoring facilities and data analysis units, wherein the status monitoring facilities include transmission module basic equipment, equipment for collecting transmission chain micro-variable signals, and fault measurement equipment. The data analysis facilities include high-performance computers and in-depth learning platforms for analyzing and processing data, and real-time classification and reporting of transmission chain fault status.

4.1 Condition Monitoring Equipment

The experimental platform adopts the automatic production line equipment of the training center of a school in Tangshan. The equipment is mainly used to simulate the assembly of automobile parts in the real environment. The parameters of the transmission chain are shown in Table 1:

Table 1. Conveyor chain parameters

Parameter name	Numerical value
Chain length	10800 mm
Width	400 mm
Altitude	1200 mm
Running speed	15 mm/s -500 mm/s
Operation mode	Parallel type
Power	600 W

During the experiment, a number of strain gauges, model 120-1AA, were used to attach to the chain plate of the conveyor chain unit according to the requirements for real-time acquisition of the change of the belt tension. The high-precision digital acquisition instrument, model INV3018CT, from Beijing Dongfang Institute of Vibration and Noise, was used to process the real-time signal and transmit it to the computer. The sampling frequency of the signal is 20KHz, each time the transmission chain rotates one cycle as a stroke, and it continuously runs 330 strokes. Pre-calibrated high-precision digital microscope, model EVDM-101, is used to measure small changes in the size of the transmission chain. Set the optical magnification to $0.7\times - 4.5\times$, the electronic magnification to $35\times - 235\times$, and the measurement accuracy to $0.1\mu m$. During the measurement process, select the chain of the sprocket at the head and tail, and use the same reference line as the standard to ensure that the position remains unchanged during the measurement process. The experimental device is shown in Fig. 4.

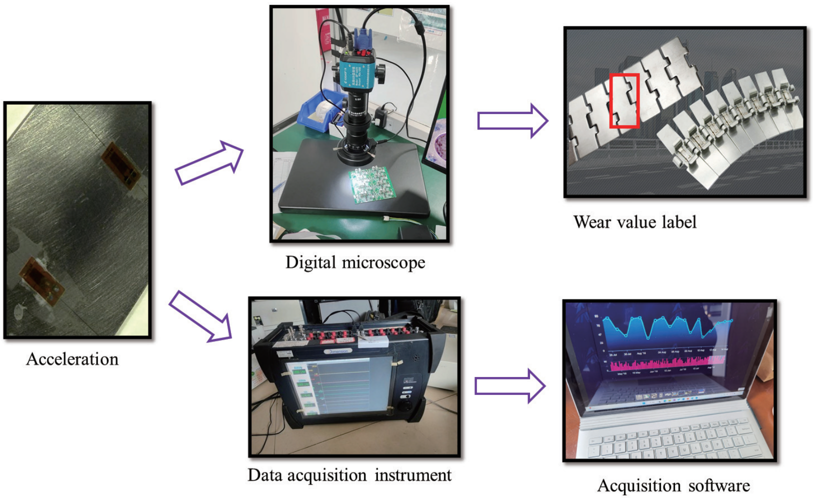
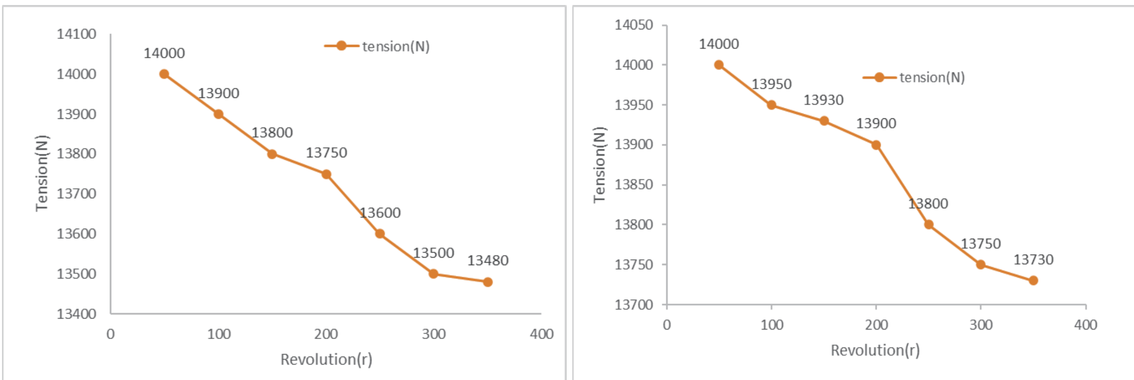


