Intelligent fault prediction of railway switch based on improved least squares support vector machine

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Abstract
The centralized monitoring system for railway signaling play an important role in signaling equipments maintenance, this article based on switch operating current curve monitoring data that centralized monitoring system for railway signal collected, proposed an improved LSSVM algorithm for railway switch intelligent failure prediction, applies genetic algorithm to preferably choose six characteristic index from 12 characteristic index for composed of railway switch failure prediction model SVM input vector, not only reduces the input vector dimension, but also to speed up railway switch intelligent failure prediction rate and improve the accuracy and reliability of the railway switch failure prediction. Evidenced by the algorithm experimental analysis: improved least squares support vector machine railway switch intelligent failure prediction algorithm has a strong self-learning ability and high prediction accuracy.
Key words: FAILURE PREDICTION,IMPROVED LEAST SQUARES SUPPORT VECTOR MACHINE,CHARACTERISTIC INDEX,GENETIC ALGORITHM

1. Introduction

Railway switch is an important safety equipment in railway transportation, the centralized monitoring system for railway signaling is the «black box» of signaling and communication department, it is used for monitoring signal equipment condition including switch and is a necessary means to achieve «repair according to condition» , In the railway signaling equipment maintenance of the electrical department staff, it can predict railway switch failure type information to facilitate the analysis, judge and deal with the switch failure through analysis and forecasting of railway switches operating current curve that centralized monitoring system collects[1], Although the signal centralized monitoring system can timely record abnormal conditions of switch, with some failure diagnosis capabilities, but according to the reaction site personnel, failure diagnosis accuracy of the sys-

tem is not high enough, so it can reduce labor intensity of electrical department staff and improve the accuracy of switch failure prediction and railway switch maintenance efficiency, through the switch failure intelligent prediction by signal centralized monitoring system.

There are currently prediction methods that based on BP neural network and time series analysis. But BP neural network structure is more complicated, its operation rules is difficult to be understood [2]. time series prediction method ignore outside interference factors, a large number of historical sample data to predict is required, anti-interference ability is weak, middle and short-term forecasting is accurate, there is often a big error in long-term forecasting results, if there are large change in the outside, it is the defects that exist in time series forecasting [3]. This article proposes improved least squares vector machine prediction algorithm for railway switch failure based on the existing sample data, in order to improve self-learning ability and accuracy of railway switch failure prediction.

SVM is a new machine learning method developed on the basis of structural risk theory on the principle of the minimum. It has advantages of strong adaptability , high training efficiency, global optimization and good generalization performance [4] , so it is suitable for railway switch intelligent failure prediction.

2. Data curve characteristic extraction

The data in database of switch operation current curve that collected by centralized monitoring system for railway signaling, is primitive data of time series, it needs pretreatment including characteristic extraction and characteristic optimization.

2.1. Railway switch operating current curve

In this article, it takes ZD6-A switch for example, the operating current curve shown in Figure 1, the horizontal axis is time, vertical axis is the current, it is divided into seven stages:

(1) T1-T2 stage time is less or equal to 0.3s, it is the time that 1DQJ relay picks up and 2DQJ relay turn to another position;

(2) T2-T3 stage time is less or equal to 0.05s, it is the time that electric motor of ZD6 getting electricity

(3) T1-T4 stage time is less or equal to 0.6s, which T3 ~ T4 stage segment is the time that switch unlock and point that closely-attached to the stock rail start operation time;

(4)T4-T7stage time is the point movement time, the length of time depends on the resistance of movement, generally takes the average current between T4 ~ T7 as switch operating current;

(5) T7-T8 stage time is less or equal to 0.25s, it is the time that point get closely-attached and switch locking time, the current value corresponds switch force of closely-attached;

(6) T8-T9 stage time is less or equal to 0.05s, ZD6 switch motor complete mechanical locking, it is the movement time that automatic switching ware speed moved contact disconnects the circuit;

(7) T9-T10 stage time is greater than or equal to 0.4s, because 1DQJ relay is slow release relay, so that the segment is 1DQJ slow release time.

