Transmission Line Visual Inspection Method Based on Neural Network Online Learning

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Abstract. In order to ensure the visual inspection effect of transmission line and improve the accuracy and effectiveness of transmission line visual inspection, a transmission line visual inspection method based on neural network online learning is proposed. The transmission line structure features are collected by neural network, and the online learning transmission line fault state recognition algorithm is combined to realize the online learning transmission line visual detection. The experimental results show that the transmission line visual detection method based on neural network online learning has high accuracy and effectiveness in the practical application process, and its overall operation effect is relatively more stable, which fully meets the research requirements.

Keywords: Neural network · Online learning · Transmission line · Visual inspection

1 Introduction

Transmission line is one of the most important infrastructure of energy Internet. The safety and stability of its operation state is not only an important premise of power transmission, but also an important guarantee for energy development. With the continuous development of power grid, transmission lines of various voltage levels are under rapid construction. During the 13th Five Year Plan period, the State Grid will add 4.01 million km of 110 kV and above voltage lines, an increase of 45% over the end of the 12th Five Year Plan. It can be seen that while accelerating the construction of transmission lines, transmission lines have a great coverage. Because the transmission line has long been in the natural environment with complex geographical location and unpredictable climate change, and is closely related to the surrounding animal activities and human activities, the transmission line has a high possibility of failure, which will inevitably lead to tripping accidents. Due to the long-term influence of wire strand, wire connection failure and other factors, the wire is loose, the bolt is broken, and the transmission line is exposed for a long time. Therefore, the visual inspection effect of transmission line is very important [1].

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Based on this, a transmission line visual detection method based on neural network online learning is proposed. Aiming at the problem of poor effect of traditional detection methods, the visual detection efficiency of transmission line is innovated by using the principle of neural network. The principle of deep neural network has the characteristics of layer by layer information processing, distributed rich model features, sufficient model complexity and so on. This method can effectively extract the more essential features in the data, and shows superior performance in the processing tasks of voice, image, video and other information. Therefore, transmission line visual detection based on neural network online learning, as the key technology of transmission line intelligent development, has important research value. Firstly, this paper summarizes the research status of vision detection methods based on deep learning and transmission line vision detection methods at home and abroad; Then, aiming at the mainstream inspection methods that can apply neural network for visual inspection in transmission line, the working principle, characteristics and the main problems in the process of deep learning are analyzed, and the key problems in the application of neural network in transmission line visual inspection are summarized; Finally, the future development direction of this research field is discussed to ensure the detection accuracy.

2 Transmission Line Visual Inspection Based on Online Learning

2.1 Transmission Line Structure Feature Acquisition Based on Online Learning

The neural network principle is used to detect the current of the transmission line, the change of the induced charge of the collection plate (induced current), and the detected induced current is used as the trigger signal of the camera. The structural characteristics of the transmission line are photographed and collected by setting the delay to observe the injection state of the current frequency at a certain time [2]. This shooting method can not only solve the problem that it is difficult for low-speed camera to shoot under high voltage, but also greatly reduce the cost of transmission line structure detection and identification of online learning. The amplification circuit is composed of a sampling resistor Ro and an instrument amplifier in parallel. The current amplification circuit is shown in Fig. 1.

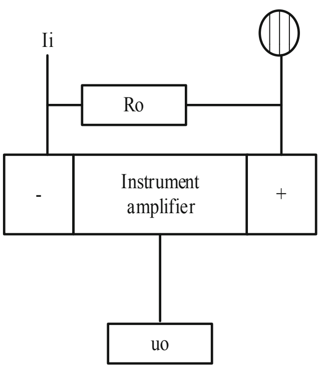

Fig. 1. Current amplifying circuit

The design method of visual inspection for industrial camera to collect high-speed and high frame rate video: an industrial camera controller needs to be designed first, and the controller is responsible for the preparation of the industrial camera. The controller sends the camera to capture the signal and control the trigger frame signal to realize the preparation work, and then the controller sends the camera exposure signal to control the industrial camera for video capture. The principle of the transmission line controller capture is shown in Fig. 2.