Fig. 4. Experimental equipments

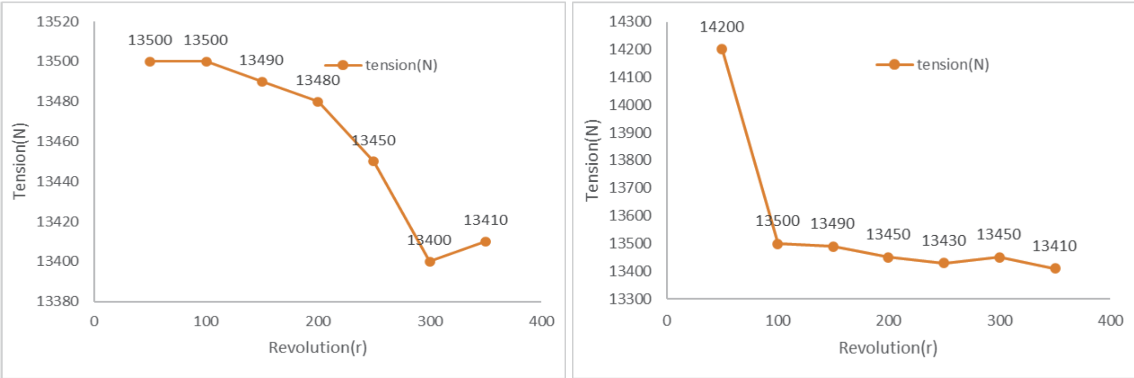
4.2 Data Analysis System

The implementation of the deep learning algorithm requires specific hardware equipment. The deep learning hardware platform in this experiment uses high-performance servers: Intel Xeon E5-2650 processor, with a main frequency of 2.3GHz, 256GB of memory, and NVIDIA Ge Force TITAN X graphics processor for GPU. The software platform uses Ubuntu 16.04.4 operating system, and the in-depth learning framework uses Keras as as the front end and TensorFlow as the back end for data analysis. During the experiment, four conveyor chains were selected, and each conveyor chain operated for 330 cycles, and 1320 original signal samples were obtained. Fig. 5 shows the change process diagram of the tension of the conveyor chain. After the original signal is de-noised by wavelet, the data of three transmission chains are used for the training set and verification set of the model, and the remaining one is used for the test set of the model.



(a) Tension of conveyor chain 1

(b) Tension of conveyor chain 2



(c) Tension of conveyor chain 3 (d) Tension of conveyor chain 4

Fig. 5. Conveyor chain tension change diagram

4.3 Digital Twin Model Signal Preprocessing

The original signal collected during the operation of the transmission chain will be mixed with noise, and the frequency band of the signal and noise cannot be determined, so the signal needs to be de-noised. In the process of signal denoising, the singularity contained in the signal is not considered. After comparing different wavelet denoising methods, this paper selects the wavelet coefficient threshold denoising method to denoise the original signal [9]. The flow of the wavelet coefficient threshold denoising method is shown in Fig. 6.

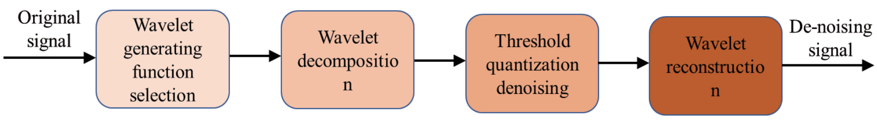


Fig. 6. Signal denoising process

The selection of wavelet mother function and wavelet threshold determines the performance of the wavelet coefficient threshold denoising method. In this paper, the soft threshold method is used to process the wavelet threshold, and the overall continuity of the wavelet coefficient is better, so that the estimated signal will not produce additional shocks. The processed signal is relatively smooth, and the expression of the processing process is as follows:

$$\hat{w}_{j,k} = \begin{cases} sign(w_{j,k})(|w_{j,k}| - \lambda) & |w_{j,k}| \geq \lambda \\ 0 & |w_{j,k}| < \lambda \end{cases}. \quad \textbf{(2)}$$