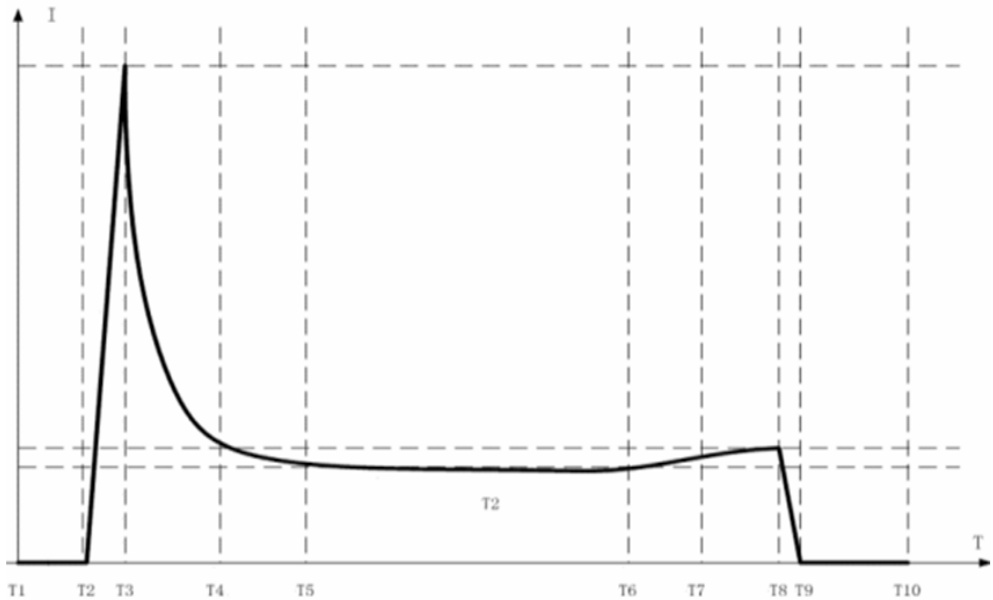

Figure 1. ZD6 single switch traction operation current curve

2.2. Characteristic index extraction and opti-mization of data curve

The operating current curve of railway switches that ZD6 motor controls is curve that time series depicts, different failure of switch will be a different time series, in order to predict the type of switch failure, it needs to calculate the statistical indicators of switch operating current curve, with a large number of experiment, the article applies 12 major statistical indicators of switch operating current curve [5]:

The maximum value is the greatest value in the time series of switch operating current curve; the average value; the minimum wave through value is the lowest wave through value; the position of minimum wave trough value; peak position; peak number is the number of intersection where rising and falling section namely peak point number; curve width is the number of time series; wave through number is the number of intersection where falling and rising section namely wave through point number; wave trough ratio is the ratio value of maximum value and minimum wave through value; peak degree is the ratio of maximum value and average value; standardized mean square deviation.

These statistical indicators form a feature vector for switch operating current curve, LS-SVM change the training problem into a linear equation solving problem, if the characteristic index is too many, the LSSVM solution contains number of support vectors of training samples because of the need to mapping to high-dimensional linear equations, it can affect learning ability and generalization performance of LSSVM. In order to ensure the high efficiency and accuracy of LSSVM algorithm, this article uses genetic algorithm to extract features and aims to use the training sample for extracting 12 characteristic values for each sample, and then determine the six optimal characteristic indicators [6]. Specific process is as follows:

(1) Enter 12 characteristic indicators as parameter sets, and encode the parameters;

(2) Initialization 12 the weight of characteristic indexes, namely initialization pheromone, by random search for solution of weight;

(3) using bit string decoded to get the parameter, calculates objective function value and calculates fitness;

(4) Evaluation group set to determine whether to find the optimal solution or the maximum number of iterations;

(5) If so, it will be end and extracts six high weight characteristic indexes, if not, it will take genetic operations such as re-crossover, mutation, selection and to get a new group;

(6) Repeat step (3), until find the optimal solution or reach the maximum number of iterations.