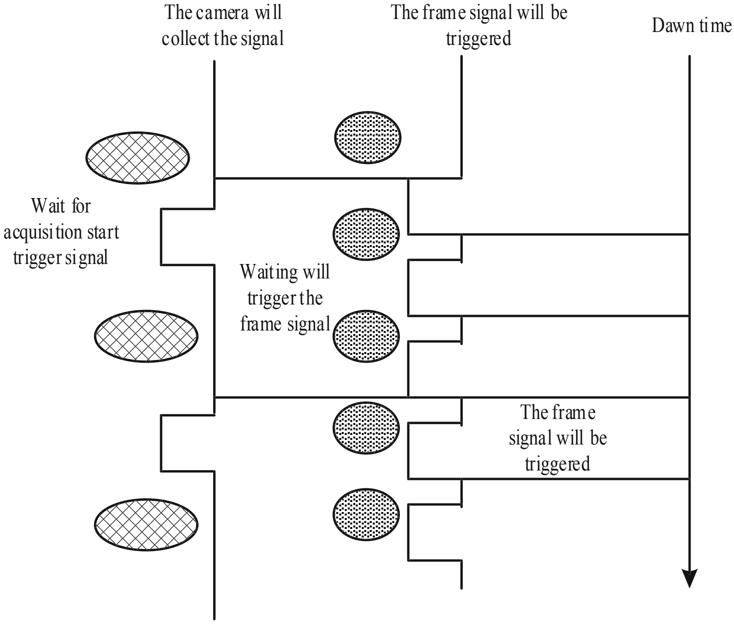

Fig. 2. Principle of transmission line controller acquisition

The visual inspection selects the Camera Link data bus type industrial camera to complete the acquisition work. The data transmission process is as follows: video data is collected through the CMOS sensor, and then the collected data is transmitted to the data receiver through the Camera Link data bus. The data is converted in series and parallel in the data receiver. The converted signal is a 28 bit data signal composed of 24 bit effective data and 4-bit data synchronization signal. The 4-bit data synchronization signals are: reserved signal SPACE, data effective signal DVAL, frame synchronization signal FVAL and line synchronization signal LVAL. Among them, because the space signal is invalid data, it does not need to be considered [3]. When the three signals of DVAL, FWAL and LVAL are at high level, the collected data can be transmitted as effective data. The data output timing is shown in Fig. 3.

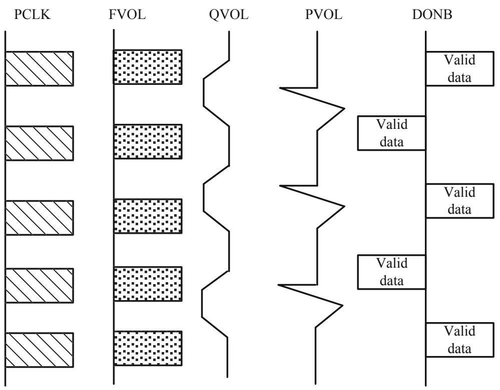

Fig. 3. Data output timing diagram

The fault tree is established according to the output sequence diagram of transmission line structure data learned online. The neural network is used to identify the circuit fault problem, and the standard type closest to the object is selected from the object to be identified. The circuit fault identification process of laser measuring instrument based on pattern recognition is shown in Fig. 4.

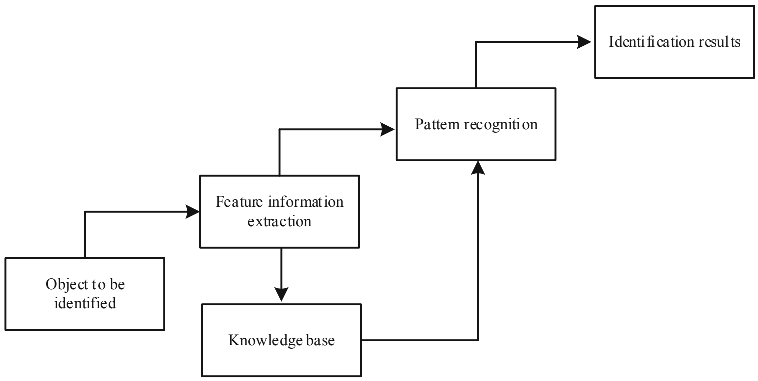

Fig. 4. Circuit fault identification process of laser measuring instrument based on pattern recognition