Where, $w_{j,k}$ is the wavelet decomposition coefficient, $\hat{w}_{j,k}$ is the estimated wavelet coefficient, $sign(*)$ is the sign function, j is the wavelet decomposition scale, k is the wavelet coefficient index sequence, and λ is the pre-wavelet threshold. Specifically, dbN and $symN$ wavelet mother functions are selected in this paper, and the decomposition scale is 3 levels. The wavelet threshold λ selects heuristic threshold to de-noise the collected triaxial vibration signals. Through the comparison of the de-noising performance of different wavelet base functions, the signal to noise ratio $24.12dB$ is selected, and the $db8$ wavelet decomposition with the best de-noising performance is selected for de-noising. The signal de-noising effect is shown in Fig. 7.

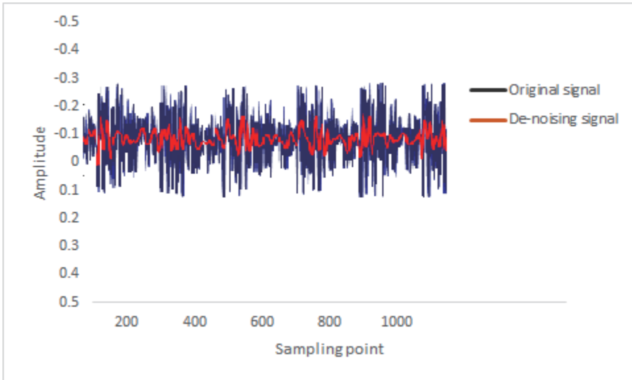


Fig. 7. Signal denoising effect diagram

The intelligent diagnosis of the digital twin model for the state of the transport chain is completed through the deep learning algorithm. During the deep learning training process, the number of samples needs to reach enough to improve the learning quality of the neural network. After signal denoising, the method of reducing and unifying the sample scale is used to meet the requirements for the detection speed and sample number. The specific processing steps are as follows: intercept 100000 consecutive points in each sampled signal, divide the intercepted points into 50 samples with 2000 as the number of samples, and these 50 samples all correspond to the same tension change status label.

4.4 Digital Twin Time Series Signal Analysis Model

The machine learning method is used to assist the digital twin model to monitor and identify the transmission chain fault. In order to solve the problem of the correlation and gradient of the timing signals, the convolutional neural network and the circular neural network are integrated in the machine learning network model in this paper, so as to further improve the attention and prediction accuracy of the whole model [10]. The improved model structure is shown in Fig. 8.

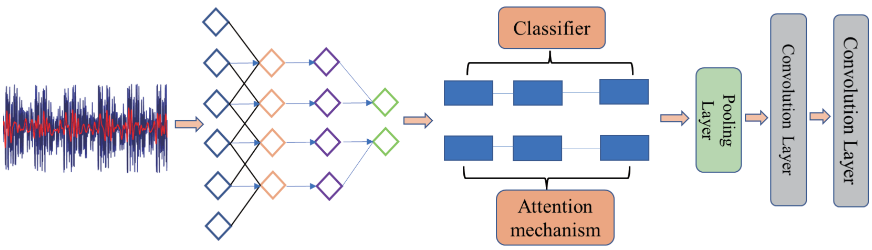


Fig. 8. Improved identification network

4.5 Program Code

It can be seen from the figure that the one-dimensional convolution neural network is used to process the timing signals generated by the rotation process of the conveyor chain. The network includes two layers of Convolution Layer and one layer of Pooling Layer. When the input signal is x, the weight vector of the convolution sum is w, the total number of samples is m, the size of the convolution kernel is n, $*$ represents the convolution operation, and the output characteristic graph y of the convolution layer can be expressed as:

$$y = x * w = \sum_{m=0}^{m} x(m) \cdot w(n-m) \ . \tag{3}$$

In the convolution layer, each neuron in layer l is only connected with neurons in a local window of layer $l-1$, forming a local connection network. The calculation formula of one-dimensional convolution layer is as follows:

$$x_j^l = f(\sum_{i \in M_j} x_i^{l-1} \cdot w_{ij}^l + b_j^l) \ . \tag{4}$$

Where x_j^l represents the j feature map of layer l, $f(x)$ represents the activation function, M_j represents the input feature vector, x_i^{l-1} represents the i feature map of layer $l-1$, w_{ij}^l represents the trainable convolution kernel, and b_j^l represents the offset parameter. The convergence function selects the modified linear element to eliminate the over-fitting phenomenon, and the function expression is as follows:

$$a_i^{(l+1)}(j) = f(y_i^{l+1}(j)) = \max\{0, y_i^{l+1}(j)\} \ . \tag{5}$$

Where, $y_i^{l+1}(j)$ is the output and $a_i^{(l+1)}(j)$ is the activation value of $y_i^{l+1}(j)$. In this paper, the maximum pooling method is used to take the maximum value of the feature points in the neighborhood:

$$P_i^{l+1}(j) = \max_{(j-1)W+1 \le t \le jW} \{q_i^l(t)\} \ . \tag{6}$$

$$t \in [(j-1)w+1, jw] \ . \tag{7}$$

Where, $q_i^l(t)$ represents the value of the t neuron in the i feature vector of layer l, w represents the width of the pooled area, and represents the corresponding value of the $l+1$ neuron. Some key information is selectively filtered out from a large number of signal features and focused. The focus process is reflected in the calculation of the weight coefficient. Different key information is assigned different weights to enhance the proportion of key information in the way of increasing the weight to reduce the loss of key information of long sequence signals. The calculation formula of attention mechanism is as follows:

$$u_t = \tanh(W_S P_t + b_s) \ . \tag{8}$$

$$a_t = soft\max(u_t^T, u_s) \ . \tag{9}$$

$$v = \sum a_t P_t \ . \tag{10}$$

P_t is the output feature vector of the feature layer at time t, u_t is the result of P_t passing through the neural network layer to the hidden layer, a_t is the weight obtained by u_t through the $Soft\max$ function, u_s is the context vector, and v is the feature vector of the text information. The improved recognition and monitoring network is shown in Fig. 9.

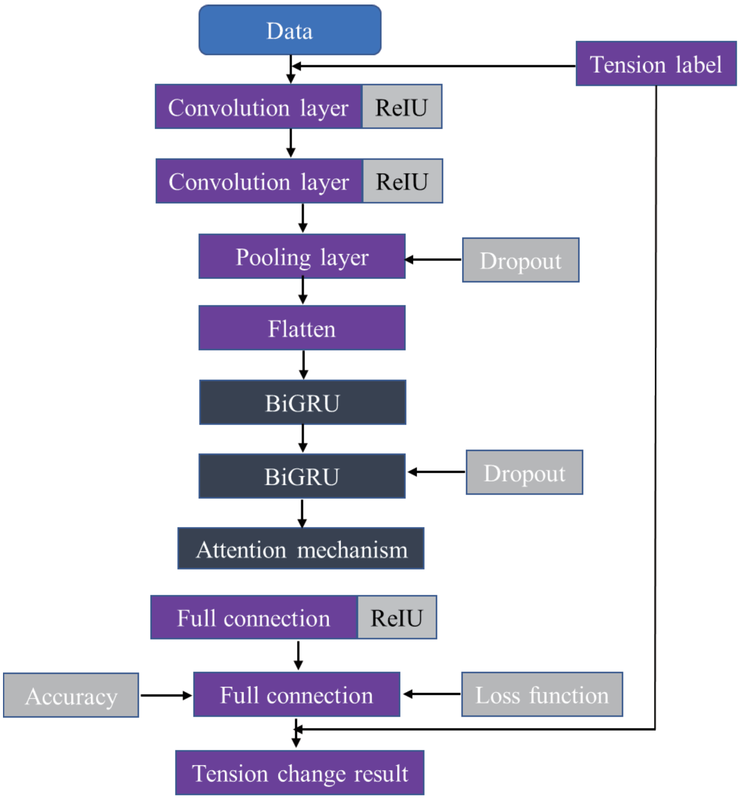


Fig. 9. Identification structure diagram

The names and parameters of each structure in the network are shown in Table 2:

Table 2. Network structure parameters

Layer name	Output feature size	Number of plies	In-layer parameters
Input layer	3×2000	1	/
Convolution layer 1	$20\times98\times128$	1	Conv1D,1; kernel size=3; stride=1
Convolution layer 2	$20\times98\times128$	1	Conv1D,1; kernel size=3; stride=1
Pooling layer	$20\times48\times128$	1	MaxPooling1D, 1; stride = 2
Attention layer	256	1	/
Fully-connected layer	128	2	Dense, 128, 3
Output layer	3	1	Softmax, Loss: Categorical_crossentropy