After calculation, the best six characteristic indexes of railway switch operating current curve can be found[5], namely:

The maximum value v_p: the greatest value detected in data time series $X = \{x_i \mid 0 \le i \le n-1\}$. The width of the curve: $w_w = n$; peak number n_p is the number of intersection where rising and falling section, namely peak point number; the average value v_a expressed as $\frac{1}{n}\sum_{i=0}^{n-1} x_i$; peak degree s_p expressed as $\frac{v_p}{v_a}$; standardized mean square deviation σ expressed as

$$\frac{1}{v_p}\sqrt{\frac{\sum (x_i - v_a)^2}{n}}.$$

These statistical indexes form the numerical characteristic of sample data curve, after the characteristic extraction and optimization, it can improve the computing speed and efficiency.

3. Railway switch fault prediction algorithm based on LSSVM

Least squares support vector machine (LSSVM) is improved based on SVM, the use of kernel functions changes quadratic programming problem into a li- near programming problem, in a given training sample set $D = \{x_i, y_i\}_{i=1}^{n}$ (there are n samples in total), the input is $x_i \in R^n$, the output is $y_i \in R^n$, LSSVM regression problem can be described as an optimization problem:

$$\min_{w,b,e} \quad J(w,e,b) = \frac{1}{2}w^T w + \frac{1}{2}c\sum_{i=1}^{n} \mathrm{E}_i^2$$

$$s.t.\ y_i = w^T \mathrm{H}(x_i) + b + \mathrm{E}_i, \quad i = 1,2,\ldots,N \tag{1}$$

In the formula, $\mathrm{H}(\bullet): R_n \to R^{nh}$ is non-linear kernel function, $w \in R_{nh}$ is weight vector of the optimized space, $\mathrm{E}_k \in R$ the error variable, b is the deviation, c is the regularization parameter. The use of $\mathrm{H}(\bullet)$ can change quadratic programming problems into linear programming problem and will become possible to construct the following model:

$$y(x) = w^T \mathrm{H}(x) + b \tag{2}$$

Weight vector w is a vector of high-dimensional target space, it will not be directly represented by the formula (1) calculations. In order to solve (1), we can calculate LS-SVM model in the dual space and elimi-

nate constraints according to the definition of the Lagrange equation, so obtain the following formula:

$$L(w,b,\mathrm{E},\sigma_k)=J(w,b)-\sum_{i=1}^{n}\sigma_i\{w^T\mathrm{H}(x_i)+b+\mathrm{E}_i-y_i\} \tag{3}$$

In the formula, $\sigma_i \in R$ is the Lagrange multiplier, according to Carlo - Kuhn - Tucker conditions, in the formula the partial derivative of w、b、E_i、σ_i is zero, we get:

$$\begin{cases}\dfrac{\partial L}{\partial w}=0,\dfrac{\partial L}{\partial b}=0\\ \dfrac{\partial L}{\partial \mathrm{E}_i}=0,\dfrac{\partial L}{\partial \sigma_i}=0\end{cases} \tag{4}$$

The formula (3) substitute into equation (4), to get the formula (5)

$$\begin{cases}w=\sum_{i=1}^{n}\sigma_i\mathrm{H}(x_i)\\ \sum_{i=1}^{n}\sigma_i=0\\ \sigma_i=c\mathrm{E}_i, i=1,\cdots,n\\ w\mathrm{H}(x_i)+b+\mathrm{E}_i-y_i=0, i=1,\cdots,n\end{cases} \tag{5}$$

After elimination of w and E, we can optimize the solution of the equation as:

$$\begin{bmatrix}0 & 1_v^T\\ 1_v^T & Q+\dfrac{1}{\gamma}I\end{bmatrix}\bullet\begin{bmatrix}b\\ \sigma\end{bmatrix}=\begin{bmatrix}0\\ y\end{bmatrix} \tag{6}$$

In the formula, y is the output, 1_v^T is a unit column vector transpose, σ is Lagrange multiplier, according to Mercer theory, you can choose kernel function $Q(\bullet,\bullet)$:

$$Q(x_k,x_j)=H(x_k)\bullet H(x_j) \tag{7}$$

From the above formula, we can further obtain w and can obtain the value of σ and b by the formula (8), so you can get the LS-SVM model for function estimation, fitting function which seeking for is:

$$y(x)=\sum_{i=0}^{n}\sigma_i Q(x,x_i)+b \tag{8}$$

After selecting kernel function, it can be seen from the formula (5), LS-SVM training is converted to a problem of solving linear equations, it is more efficient and simple than quadratic programming, so LS-SVM has less computational complexity [4].