It can be seen from Fig. 4 that due to the influence of external noise, the shape of voltage waveform cannot be completely consistent, but it is roughly the same. Therefore, the identification of the change degree of voltage waveform shape belongs to fuzzy pattern recognition. Describe and classify the circuit characteristics in the fault state, and then form several standard types. In the actual operation process, only the circuit fault characteristic information can be obtained for fault identification [4]. The nearest neighbor method is used in pattern recognition theory, and the recognition result can be obtained quickly. The basic principle is: Assuming that there are n categories M_n, and each category contains K_i samples, thus, it can be specified that the fault identification judgment function f_i with fault status M_i is:

$$f_i(y) = M_i Y_1^g \sum g \times f_i - \min\|\mathrm{M_n} - K_i\| \tag{1}$$

In formula (1), Y_1^g represents the fault point, while f_i represents a sample in K_i. Set the test nodes as B, locate different fault states into different types, and divide the total number of fault states accordingly. For the identification of the actual circuit, it is necessary to take the test values of each fault test point as samples to investigate the voltage value relationship under different states. Within the scope of neural network, the set attribution degree is extended to each interval, and a value is randomly selected to quantitatively describe the type of specific fault degree of the event [5]. The membership degree under different fault states is analyzed according to the parameters in the neural network. Because the circuit is affected by the tolerance, a fault type cannot be determined in the classification results of determining the specific fault degree. Therefore, it is necessary to select a smaller membership degree as the attribution category. Select a fault test point in the circuit as a sample, check the attribution degree under different fault states corresponding to the test point, record each category with large membership degree and record it as a nearest neighbor, so as to identify the category identification under different fault states.

2.2 Transmission Line Fault Identification Algorithm Based on Online Learning

In order to ensure the effectiveness of data visual detection, the characteristics of network data are collected, combined with the high-level dimension characteristic samples of transmission lines, the data to be collected are generally selected and clustered, the corresponding network environment characteristics and attribute information are collected and classified, and the characteristic categories of the collected results are further expanded [6]. According to the feature classification results, the detection numerical features are strengthened, and then the acquisition of the detection target features is completed, which is denoted as (x_n, y_n). Due to the relatively high computation W and complexity r of the traditional data visual tracking algorithm, the tracking accuracy is affected in a specific environment. Taking into account the above problems, collect the characteristic data and standardize the specified collected samples, which are recorded as:

$$T = [f_i(y) - (x_n, y_\mathrm{n})/(R + W)] \tag{2}$$

Perform linear processing of task features to find a common ridge regression curve equation $h(n) = u_{ij}$ to minimize the squared difference between the sample set and the regression target λ. The specific data feature regression algorithm is:

$$L = \min \sum [h(n) - x_n \times y_n]^2 + \lambda\|T\| \tag{3}$$

Further calculate the detection common feature w_{ij}. If the simulation parameter after detection and collection is e, and the formula has a closed parameter s, the algorithm of w_{ij} is:

$$\left\|w_{ij}\right\| = \log[e \times (L - 1)]^2 - s \tag{4}$$

Generate the corresponding single-layer cyclic matrix A according to the basic sample R, if k is the feature acquisition transposition in the process of data detection. In the field of neural network, the recognition background of transmission line equipment is extremely complex, and the illumination will change at any time, and its recognition accuracy can not reach a satisfactory level. Therefore, the use of neural network has large operation, strong popularization and good real-time performance [7]. When using neural network method for recognition and classification, the core function needs to be selected first. For the mapping of sample space, it needs to be transformed into space first, then total, and then hyperplane classification; According to the classification results, the appropriate hyperplane can be selected and the support vector can be given; The classification and recognition problem is transformed into a function relationship problem. Because there are many kinds of transmission line equipment, different kinds of classifiers need to be combined into a variety of classifiers. Although the training time is prolonged, it fully reflects the constraints between different samples. Taking the characteristics as the input vector, it can identify and analyze the transformer equipment and ensure the accuracy of the identification results. In the acquisition process, the poor focus of the camera will introduce noise, seriously affect the quality, and bring difficulties to the identification and analysis of transmission line equipment [8]. The camera obtains the video from the received and preprocesses it first. After preprocessing, it can improve the quality, segment the target area where the transmission line equipment is located, and obtain the main characteristics of the transmission line equipment after binarization. The invariant features are mainly reflected in different equipment types. The feature vector is input into the neural network. After training, the location of transmission line equipment can be identified, and the fault equipment can be found in time by comparing it with the historical database. The specific transmission line fault identification and processing process is shown in Fig. 5.

