Track Circuit Fault Diagnosis Method based on Least Squares Support Vector

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Abstract. In order to improve the troubleshooting efficiency and accuracy of the track circuit, track circuit fault diagnosis method was researched. Firstly, the least squares support vector machine was applied to design the multi-fault classifier of the track circuit, and then the measured track data as training samples was used to verify the feasibility of the methods. Finally, the results based on BP neural network fault diagnosis methods and the methods used in this paper were compared. Results shows that the track fault classifier based on least squares support vector machine can effectively achieve the five track circuit fault diagnosis with less computing time.

1. Introduction

LS-SVM (least squares support vector machines) is proposed by Suykens first, a machine learning method based on the limited sample statistical learning theory. The training process follows the principle of structural risk minimization, which is not easy to occur during the training process Local optimization and over-fitting phenomenon, it obtains the global optimal solution by solving a set of linear equations, which can solve the practical problems such as small sample, nonlinear and high-dimensional pattern recognition, and improve the convergence rate and have good Promote the performance, successfully overcome the artificial neural network of the above shortcomings.

In order to obtain a more reliable fault diagnosis model of the track circuit, this paper intends to carry out LS-SVM theory to achieve a variety of fault diagnosis of the track circuit, using a section of the measured data to verify and compare with the neural network method.
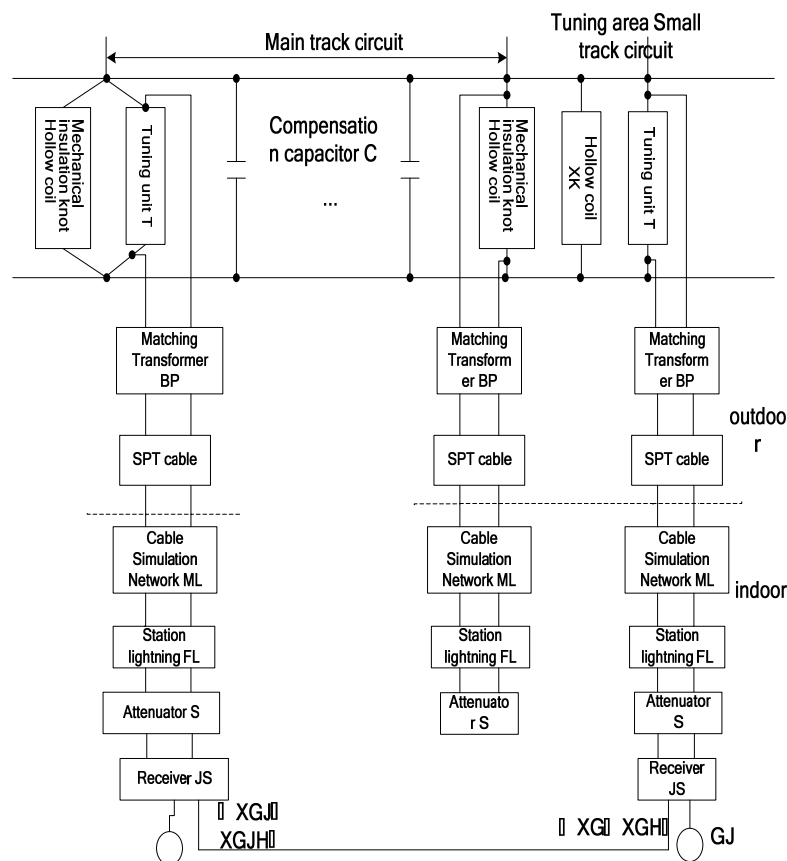
2. Fault Analysis of ZPW - 2000A No Insulated Track Circuit

2.1. ZPW-2000A non-insulated track circuit

ZPW-2000A non-insulated frequency-shift track circuit is used to isolate the electrical insulation section, divided into two parts: the main track circuit and the tuning area small track circuit, from the transmitter to the receiver by the transmitter FS, cable simulation network ML, Transformer BP, tuning unit T, hollow coil XK, compensation capacitor C, attenuator S, receiver JS and other equipment. The transmitter of the main track circuit is controlled by the coding condition to generate low-frequency signals indicating different meanings into the main track circuit and the tuning area small track circuit. The small track signal of the harmonic region is sent to the relay execution condition of the adjacent track circuit receiver This section of the receiver, the receiver at the same time to receive the main track

frequency shift signal and small track circuit relay implementation conditions, to determine the correct drive rail circuit relay suction, thus to determine the section of the idle and occupied. ZPW-2000A non-insulated track circuit system structure is shown in Figure 1.