4. Railway switch fault prediction simulation example analysis

In this article, it takes the railway switch failure operation current curve data as training set and test set, the training set for getting the regression model of least squares support vector machine SVM, the test set is used to assess predictive ability of support vector machine model[7].

The article compares classification performance of LS-SVM method with time series, BP neural network (BP network structure with three layers: there are 5 nodes in input layer and 4 nodes in output layer).

In the model training stage, we selects 1000 training samples from the switch controlled by ZD6-A type switch motor in station for some time, the training samples contains four kinds of failure types During the testing stage, we use the obtaining model in training phase for classification of 800 test samples [8].

Four kinds of typical failure types graph shown in Figure 2-5[8]. Figure 2 is a graph showing the switch operating current caused by contact failure of one relay in starting circuit. Figure 2 is a graph showing switch operating current curve that several axis such as automatic switching ware crutch axis, automatic switching ware speed pawl axis and connected plate axis are not flexible, Figure 4 is a graph showing switch operating current curve that the switch is adjusted too tight, Figure 5 is a graph showing switch operating current curve that due to slider bed boards resistance.

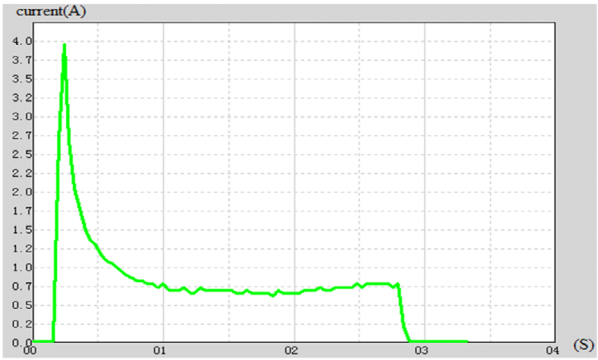

Figure 2. The curve of contact poor contacting

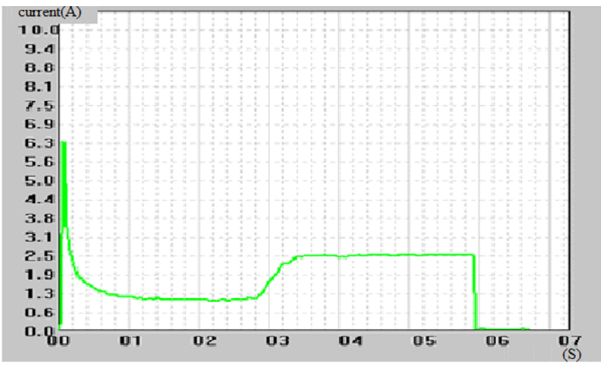

Figure 3. The curve of automatic switching ware movements are not flexible

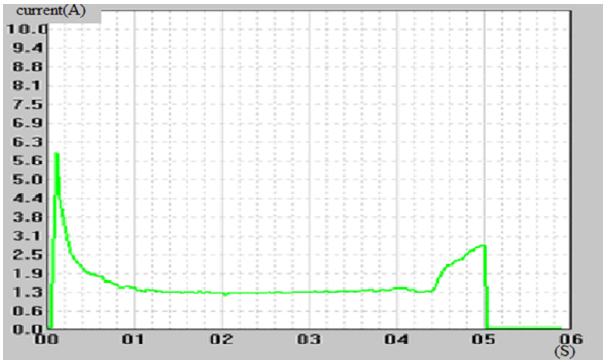

Figure 4. The curve of closely-attached too tight

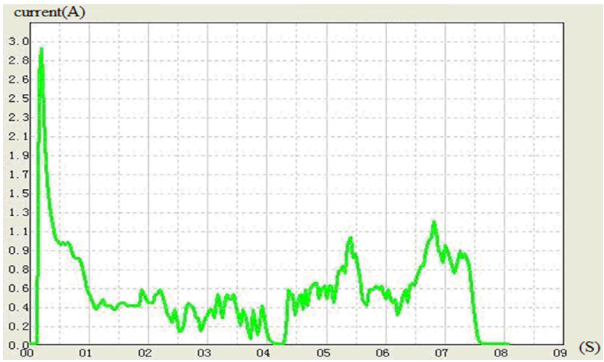

Figure 5. The curve of switch slip bed board jamming resistance

In the example, we selects 6 characteristic property that have been characteristic extraction as LSSVM input vector. We select the radial basis function as kernel function, fitting function is found by the training of observing samples, the characteristic vector is substituted, and according to the difference of characteristic vectors combination, we predict railway switch failure by using railway switch failure prediction computer algorithm program based on support vector machine in railway signal centralized monitoring system. Specific flow chart is shown in Figure 6.