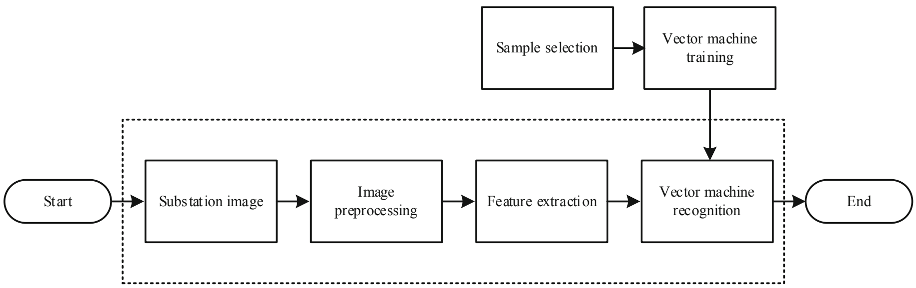

Fig. 5. Transmission line fault identification and treatment process

Combined with the identification processing process shown in Fig. 5, the application of artificial intelligence method can greatly improve the automation level of transmission line equipment operation condition detection. On this basis, the transmission line equipment operation condition detection model is established as ϖ. If the multi-layer cyclic matrix in the transmission line is B, and each row of elements in B is a simulation sample y obtained from the basic sample x through continuous cyclic displacement. is the regression target of xi, and the base element yi is the regression target of the sample element xi. In order to complete the efficient calculation, the formula is transformed into the form as follows:

$$\Delta\varpi = \sum\sum \lim_{x\to\infty} R[A \to B] + \left\| w_{ij} \right\| x_{\mathrm{i}} y_i \tag{5}$$

If x^H is the conjugate transpose of matrix A, and y^H is the eigenvalue of the co-circulation of matrix B, which is represented by the discrete Fourier transform as the diagonalization of the base sample X:

$$n = \Delta\varpi diag\ (x^H, y^H) \tag{6}$$

The style value of the transformed neural network is standardized, denoted as $\hat{x} = Rdiag(y_n - 1)$, and the unit diagonalization matrix of the data feature vector G is C. $R(n)$ is a constant level matrix independent of the base sample A, and $R(\mathrm{n}) = \sqrt{n} \log \hat{x}$, $\hat{x}$ represent the unit scale of the base sample. a represents the variable in the neural network. Based on the above factors, the characteristic attributes of the circulant matrix are further standardized, and the specific algorithm is as follows:

$$\xi = \sum\sum C \times n + G \frac{\log R(n)\left(1 - \hat{x}\right)}{\log a\,(1 - y_n)} \tag{7}$$

In the process of data acquisition, it is necessary to study the nonparametric index density in the transmission line, so as to better complete the detection of transmission line data, locate the target tracking field according to the detection results, and realize the accurate detection of target data. Transmission line detection and management objects mainly include transformer, capacitor equipment, switchgear and other disposable equipment, and the basic attributes of physical equipment assets concerned in the detection process are not clearly specified. Therefore, based on the CIM assets of computer integrated manufacturing, an equipment detection model is established for transmission line detection, so as to meet the detection requirements of transmission line operating conditions. The transmission line detection equipment model is shown in Fig. 6.

It can be seen from Fig. 6 that the transmission line equipment detection is modeled from the perspective of the physical equipment entity, and the computer integrated manufacturing CIM is used to describe the transformers, switches and other equipment respectively. Use TypeAsset to describe equipment classification information, and further describe the operating conditions of a specific type of equipment. When analyzing the overall structure and equipment of the transmission line through this model, it is found that once the state detection master station has constructed the power grid structure and equipment working model under its jurisdiction, the transmission line network structure file model can be directly obtained from the detection master station. And loaded into the transmission line model database, the original model data can be obtained after verification, and then the sharing of the detection master station model can be realized to ensure the consistency of primary equipment, secondary equipment and auxiliary equipment.

2.3 Realization of Actual Detection of Transmission Lines

The trough mean value corresponds to the background gray value, while the peak position corresponds to the position of the transmission line. When the transmission line is

