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Methods of Track Circuit Fault Diagnosis Based on Hmm

Gao Tongfei[1], Zhang Wenyan[2], Deng Renzhen[3]
College Of Urban Railway Transportation, Shanghai University Of Engineering Science, Shanghai, China

ABSTRACT: A fault diagnosis method of track circuit based on HMM (Hidden Markov Model) was proposed. On the basis of division of failure mechanism of the track circuit, a training mechanism of multi - sample HMM model was established, and a track circuit fault diagnosis system was composed by multiple fault classifiers. Because of the universality of this system, taking the hump section of railway and a section of ZPW-2000A non-insulated track circuit as examples, the correctness and effectiveness of the system were verified. The result shows that the fault diagnosis method of track circuit which is based on HMM can effectively achieve six kinds of track circuit fault diagnosis. And compared with BP Neural Network fault diagnosis, it has a higher accuracy rate and has a faster computing speed, which can be used as a new solution for fault diagnosis of track circuits.

Keyword: Track circuits, Fault diagnosis, Hidden Markov Model, Multi-sample training

I. INTRODUCTION

Track circuit is the basic equipment of the rail transit signal automatic control. The track circuit fault affects the normal driving, shunting operations, and even security risks. In the actual work, the track circuit fault diagnosis almost uses the manual regular maintenance. And the maintenance personnel professional standards, experience accumulation and accuracy of the measurement equipment may have different degrees of impact to track circuit fault diagnosis. Therefore, it has a great practical significance through scientific means to diagnose the track circuit fault.

There are also a few applications on the various types of algorithms in the track circuit fault diagnosis. In recent years, fault diagnosis algorithms based on expert system, neural network, genetic algorithm, support vector machine algorithm and other algorithms have been widely studied, and they also made a lot of achievements. In addition, the algorithm based on state space model is more and more applied in the field of fault detection and prediction. Among them, Hidden Markov Model (HMM) has become a new research direction in the field of fault diagnosis as it reveals the transition process of hidden state and it is easy to achieve by using programming software. There are some literatures discuss the possibility of HMM applied to the rolling bearing fault diagnosis. In addition there are many cases of HMM model optimization or complex for the fault diagnosis study. Combined with the application of HMM in the field of related machinery, it is introduced into the track circuit fault diagnosis research, putting forward more possibilities for the track circuit fault diagnosis method. In this paper, HMM-based track circuit fault diagnosis method is universal. The following is the railway hump section data as an example to introduce.

Fault Analysis of Hump Section Track Circuit

Principles of Hump Section Track Circuit

JWXC-2.3 AC closed-circuit hump track circuit is one of the main equipment of various hump marshaling yards in China. From end to end, it is composed of interactive rheostat, two groups of diodes composed of bridge rectifier, transformer BG1, breaker and track relay DG. In addition, the hump track circuit set the two-segment track circuit at the shunt turnout, respectively, to protect the section DG1 and turnout section DG. When the vehicles enter the protection zone, the track relays of the two sections immediately demagnetize and drop. When the vehicles in the protection section lost shunt in a short time, DG section of the track relay slowly pick up; and when the vehicles clean from the DG section, DG section of the track relay immediately pick up, which prevent the track circuit's wrong action caused by the shunt faults. JWXC-2.3 AC closed-circuit hump rail circuit figure is as follows.