Figure 1. ZPW-2000A non-insulated track circuit schematic

2.2. Fault Analysis of ZPW - 2000A No Insulated Track Circuit
ZPW-2000A no insulation track circuit failure is usually divided into alarm and no alarm failure. Transmitter and receiver When the fault occurs, the console sound and light alarm (YBJ fall), this is a fault alarm. No fault alarm by the console red light with instructions and drivers blocked reports that such failures can only be based on field personnel experience maintenance diagnosis. By analyzing the common fault mechanism analysis of ZPW-2000A non-insulated track circuit, it is concluded that the fault area belongs to the indoor fault or the outdoor fault. According to the summary of the actual fault, the main fault types are summarized: main track fault, common transmission channel fault, Small track faults, indoor faults, and attenuator failures. In the fault diagnosis, select the input to meet the two criteria: First, the choice of input on the output of large and can detect; second, the selected amount between the smaller correlations. In this paper, we choose the main input voltage, the small rail input voltage, the rail voltage, the emitter blank and the analog disk voltage as the fault diagnosis feature.

3. The basic theory of LS-SVM
SVM has excellent learning generalization ability for small sample data, and maps the input sample space to the high-dimensional linear feature space through the nonlinear kernel function, so SVM can deal with the problem of high degree of nonlinear classification and regression. LS-SVM is an extension of standard SVM. It introduces the least squares linear system into SVM, and uses quadratic programming method to solve the problem of function estimation.

In order to improve the efficiency and accuracy of track circuit fault handling, this paper designs LS-SVM multi-fault diagnosis classifier of track circuit. The training data set is $\{x_k, y_k\}_{k=1}^{l}$, $x_k \in R^l$ is the input pattern of the k-th sample, $y_k \in R^l$ corresponds to the expected output of the k-th sample, and l is the number of training samples. For a class of two types of classification, the process of finding the optimal hyperplane with the largest gap between the two classes can be reduced to solving the quadratic programming problem shown in equation (1), finding the objective function:

$$\min J(\omega, \xi) = \frac{1}{2}\omega^T \bullet \omega + \frac{1}{2}c\sum_{i=1}^{l}\xi_i^2 \tag{1}$$

Constraints are: $y_i\left[\omega^T \bullet \varphi(x_i) + b\right] - 1 + \xi_i = 0$, the formula, = 1, 2, ... Where: $w^T \bullet w$ is the inner product between the two vectors; ξ_i is the error; c is the tunable parameter, which controls the penalty error for the error sample; w, b is the weight vector and the threshold in the decision function $f(x) = w^T \varphi(x) + b$.

Define the Lagrangian function:

$$L(\omega, b, \xi, \alpha_k) = \frac{1}{2}\omega^T \bullet \omega + \frac{1}{2}c\sum_{i=1}^{l}\xi_i^2 - \\ \sum_{i=1}^{l}\alpha_i\left\{y_i\left[\omega^T \bullet \varphi(x_i) + b\right] - 1 + \xi_i\right\} \tag{2}$$

In the formula, α_i (i = 1 ... l) is the Lagrangian multiplier. According to the KKT optimal conditions,

$$\begin{cases} \dfrac{\partial L}{\partial \omega} = 0 \rightarrow \omega = \sum_{i=1}^{l}\alpha_i y_i \varphi(x_i) \\ \dfrac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{l}\alpha_i y_i = 0 \\ \dfrac{\partial L}{\partial \xi_i} = 0 \rightarrow \alpha_i = c\xi_i \\ \dfrac{\partial L}{\partial \alpha} = 0 \rightarrow y_i\left[\omega^T \bullet \varphi(x_i) + b\right] - 1 + \xi_i = 0 \end{cases} \tag{3}$$