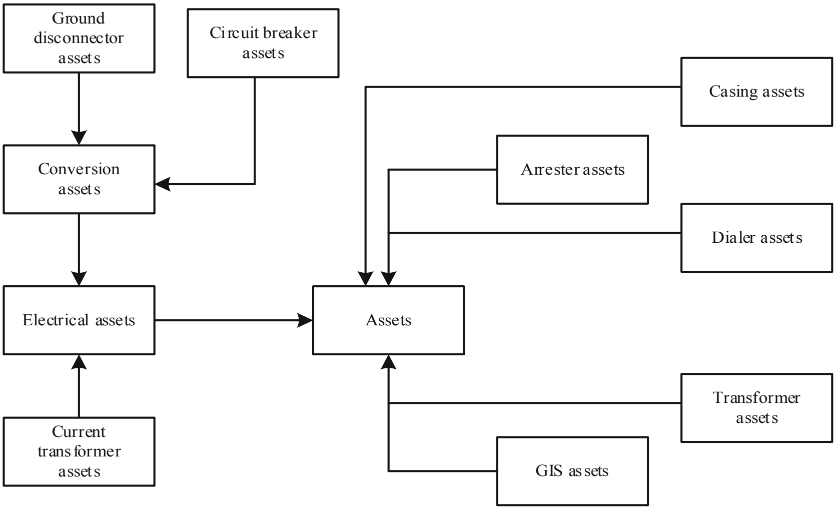

Fig. 6. Transmission line detection equipment model

normally wound, the position and number of transmission lines are basically unchanged. The winding characteristic information to be detected is extracted and compared with the stored transmission line characteristic value threshold through the anomaly detection method. That is, in the process of transmission line detection, the proposed method needs to detect the transmission line power supply of high-speed electromechanical equipment, and detect the voltage value, current value and power characteristics of the transmission line power supply respectively. In order to test these three aspects at the same time, this paper designs a power detection system, and the composition of the power detection system is shown in Fig. 7.

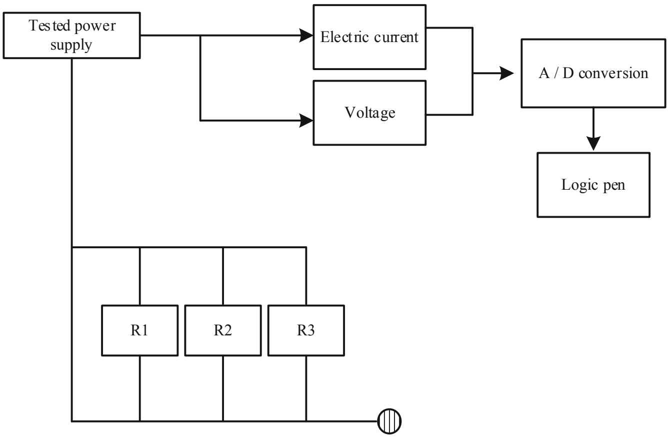

Fig. 7. Composition of power supply detection system

In visual detection, the statistical value of the number of columns where the wave crest is located, the number of wave peaks and the gray mean value are the feature values to be extracted, which are included in the column projection map. The gray mean value is the value of anomaly detection, which can represent the stability of the detection environment. If the gray mean value fluctuates greatly, the light around the platform will change significantly. Through the analysis of transmission lines, it can be seen that the number of wave crests represents the number of transmission lines; the position information of wave crests represents the position of transmission lines. The influence of circuit tolerance is determined within the left and right range of the standard value, so the normal fuzzy distribution function is selected as the mapping to establish the fault tree, as shown in the formula:

$$m(\mathrm{a}) = \exp\left[r(a-b)^2\right] = \exp\left[r\delta^2\right] \tag{8}$$

In formula (8), b is the fault scale parameter, r is the nominal value of different fault states of the same node, δ is the intermediate parameter, and a is the mapping. Since the normal distribution function curve is symmetric with the center value, its normal distribution neural network curve is shown in Fig. 8.

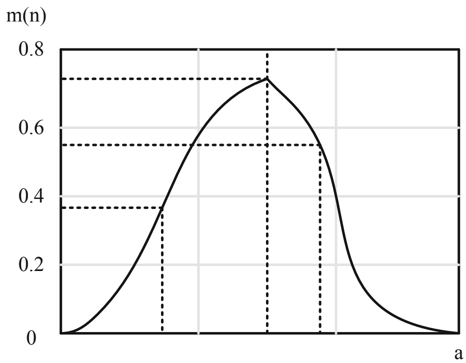

Fig. 8. Normal distribution neural network curve

It can be seen from Fig. 8 that the curve of normal distribution neural network is an axisymmetric graph, and the maximum peak value can reach 0.8 m (n). Therefore, the fault scale value is set as the parameter b, and then r is determined according to the correlation of the scale values of different fault states of the same node. The steps of the fault tree thus established are shown in Fig. 9.