4.6 Model Training

The activation function of the model is expressed as follows:

$$y = soft\max(v) = \frac{e^{vi}}{\sum_{m=1}^{M} e^{vm}} . \tag{11}$$

In the formula, y is a vector whose latitude is the number of categories, $y \in [0,1]$, and the sum of all latitudes is 1. M is the number of possible categories [11]. The cross entropy error in the training process is expressed as:

$$loss = -\sum_{i=1}^{n} \hat{y}_{i1} + \hat{y}_{i2} \log y_{i2} + \cdots + \hat{y}_{im} \log y_{im} \,. \tag{12}$$

$$\frac{\partial loss}{\partial y_{i1}} = -\sum_{i=1}^{n} \frac{\hat{y}_{i1}}{y_{i1}} \,. \tag{13}$$

$$\frac{\partial loss}{\partial y_{i2}} = -\sum_{i=1}^{n} \frac{\hat{y}_{i2}}{y_{i2}} \,. \tag{14}$$

$$\frac{\partial loss}{\partial y_{im}} = -\sum_{i=1}^{n} \frac{\hat{y}_{im}}{y_{im}} \,. \tag{15}$$

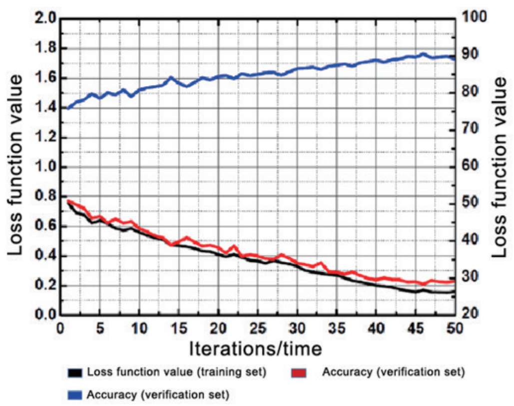
Where: m represents the number of categories, n represents the number of samples, $\hat{y}_{im}$ represents the i value in the real category label vector of tension state, and y_{im} represents the i value of the output vector y of $Soft\max$ classifier. For the cross entropy error obtained, the average is taken as the loss function of the model.

5 Experimental Results and Analysis

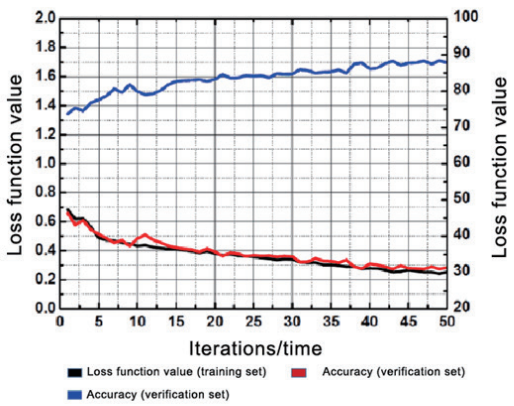
The original signal generated in the transmission process of the experimental transmission chain is de-noised by wavelet. After sampling and clipping, it is input into the deep learning neural network model. The model adaptively extracts the high-dimensional features hidden in the timing signal, calculates the error distance between the actual output value of the model and the real value, and uses the Adam algorithm to reduce the loss and constantly update the network weight, so that the actual output value of the model is closer to the real value. Select other algorithms for comparison. For the convenience of description, the algorithm in this paper is referred to as model $DT-D1NN$. The model parameter settings are shown in Table 3. The model parameters and the comparison model parameters are set as Fig. 10.