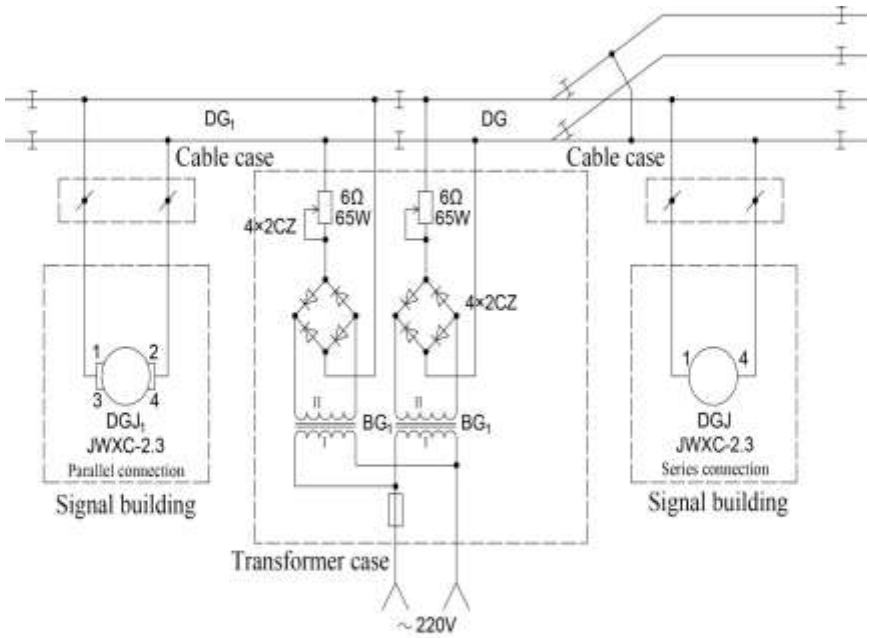

Figure 1 JWXC-2.3 AC closed-circuit hump rail circuit

The Fault Analysis of Hump Section Track Circuit Through the fault status analysis of JWXC-2.3 type AC closed-circuit hump track circuit, the fault is divided into indoor faults and outdoor faults. Indoor faults include indoor open circuit, indoor short circuit, while outdoor failure including outdoor open circuit (open circuit point before the test point, open circuit point after the test point), outdoor short circuit (short circuit point before the test point, short circuit point after the test point). Compared the measured voltage of the fault track circuit in a certain section of the hump section, these five data about the current limiter step-down of sending side, rail voltage of sending side, rail voltage of receiving side, the adjustment state voltage of relay and the adjustment state voltage of relay after throwing the line are selected to describe the fault.

The Fundamental of HMM

The principle cognition of HMM

The Hidden Markov Model (HMM) is based on the Markov chain. The Markov chain is a stochastic process that describes a state sequence. In this sequence, the state of the future (which is the future of now) is independent of the state of the past (which is the past of now), and each state data depends only on one of its previous states, namely, assuming the value of

means the state at time and the value of depends only on the value of . At the same time, the probability distribution of the system state at time depends only on the state at time, namely,. The Markov chain model can be described by three elements. The first one is the non-empty state set composed by all possible states of the system. The second one is the state transition probability matrix of the system, and the last one is the initial probability distribution of the system. In the state transition probability, since each state transition probability is positive, it is available that, and each state transition process is transferred from one state to another (or the same) state. So there is, in which means the probability of state turns into state.

In the Markov chain, since all states are directly visible, the state transition probability is the only parameter. However, for some practical reasons, the observer cannot directly observe the real state of the system, but they can observe the output depends on its state. At this time, there is a possible probability distribution for each state to each output. This model is called the hidden Markov model, which describes a Markov process with implicit unknown parameters. It can be seen that the hidden Markov model is a double stochastic process. One is a hidden Markov chain with a certain number of states, and the other is a set of random functions.