It can be seen from Fig. 9 that the fault standard values under different nodes are used as parameters, and no processing is required. To analyze the tolerance problem in the circuit, in order to ensure that the membership degree under each faulty node is a reasonable value, the initialized intermediate parameter δ is set to 10% of b. The scale values under each fault status node are arranged from small to large, and the proximity of adjacent voltage scale values is observed to determine each parameter. For some problems with a small fault state scale value, using 10% of the initial definition scale

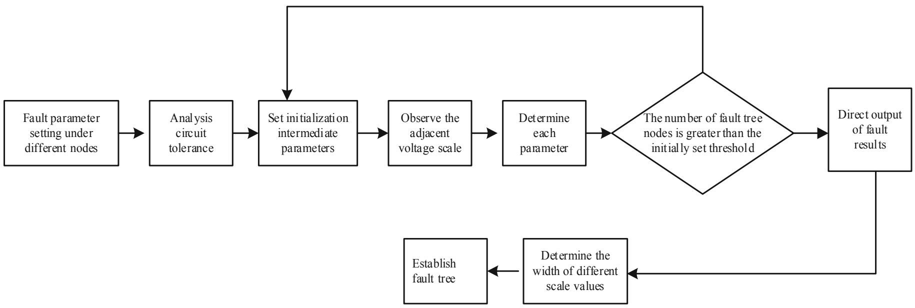

Fig. 9. Implementation of fault tree establishment steps

value, the neural network degree will drop rapidly. Therefore, in the case of small scale values, it can be processed separately. If the number of fault tree nodes is greater than the initially set threshold, the fault result needs to be output directly, otherwise, go to the next step. Determine the width of different scale values, according to this step, the neural network parameters b and r can be determined, and the fault tree can be established. In the normal winding process, the number of peaks projected in the column direction is used as one of the characteristic values. The variation range of transmission line position is very small. In normal winding, the statistical value of left and right variation of all transmission lines will approach 0. Although the influence is very small in calculation, it still needs to be eliminated by accumulation method. The gray level is segmented by threshold, and the number of black-and-white alternation times of binarization is counted to obtain the number of transmission lines. The transmission line data flow detection management is shown in Fig. 10.

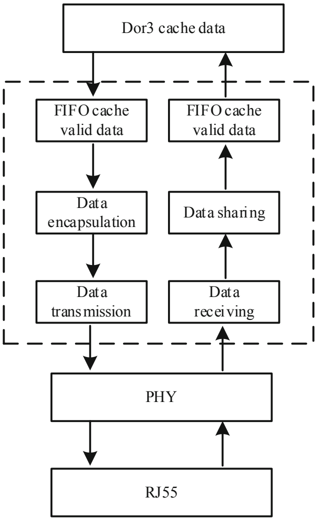

Fig. 10. Schematic diagram of transmission line data flow detection management

The first-order difference operation is carried out for the pixel value on a line of the transmission line, and the difference operation is carried out again for the symbolic function value of the value obtained by the first-order difference, then the possible value of the second-order difference is –2, –1, 0, 1, and the pixel point with the order difference value of –2 is the maximum point, and then the position of the peak value is determined through simple analysis. In order to prevent multiple extreme points in the same black or white area, extreme correction is required. By analyzing the relationship between the pre gradient and post gradient in the data of gray-scale column projection, the properties of gray-scale column projection points can be judged. When there are connected extreme points, remove one extreme point and store its projected column value in the register. When the calculated characteristic value is greater than the statistical value of the total number of peaks, and the register is not 0, the total number of peaks increases by the corresponding value. The value of the extracted register will be subject to subsequent operation. The principle of the transmission line detection algorithm proposed in visual detection is to detect the transmission line according to the sum of the statistical values of the columns where each wave peak is located and the number of numbered wave peaks.

3 Experiment

3.1 Experimental Analysis

In order to verify the effectiveness of visual detection methods for transmission line detection data based on neural network, comparative detection is carried out. In order to ensure the experimental effect, the experimental environment and parameters are standardized. Select the device with i6-CPU processor, Intel i7 6.0 GHz CPU, 64 GB RAM, Windows 10 operation, MatlabR2015a processing platform. There are two transmission line environments: one is a reasonable layout and no channel interference; the other is a reasonable layout and is subject to channel interference. In the two transmission line environments, the power supply radius is 15 km, 30 km, and 60 km, respectively, and simulation experiments are carried out within these three power supply radiuses. The initial values of basic parameters are shown in Table 1.

Table 1. Initial values of basic parameters

Parameter	Numerical value
Weight matrix	Less than 0.09
Offset vector	Less than 0.03
Voltage threshold	0.2–0.4
Current threshold	0.2–0.6
Inductance threshold	6–9

The weight matrix is used to measure the proportion of channel interference indicators in transmission lines; The offset vector is used to measure the displacement direction in the transmission line; Voltage threshold refers to the adjacent value in data detection; The current threshold value refers to the adjacent value currently measured; Inductance threshold refers to the adjacent value in the closed loop. Transmission lines will be affected by factors such as the surrounding environment or equipment aging. Therefore, the resistance threshold parameters need to be set under the equivalent circuit. The data source is based on the data of 52 structural points in the standard tracking data set. The detection index adopts the standard data set to standardize the position of the original first screening, operate the tracking calculation, complete the target situation of subsequent screening, and calculate the average accuracy and success frequency at the same time. Taking 50min as the predetermined detection time, the specific changes of the abnormal values of the modular transmission lines after applying the detection methods of the experimental group and the control group during this period of time are respectively recorded, as shown in Table 2.