Table 3. Setting of network model parameters

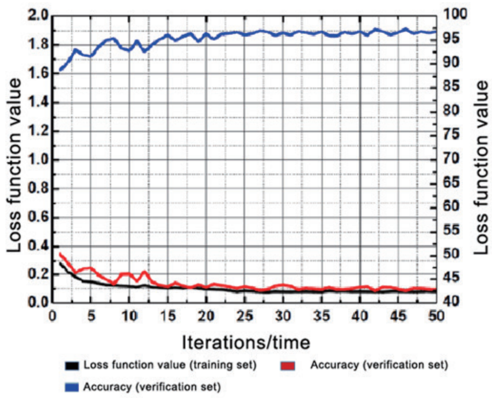
Parameter	CNN	BiGRU	CBLSTMs	$DT-D1NN$
Basic learning rate	0.001	0.001	0.001	0.001
Learning strategy	Step	Step	Step	Step
Iterations	200	200	200	200
Optimization algorithm	Adam	Adam	Adam	Adam



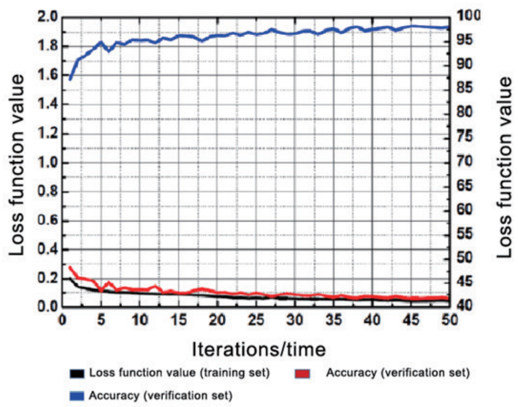
(a) Accuracy and loss function of CNN model



(b) Accuracy and loss function of BiGRU model



(c) Accuracy and loss function of CBLSTMs model



(d) Accuracy and loss function of $DT-D1NN$ model

Fig. 10. Comparison results of various models

It can be seen from the above figure that the accuracy of the training model proposed in this paper is the highest, and the overall network model is relatively stable, the loss function continues to decline, and finally converges. There is no gradient explosion and dispersion in this case, and the network convergence speed is also fast. The above advantages are obviously better than the other three network structures. At the same time, the $DT-D1NN$ -structure proposed in this paper has achieved high prediction accuracy. After 22 iterations, the accuracy of the verification set basically remains above 96%, and after 50 iterations, the accuracy remains at 97.25%. In addition, due to the introduction of attention mechanism, the model can filter out key information from a large amount of information, and focus on the information, reducing the loss of key information features of long sequence of text. After the final iteration, the accuracy rate can reach 98.23%, and the loss function value is 0.0587. The specific loss function values and validation accuracy of each model are shown in Fig. 11.

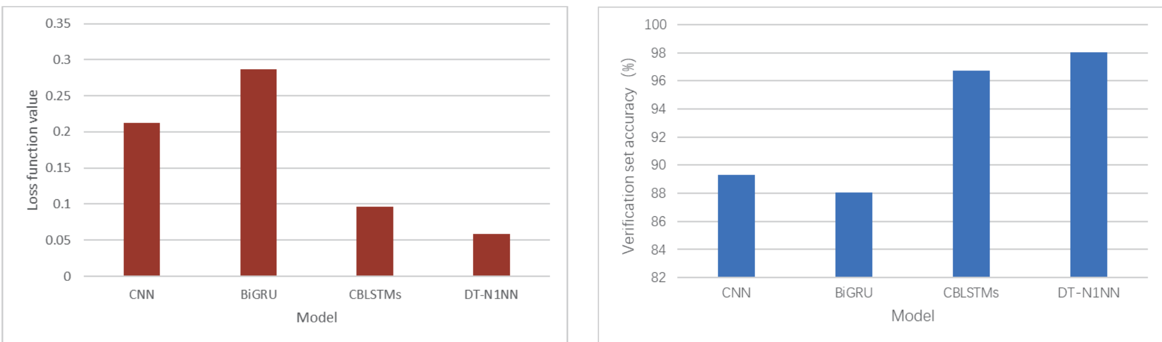


Fig. 11. Comparison diagram of loss function and accuracy

6 Conclusion

In order to realize the monitoring of the status of the transmission chain in the production line, this paper makes some improvements on the basis of the existing research results, improves the accuracy of the monitoring, and establishes the foundation for the construction of the digital twin model. This paper analyzes the fault and failure mechanism of the transmission chain, and then builds the hardware environment of the transmission chain monitoring. Signal acquisition, processing and analysis are the core parts of this paper. Intelligent algorithms are added to the digital twin model to improve the ability of self-diagnosis. Through experimental analysis, the effectiveness of the proposed method is proved. The next research focus is to fully integrate the method proposed in this paper into the digital twin model, and verify and display it in the model.

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