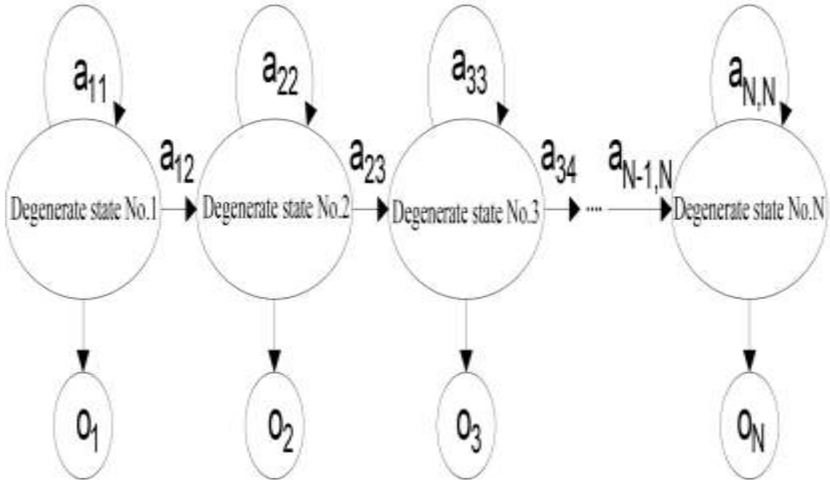

Figure 2 The evolution process of HMM model running state

At this point, the hidden Markov model can be expressed by five corresponding elements:
Implied state : These states usually can't be obtained by direct observation, and it can use state collection to be expressed as , in which means the number of imply states.
Observable state : they are associated with the implied state and they can be obtained by direct observation, and it can use state collection to be showed as , in which means the number of observable states.

Initial state probability matrix : it represents the probability matrix of the implied state at the initial moment, and it can be represented as , in which means the probability of imply state at the initial moment, namely
Implicit state transition probability matrix : it describes the transition probability between each hidden state. So we can get , which shows the possibility of state turn into state .
Observation state transition probability matrix : it describes the probability of transition between the observed states, in which . And this indicates that at some point, the probability of implied state is while the observing state is .
In summary, the hidden Markov model has a successful application as a statistical model in the field of fault diagnosis.

The basic problem of HMM

Assessment problem: For a given model, find the probability of an observation sequence. Give an observation sequence and model parameters. The question is how to calculate the probability of generating this observation sequence, and then make the relevant assessment of the HMM. The forward algorithm is a powerful way to solve this problem. It can compare each probability of generating sequence produced by hidden Markov model after calculating and select the optimal HMM model among all the results.

Decoding problem: For a given model and observation sequence, find the state sequence with the highest probability. Give an observation sequence and model parameters . The question is how to find the optimal hidden state sequence. In such problems, the Viterbi algorithm is usually used to find.

Learning problem: For a given sequence of observations, adjust the parameters and make the probability of observations is greatest. That is, when the HMM model parameters are unknown, how to make the probability of the observation sequence as large as possible by adjusting these parameters. The Baum-Welch algorithm and the Reversed Viterbi algorithm can be used to solve this problem properly.

Fault Diagnosis Method of Rail Circuit Based on HMM

Sample normalization

In the 1.2, the study objects of fault are indoor open circuit, indoor short circuit, outdoor open circuit (open circuit point before the test point, open circuit point after the test point), outdoor short circuit (short circuit point before the test point, short circuit point after the test point). These five feature data about the current limiter step-down of sending side, rail voltage of sending side, rail voltage of receiving side, the adjustment state voltage of relay and the adjustment state voltage of relay after throwing the line are selected to describe the fault. And 240 sets of sample data (including training data and verification data) are selected as normalized pretreatment in order to prevent the sick matrix during the training process and easy to discriminate the program. The parameters are normalized using the following formula:

Among them, is raw data, while, mean the maximum and minimum of the 240 groups of raw data respectively. is the data after the normalization process. Partially processed data are shown as follows:

Table 1 Partially processed data

Number	sending side		receiving side	relay		Fault type
	current limiter step-down	rail voltage	rail voltage	adjustment state voltage	adjustment state voltage of relay after throwing the line	
1	0.0285	0.9915	0.9801	0.9972	0.9943	indoor open circuit
2	0.0456	0.9972	0.9685	0.9915	0.9986	indoor open circuit
3	0.9744	0.0399	0.0285	0.0684	0.9801	indoor short circuit
4	0.9715	0.0427	0.0313	0.1254	0.9772	indoor short circuit
5	0.9858	0.7293	0.7179	0.1880	0.1795	outdoor short circuit(before)
6	0.9915	0.7236	0.7123	0.1083	0.1026	outdoor short circuit(before)
7	0.9886	0.0342	0.0228	0.1339	0.1282	outdoor short circuit(after)
8	0.9858	0.0370	0.0256	0.1852	0.1766	outdoor short circuit(after)
9	0.0256	0.7236	0.7123	0.0598	0.0285	outdoor open circuit(before)
10	0.0370	0.7208	0.7094	0.0712	0.0342	outdoor open circuit(before)
11	0.0256	0.9915	0.9801	0.0570	0.0285	outdoor open circuit(after)
12	0.0342	0.9801	0.9687	0.0570	0.0256	outdoor open circuit(after)