Table 2. Comparison of abnormal values of modular transmission lines

Paper method/ (PCs.)	Test time/(min)	Traditional method/(PCs.)	Change trend
26	5	99	
28	10	102	Enlarge
21	15	108	Enlarge
28	20	113	Enlarge
22	25	118	Enlarge
25	30	116	Enlarge
28	35	116	Stable
28	40	118	Stable
28	45	115	Reduce
22	50	108	Reduce
Average value	113		

Analysis of Table 2 shows that with the increase of detection time, the abnormal values of modular transmission lines in the experimental group have always maintained a rising trend, and the global maximum results have reached 28. The abnormal value of the modular transmission line in the control group increased continuously in the early stage, and began to gradually decrease after reaching a steady state. To sum up, with the application of neural network visual detection model, the abnormal value of modular transmission line will indeed rise sharply. The specific changes of the significant values of the experimental group and the control group within the detection time of 50min are shown in Fig. 11.

According to the analysis of Fig. 11, the initial level of the significant value of the control group is very low. With the increase of the detection experiment, although there is an obvious upward trend, the maximum value level can only reach 0.24; The initial level of the block significance value in the experimental group is relatively high. Although

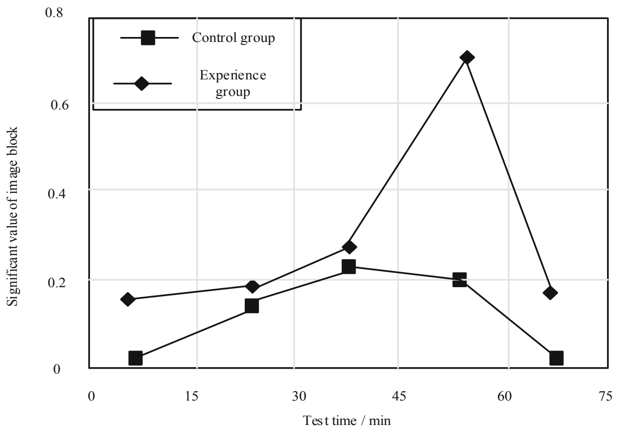

Fig. 11. Comparison of significant values of blocks

the rise range in the early stage is not obvious, it quickly reaches the extreme value of 0.70 at the 40 min, which is much higher than that in the control group. To sum up, with the application of neural network visual detection model, the block significance value also shows an obvious upward trend. During the experiment, firstly, the photographic component of transmission line visual detection is put into the transmission line of high-speed electromechanical equipment. The transmission line visual detection uses the logic pen to determine the range of fault data in the transmission line, and then the data is transmitted to the operator through the display screen, and then the operator analyzes the fault data. When the working frequency of the transmission line changes, the operator starts the sequential circuit fault detection program to detect the fault data of different frequencies again. According to the parameter changes of different frequencies, this method mainly adopts the following formula as the frequency detection support:

$$L = \frac{U}{I_1 + I_2} Z \tag{9}$$

In formula (9), L represents the distance to the fault point, U represents the rated voltage of the transmission line, I_1, I_2 represents the line current of the transmission line and the detection device respectively, Z represents the impedance of the transmission line, and the traditional current detection method applies the formula:

$$L = \frac{U}{I_1 + I_2} \tag{10}$$

In formula (10), there is no impedance for frequency limiting work, resulting in the inability to switch the detection state quickly.

3.2 Experimental Results

In order to further verify the effectiveness of this method, the experimental result of the fault detection deviation value is shown in Fig. 12.