After eliminating the original variables ξ_k and ω, the following linear equations are obtained:

$$\begin{bmatrix} 0 & I^T \\ I & \varphi(x_k)^T \varphi(x_i) + D \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{4}$$

In the formula, $y = [y_1; \ldots; y_l]$, $I = [1; \ldots; 1]$, $\alpha = [\alpha_1; \ldots; \alpha_l]$, $D = \text{diag}[c_1; \ldots; c_l]$.
Select the kernel function that satisfies the Mercer condition:

$$K(x_k, x_i) = \varphi(x_k)^T \varphi(x_i) \tag{5}$$

In the formula, $k, i = 1, \ldots, l$.

By solving the linear equations (4), solving α and b, the classification hyperplane is: $\sum \alpha_k y_k K(x, x_k) + b = 0$.

Finally get the decision function:

$$f(x) = \mathrm{s}\,gn(\sum_{i=1}^{l} \alpha_k y_k K(x, x_k) + b) \tag{6}$$

In the formula, α_k and b are the solutions of the linear equations (4), l is the number of support vectors, $K(\bullet, \bullet)$ is the kernel function, the kernel function is an important component of the least squares support, and the appropriate selection produces a nonlinear transformation Linear classification. RBF function parameters are relatively small, and the numerical limit of less, you can improve the training speed, reduce the complexity of the model:

$$K(x, x_i) = \exp(-\frac{\|x - x_i\|}{2 \bullet \sigma^2}) \tag{7}$$

In the formula, σ is a positive real constant?

4. Fault Diagnosis Model of Track Circuit Based on LS-SVM

4.1. Selection of the input variable

In this paper, the typical fault data of ZPW-2000A is taken as an example, and the following typical faults are selected as the research object: main track fault F1, small track fault F2, common transmission channel fault F3, indoor fault F4, and failure F5.

According to the change of the characteristic parameters after the above fault, the input voltage of the main rail, the input voltage of the small rail, the rail voltage and the "XGJ" of the attenuator are selected to test the empty voltage and the analog disk voltage as the fault diagnosis feature.

4.2. Normalized pretreatment of the sample

Since the fault parameters often have different dimensions and orders of magnitude, in order to prevent the occurrence of morbid matrix in the training, the need to input the parameters of the failure parameters of the normalized. Therefore, the first formula (8) to deal with the parameters:

$$y_i = \frac{x_i - \min(X)}{\max(X) - \min(X)} \tag{8}$$

In the formula, x_i is the original data; $\max(X)$ and $\min(X)$ are the maximum and minimum values of the original data; where y_i is the normalized data. In this paper, 200 samples of samples were selected from the example data for normalization, and the samples were processed as shown in Table 1.

Table 1. Pretreated training sample data

Number	Main rail input voltage	Small track input voltage	Rail voltage	The attenuator measures the empty voltage	Analog disk voltage	Fault type
1	0.92334	0.48424	0.79121	0.86921	0.52102	F1
2	0.85241	0.43376	0.75523	0.87586	0.51061	F1
3	0.61402	0.87548	0.71087	0.83141	0.53201	F2
4	0.69005	0.82356	0.67841	0.87892	0.55934	F2
5	0.89221	0.86405	0.73094	0.84924	0.60212	F3
6	0.86482	0.88713	0.79813	0.78401	0.58315	F3
7	0.65505	0.49642	0.76167	0.81124	0.60667	F4
8	0.58853	0.40174	0.68982	0.77431	0.50224	F4
9	0.50177	0.46863	0.19216	0.81943	0.50176	F5
10	0.58019	0.41241	0.26670	0.75851	0.54475	F5