The Realization and Application of Fault Diagnosis Method for Rail Circuit Based on HMM In this paper, the fault diagnosis method of track circuit is based on evaluation and learning problems of HMM. Six kinds of HMM models are designed to perform multi-sample HMM model training for six different types of faults. The fault classification is written in the Matlab environment. First, the number of hidden states is 6, and the Markov chain in this case is shown in Figure 3. Then, the observation sequences of HMM are composed of training data in five types of data after normalization, and as input variables, they will be input into six track circuit fault classifications. The "Forward-Backward algorithm" is used to train the fault recognition and the state transition probability matrix, output probability matrix and initial probability distribution of each model are obtained. Finally, the fault classification model is completed. After that, the pre-processed verification data is used as the observation sequence in order to input classification. The probability of the fault diagnosis model generating a specific observation sequence is calculated by using the "Forward algorithm". The fault state of the fault classification with the maximum probability is the fault state of the track circuit.

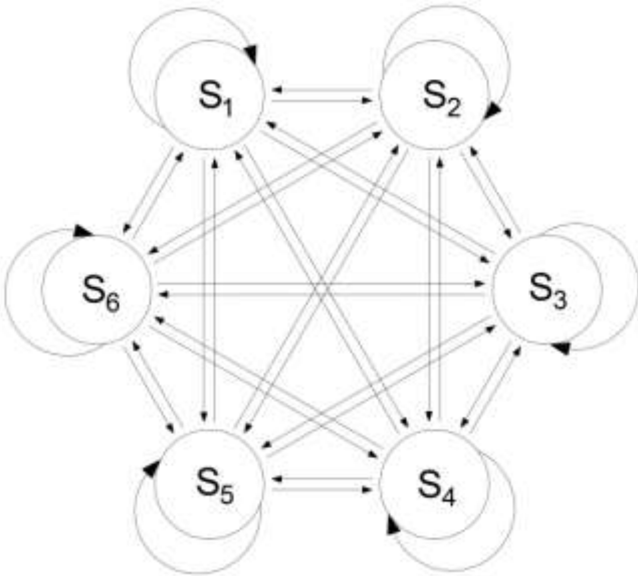

Figure 3 The Markov chain with six hidden states

The results and analysis of examples

There are 240 sets of data and six fault types in this paper. Because of its same implementation and application, only take the outdoor short circuit fault (short-circuit point before the test point) as an example of a detailed demonstration.

Get data: The collected data samples are pre-processed in 3.1 and divided into 30 groups of training samples and 10 groups of test samples.

Train HMM fault diagnosis model: The 30 sets of training data are input into HMM model as observation sequences, which constitute the outdoor short circuit detection classification (short-circuit point before the test point). Set the maximum iteration step to 30 steps and convergence error to. From the following diagram of HMM model training curve we can see that the observed values of HMM model gradually converge after training with the increase of the number of iterations. When the number of iterations reaches 14, the model achieves the convergence requirement. In the actual training, the six models satisfy the convergence condition in the 20th iteration, and it can also be seen that the HMM model has the advantage of rapid training.

Figure 4 The HMM training curve of outdoor short circuit

The implicit state transition probability matrix of outdoor short circuit (short-circuit point before the test point) is

Thus, the fault classification of outdoor short circuit (short-circuit point before the test point) is completed.

Test fault classification: The 10 sets of test data of outdoor short circuit (short-circuit point before the test point) are input into six fault classification respectively in order to test the effect of the fault classifier. The figure below shows the output probability. It is clear that when verify the data into their own fault classification (outdoor short circuit, short-circuit point before the test point), the maximum output probability is 50%, the minimum output probability is 12.5%. However, when verify these ten data into other five fault classifications; the output probability is close to 0%. The results of the other five faults are basically the same as those of the outdoor short circuit (short-circuit point at the test point).. The statistical results are shown in the figure below.