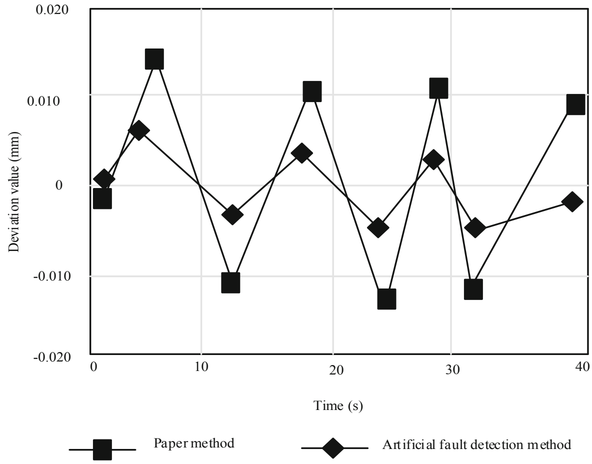

Fig. 12. Experimental results of fault detection deviation value

It can be seen from Fig. 12 that as time goes on, the fault detection deviation value results of this method and the manual fault detection method have some deviation. But the deviation value of the method in this paper is kept at 0 or above; The deviation value of the manual fault detection method is about –0.012 mm–.015 mm, and the fluctuation of the deviation value is higher than that of the method in this paper. The experimental results of frequency conversion deviation value of transmission line are shown in Fig. 13.

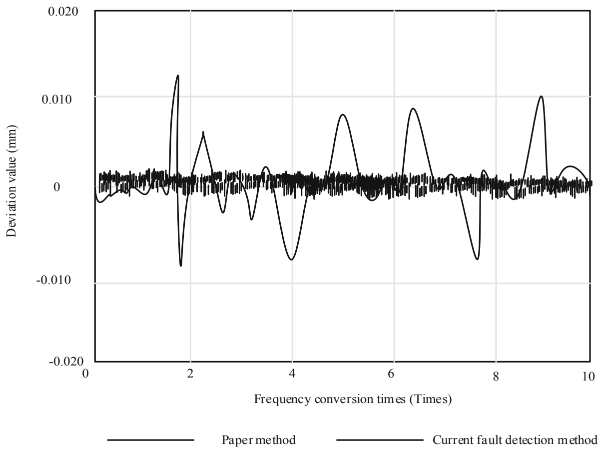

Fig. 13. Experimental results of frequency conversion deviation value of transmission line

It can be seen from Fig. 13 that the deviation value of frequency conversion of transmission line changes with the increase of frequency conversion times of this method and manual fault detection method. The deviation value of this method is maintained at about 0, while the deviation value of manual fault detection method is about –0.008–.013, and the fluctuation of deviation value is higher than that of this method.

According to the comparison results, the fault calibration accuracy of this method is higher than that of manual fault detection method. This method adopts the mode of neural network and uses the parts that are difficult to detect by traditional methods for fault detection. Moreover, this method can convey the fault state to the operator in the form of, which is convenient for detection and interaction. When the transmission line is frequency conversion, the current fault detection method can not switch the fault detection mode in time, and needs a certain transition time. This method can start the sequential circuit fault detection method through the program to detect the transmission line faults with different frequencies in time. Based on the above experimental environment, the error values generated in the process of data visual detection under the guidance of traditional methods and this method are recorded. The specific experimental results are shown in Fig. 14.

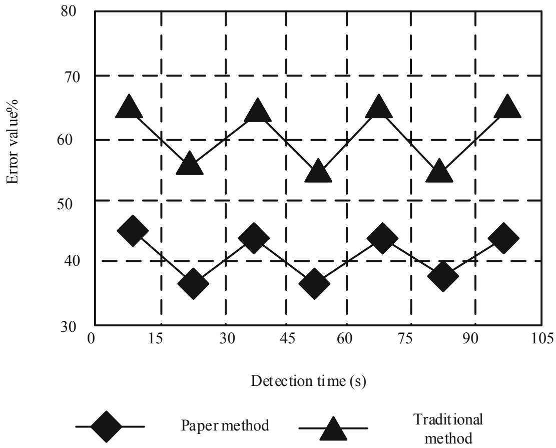

Fig. 14. Error value generated during data visual inspection

According to the detection results in Fig. 14, compared with the traditional data detection method, the visual detection method of transmission line detection data based on neural network proposed in this paper has relatively low error value, and the overall operation effect is relatively more stable compared with the traditional detection method. It is proved that the visual detection method of transmission line detection data based on neural network has high accuracy and effectiveness, and fully meets the research requirements.

4 Conclusion

In order to better ensure the detection effect of transmission line and improve the operation quality of transmission line. A visual inspection method of transmission line based on neural network online learning is proposed. The current of transmission line is collected by using the principle of neural network, and the collected data are processed in combination with the high-level dimensional characteristics of transmission line. The transmission line detection is completed according to the number of wave peaks by comparing the anomaly detection method with the transmission line eigenvalue threshold. The experimental results show that the transmission line visual inspection method based on neural network online learning can greatly improve the speed of data processing and promote the construction of the power Internet of things. It has high adaptability and high application value.

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