4.3. Fault diagnosis of track circuit based on LS - SVM

The input vector of LS-SVM is input to the input of the trained LS-SVM, and the input voltage of the main rail input voltage, the small rail input voltage, the rail voltage, the measured voltage of the attenuator and the analog disk voltage are input to the input of the trained LS-SVM. , The output fault category, that is, to achieve the input of the fault diagnosis classification, as shown in Figure 2.
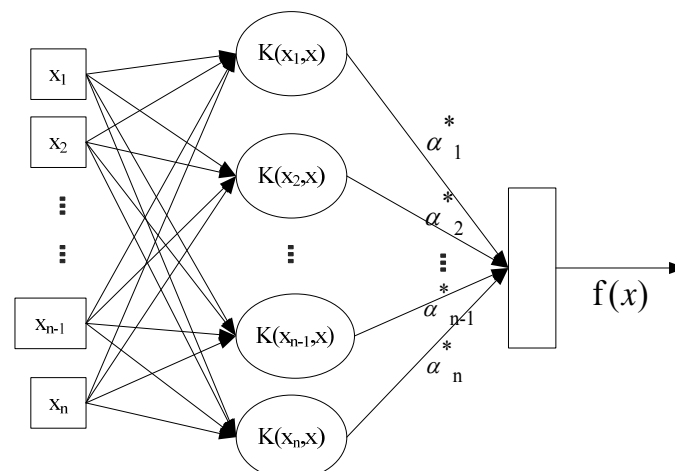

Figure 2. LS-SVM network structure

Based on the principle of LS-SVM classification method, aiming at the failure of track circuit, this paper adopts one-to-one method to diagnose k-type track circuit, and compare one to one between each sample and other category (K-1)/2 binary classifiers can be constructed by constructing the binary classifier with each of the two types of training samples. The "voting method" is used to identify the test sample. The test samples are input to the binary classifier constructed from the m-th class and the nth class of samples in the k class. If the output result determines that the test sample belongs to the m-th class, then the first m plus one vote; if the output to determine the test sample belongs to the first n class, then the first n class plus a vote. When all k (k-1)/2 binary classifiers classify the test samples, which class of k class is the most votes, it is determined that the test sample belongs to this category.

4.4. Examples of results and analysis
In order to verify the feasibility of applying the LS-SVM-based track circuit fault diagnosis method, the model data of the normalized preprocessing is used to simulate the developed fault diagnosis classifier. Specific steps are as follows:

a). Obtain the track circuit fault characteristic data: Obtain the data of the track circuit fault according to the method described above. This data will be used to train and test LS-SVM.

b). Training LS-SVM: According to the track circuit fault sample data, select the width of the kernel function $\sigma=1.558$ and the initial value of the adjustment constant is set to 5, by solving the equation (4) expressed linear equations, obtained formula (6) α_k and b, to complete the LS-SVM training, that is, contains the track circuit fault classification LS-SVM model.

c). Test LS-SVM: Select part of the sample data to test, verify the classifier classification effect.

In view of the actual running data of ZPW2000A, the results of five different fault diagnosis methods are shown in Fig. 3, and the projection of the test data in the two-dimensional space is classified. It can be seen from the figure that the method used in this paper can be used to diagnose and classify different faults.
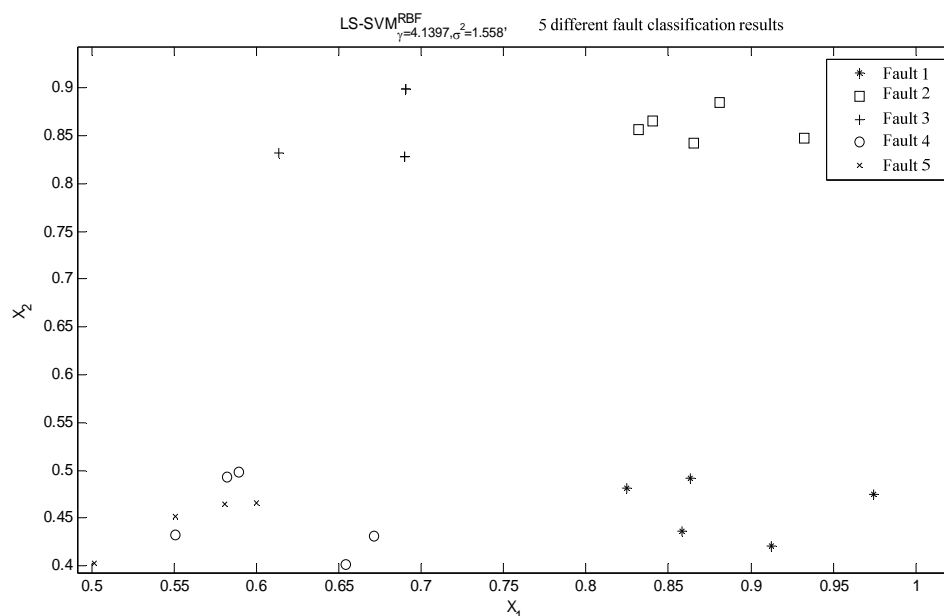

