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DIAGNOSIS METHOD FOR THE SAFETY CONDITION OF TRAIN BRAKE PIPE BASED ON HMM

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Abstract. *Considering the non-stationary nature of the high-speed train brake pipe pressure data under working conditions, and analyzing the characteristics of the Hidden Markov Model (HMM), a diagnosis method for the safety condition of train brake pipe based on HMM has been proposed. The safety condition diagnosis of train brake pipe was carried out by using a way, which is statistical analysis of fault characteristics based on HMM, including the extraction and preprocessing of observed data, the training of normal condition and fault condition. So the proposed diagnosis method is effective in safety condition diagnosis for train brake pipe, and it will give a theoretical support to the train fault diagnosis.*
Keywords: Train brake pipe, Hidden Markov Model (HMM), Fault diagnosis

1. **Introduction.** High-speed trains have undergone rapid development these years, but what comes along are the great challenges of these trains' safety. Currently, one of the most important directions of research is how to ensure the safe operation of trains. The air braking method is a basic braking method, and also the basic control method to ensure the safe operation of high-speed trains. The air braking system consists of brake pipe, compressor and some other components, and these components in the process of long-term use would inevitably damage, age and lose. Therefore, railway traffic accidents would easily be incurred without on-time maintenance of these components. To deal with this problem, some institutions such as railway administration, and vehicle manufacturers have proposed and respectively carried out a number of maintenance measures [1]; however, the majority of the current maintenance are still limited in periodical repair, inspection and fault repair. Though the first two measures can serve as precaution, they still lack timeliness and adjustment to changes, and fault repair is a rescue measure adopted after a breakdown; these measures significantly affect and even threaten the safety of trains. All these measures are not always helpful for predicting a sudden breakdown, and undertake the risk of damage at the same time.

Based on Condition Based Maintenance (CBM), the principle of which is to adjust, and maintain the maintenance object when there is a potential breakdown, thus avoiding a breakdown [2], the writers make a diagnosis of the condition of brake pipe in high-speed trains through HMM. HMM is a statistical model used to describe the hidden parameters. It can train several HMMs to find out the most familiar model to the hidden state. At present, HMM is used in various areas; for example, Lin et al. apply it in abnormal interaction recognition [3]; Yu et al. put forward the research of HMM's diagnosis of electronic machines' breakdown [4]; Smyth succeeded in monitoring the state of network data through HMM [5]; Atlas et al. realized the wear condition monitoring through HMM [6]; and Ocak and Loparo use it in the fault diagnosis of rolling bearing [7]. The utilization of HMM is also applied in many researches regarding railway sector; for instance, Cao et al. applied it in the monitoring of the state of safety computer in railway signal system [8]; Wang et al. utilized it in the automatic algorithm of train track occupancy recognition [9]. This paper realizes the diagnosis for the safety condition of train brake pipe based on HMM through a diagnosis method, thus providing the safe operation of trains with technical support. This diagnosis method provides a new idea of fault diagnosis, and this method can provide decision support for anomaly detection, fault analysis and fault diagnosis of high-speed trains; furthermore, this method is capable of supporting the maintenance and repair work of high-speed trains; moreover, it is compared with conventional methods, and this method can improve the detection efficiency and reduce labor costs.

2. **HMM (Hidden Markov Model).**

HMM originates in Markov Model, a result of modeling the Markov Process. Markov Process is used to describe a system or process that follows the statistic principles. If we assume that the state of system or process at the time of t_0 is a known condition, the state of system or process at the time of $t > t_0$ is only related to the state at the time of t_0 and not to the state before t_0. Moreover, system or process can only have one state at each moment, and each state has only one corresponding observation. Markov Process is represented by conditional probability, Markov property is expressed by the distribution function as shown in Formula (1):

$$\begin{aligned} &P\left\{X(t_n) \leq x_n \left| X(t_1) = x_1, X(t_2) = x_2, \ldots, X(t_{n-1}) = x_{n-1}\right.\right\} \\ &= P\left\{X(t_n) \leq x_n \left| X(t_{n-1}) = x_{n-1}\right.\right\}, \quad x_n \in R \end{aligned} \tag{1}$$

Formula (1) means that on condition of $X(t_i) = x_i$, $x_i \in I$, $i = 1, 2, \ldots, n-1$, $X(t_n)$ is equal to the conditional distribution function of $X(t_n)$ in the condition $X(t_{n-1}) = x_{n-1}$.

HMM is a double-embedded stochastic process, which consists of two random processes, one is the state sequence of the Markov Chain in finite state, and the other is the observation value sequence determined by system state sequence. HMM's state transition is a random process, and each observation value corresponding to the system state is also a random process. Observation value sequence can be observed directly, whereas the state transition sequence can only be inferred from the observation value sequence [1]. Through probability distribution the state value and the observation value of a system are correlated, which is called the Observation Probability Matrix. HMM is a quintuple, represented by λ, $\lambda = (\Omega_s, \Omega_o, \pi, A, B)$ or shortly $\lambda = (\pi, A, B)$. Ω_s represents system model state sets, and Ω_o represents the probable observation value sets of system state, and π represents the probability distribution of initial system state, and A represents the probability matrix of model state transition, and B represents the probability distribution of the observation value under a given condition [8].