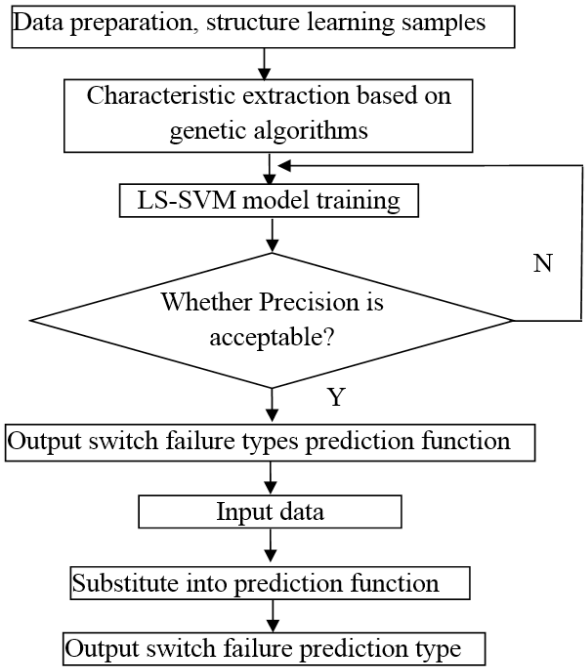

Figure 6. The flowchart of railway switch failure prediction based LSSVM

The classification performance results comparison of LSSVM method and time series analysis, neural network is shown in Table 1 (Note: In the table the last column is average accuracy rate, each other column is failure type accuracy rate separately). Among them, the failure of switch closely-attached too tight, the prediction accuracy of LSSVM method is higher 5 percentage points than BP neural network method and is higher 11.9 percentage points than time series method.

By comparing in table 1, it can be concluded that prediction accuracy rate of improved LSSVM is higher than neural network and time series analysis in various failure types and the average accuracy rate, the average accuracy rate of time series prediction method is 82.6 percent and BP neural network can reach 92.2 percent, while the improved LSSVM is as high as 94.5%, thus it indicates the prediction performance of improved LSSVM algorithm combined with genetic method is better than the time-series method and BP neural network to in the conditions that limited samples.

Table 1. LSSVM prediction performance compared with BP neural network and time series analysis method

Test items	Contact poor contacting	Automatic switching ware movements are not flexible	Closely-attached too tight	Switch slip bed board jamming resistance	The total number of samples
Number of samples	200	200	200	200	800
Accuracy number of Time series	164	156	163	178	661
Accuracy number of BP neural network	188	187	181	182	738
Accuracy number of LSSVM	192	190	185	189	756
Accuracy rate of Time series (%)	82.0	78.0	81.5	89.0	82.6
Accuracy rate of BP neural network (%)	94.0	93.5	90.5	91.0	92.2
Accuracy rate of LSSVM (%)	96.0	95.0	92.5	94.5	94.5

5. Conclusions

This article proposes railway switch intelligent failure prediction method based on improved least squares support vector machine. In order to improve the learning and generalization ability of least squares support vector machine, we use genetic algorithm for optimization of LSSVM input characteristic vector and select six characteristic indexes that the most significant impact on switch operating current curve, then use these characteristic indexes for switch operation current curve failure prediction based on least squares support vector machine. The experimental results show: this method can effectively achieve failure prediction of switch operating current curve, the prediction accuracy is higher than the traditional way of time series and BP neural network, it is a new method of effective switch intelligence failures prediction. it is suitable for railway switch failure intelligence prediction of centralized monitoring system for railway signaling.

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Design and implementation of material position detection system based on FPGA

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