Figure 5 The output probability of the fault classification

Table 2 Results of fault state classification based on HMM

Types of fault	Indoor open circuit	Indoor short circuit	Outdoor short circuit (before)	Outdoor short circuit (after)	Outdoor open circuit (before)	Outdoor open circuit (after)	recogniti on rates
Indoor open circuit	10						100%
Indoor short circuit		10					100%
Outdoor short circuit (before)			10				100%
Outdoor short circuit (after)				10			100%
Outdoor open circuit (before)					10		100%
Outdoor open circuit (after)						10	100%

Thus, methods of track circuit fault diagnosis based on HMM are completed.

Model comparison and expansion

First, compare HMM fault diagnosis model with BP neural network fault diagnosis model. When 120 sets of sample data are brought into the BP neural network, it can be seen that although the successful recognition rate is consistent with the HMM model, the BP model repeats 3 iterations (360 calculations) to meet the convergence conditions, far more than 20 calculation of HMM model. As a result, there are obvious advantages for the model of track circuit fault diagnosis based on HMM in computing speed.

Second, it is observed that all fault recognition rates are 100% in the matter of practical application in hump section. The reason for this result may be due to the quite different voltage and other related data. So there is no cross-overlapping area between fault data. Then, adjust the sample to a section of ZPW-2000A non-insulated track circuit to the actual data. The faults are divided into the main track fault, small track fault, common transmission channel fault, indoor fault and attenuation box fault. The input voltage of the main rail, the input voltage of the small rail, the rail voltage, the measured voltage of the attenuation box and the voltage of the simulation disk are used as fault characterization data, and then normalize these data and bring them into the HMM fault diagnosis system. Take small track fault as an example and the result is shown below. It is obvious that HMM fault detection classification output still has a clear degree of recognition of output fault probability.

Figure 6 Output fault probability of small track fault classification

However, when the sample data is brought into the BP neural network model for diagnosis, the obvious diagnostic results are appeared. First, bring 110 sample data into the model. It can be seen that the model repeats 4 iterations to meet the convergence conditions, which is, a total of 440 calculations. Nevertheless, HMM model's iterations still kept within 20 times. It is obvious that HMM model has distinct advantages in terms of computing speed. What's more, there are some problems of the fault diagnosis by BP neural network. Some of the errors are shown in the following table.

Table 3 Verification sample classification T/F of BP neural network

Verification sample number	The verification sample classification result of BP neural network					Verification sample classification results	Verification sample Source	Classification T/F
	Main track fault	Small track fault	Common transmission channel fault	Indoor fault	Attenuation box fault			
1	0.86843	0.44578	0.76396	0.87501	0.51145	F1	F1	√
2	0.91152	0.46935	0.7845	0.86147	0.52032	F1	F1	√
3	0.62587	0.86775	0.70534	0.84636	0.53875	F2	F2	√
4	0.68947	0.82456	0.67742	0.87803	0.5977	F3	F2	×
5	0.86726	0.88378	0.78853	0.78732	0.58523	F3	F3	√
6	0.86575	0.88524	0.79249	0.78651	0.58479	F3	F3	√
7	0.69322	0.46722	0.63455	0.84035	0.53244	F3	F4	×
8	0.57778	0.41799	0.64325	0.72455	0.69454	F4	F4	√
9	0.59462	0.41234	0.1349	0.84532	0.52378	F5	F5	√
10	0.59342	0.40154	0.2589	0.8923	0.58923	F5	F5	√

Compare the result of HMM fault diagnosis method with the result of BP fault diagnosis. And the result is shown in the table below.

Table 4 The correct rate comparison of two fault diagnosis methods

Method	Main track fault	Small track fault	Common transmission channel fault	indoor fault	Attenuation box fault
BP	95%	80%	90%	85%	80%
HMM	100%	100%	100%	100%	100%

In summary, high accuracy and faster computing speed can be provided by methods of track circuit fault diagnosis based on HMM. It's a good choice to introduce HMM algorithm and HMM optimization algorithm into track circuit fault diagnosis field. And it's clear that this fault diagnosis will become a new direction for the development of track circuit fault diagnosis method.

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