Figure 3. 5 different track circuit fault classification results

5. Comparison of LS - SVM Method and BP Neural Network in Diagnosis of Track Circuit Fault

In order to further study the effectiveness of the method in the multi - fault diagnosis of the track circuit, the fault diagnosis method of the track circuit based on BP neural network is selected as the contrast. The same training and test data are used to diagnose and classify the above faults, and the correct rate

and the operation time of the track circuit fault diagnosis method proposed in this paper are compared and analyzed.

Application of MATLAB neural network toolbox on the five track circuit fault training and test error results shown in Figure 4, the convergence effect is not ideal. Figure 3 shows that the training sample and the test sample mean square error of about 0.1.
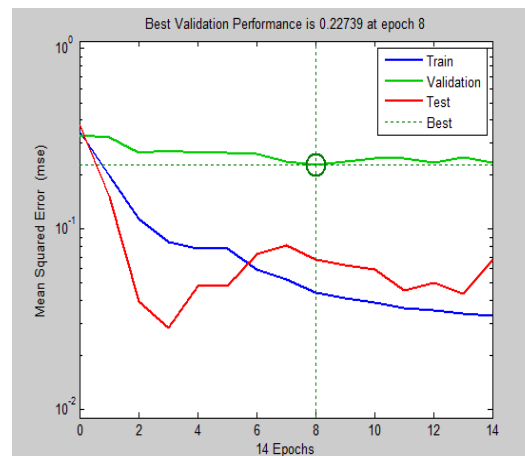
Figure 4. Neural network training and test error results

Table 2. Comparison and Analysis of Correctness and Operation Time of Fault Diagnosis of Neural Network and LS - SVM Track Circuit

Fault type: Method	F1	F2	F3	F4	F5	Computing time
Neural Networks	80%	78%	70%	71.4%	100%	4.52s
LS-SVM	98%	95%	97%	95%	98%	1.42s

In this paper, we compare the correctness of fault diagnosis results based on LS-SVM and five kinds of track circuits based on BP neural network and the time of fault diagnosis calculation, as shown in Table 2. It can be seen that the correct diagnosis result of the neural network is 85%, and the correct diagnosis result of the LS-SVM with the radial basis function is 96%. The results of this paper are as follows: LS-SVM method on the track circuit fault diagnosis results as a whole on the correct rate is higher, shorter computing time.

6. Conclusion

In order to improve the efficiency and correctness of ZPW-2000A fault-free track circuit fault diagnosis, a multi-fault diagnosis classifier of track circuit is constructed based on the least squares support vector binary classification principle. Based on LS-SVM, the fault diagnosis model of track circuit based on LS-SVM is selected as the training sample. The test data test is selected based on LS-SVM. The method can effectively realize the multi-fault diagnosis of track circuit. In order to verify the effectiveness of the method, the fault diagnosis method based on MATLAB neural network toolbox is used in the same training samples and test samples. The results show that the method used in this paper can use less training samples, more accurate and rapid realization of the track circuit fault diagnosis.

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