3. **Principe and Procedure of the Safety Condition Diagnosis of Train Brake Pipe.**

3.1. **The working principle of train brake pipe.**

Primarily, high-speed train braking is to realize the control of the train wheels through compressing air and using brake mechanical action. When the brake pipe's pressure abates, the air distribution valve makes the compressed air into the cylinder, moving the piston, making brake shoe press the wheel tread block, thus impeding the wheel rotation. When the brake pipe is inflated, pressure rises, then the air distribution valve blocks the vice brake pipe, thus discharging the compressed air inside the cylinder atmosphere, then the restoring spring makes the piston within the cylinder return to the normal position, and brake shoe leaves wheels, so as to release.

3.2. **Safety condition diagnosis steps.** There is a problem that the system model is unknown or inaccurate when diagnosing the safety condition of high-speed train brake pipe; in this case, two problems may incur concerning how to obtain or adjust model parameter through the observation state sequence and how to do state diagnosis through the obtained sequence (the data to be measured) after finishing training the model. And the solutions to the two problems are as follows [10].

(1) HMM model training, in other words, for the initial model and the known observation state sequence, is how to adjust the parameters of the equation λ, so as to make the λ the closest to the observed data. The author achieves this through the EM algorithm.

(2) Likelihood probability calculation, $P(O|\lambda)$ is calculated under the condition of given the model parameters $\lambda = (\pi, A, B)$ and the observation sequence O, that is, to give the degree of accuracy regarding the observation sequence O of the model parameters λ. The authors make this by using the forward-backward algorithm to apply traversal to HMM.

There are three steps to diagnose the safety condition of high-speed train brake pipe, as shown in Figure 1 [10].

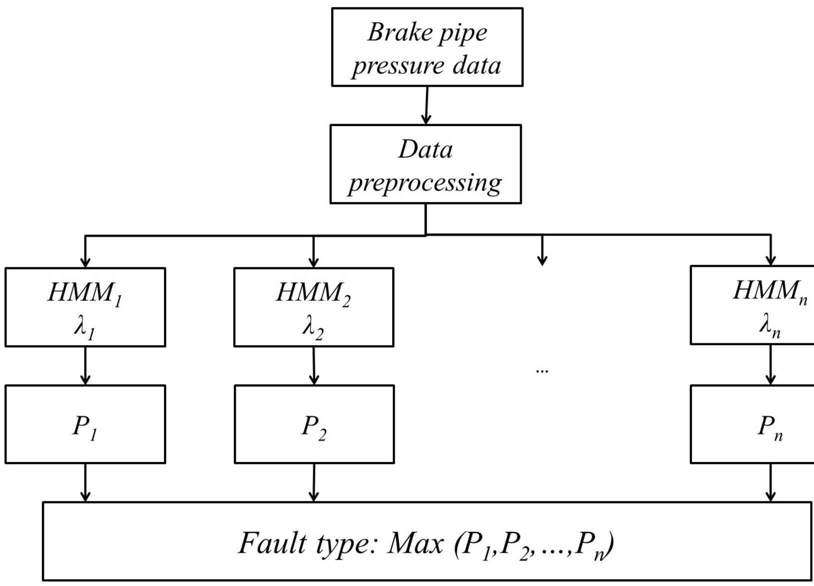

Figure 1. The steps to diagnose the safety condition of high-speed train brake pipe through HMM

Step 1: The original data preprocessing. Actually, the safety condition of high-speed train brake pipe is hidden, so there is no direct data that can reflect if the high-speed train brake pipe is safe, and what can be monitored in general is the high-speed train air pressure data, which are corresponding to the different conditions that the high-speed train brake pipe is in. However, practically, the air pressure data will probably be featured by high redundancy, the lack of some data and so on. Therefore, it is necessary to preprocess the air pressure data.

Step 2: HMM model training in normal condition and fault condition. Through the recombination of several observed data and the fixation of observation times, the author formed some observation sequence sets. Then the author randomly selected several sets out of four kinds of sets to do HMM model training. Each set corresponded to one HMM model.

Step 3: Condition diagnosis. The observation data were put into four different HMM models, and then the four likelihood probabilities were calculated through the forward-backward algorithm. By comparing different likelihood probabilities, it can be more intuitional to see how accurate the observation sequence fits the HMM model; the greater the likelihood probability is, the higher the degree of fitting is, so one can identify the current condition of the system.

4. Implementing Safety Condition Diagnosis for High-Speed Train Brake Pipe.

4.1. HMM modeling. In this paper, the safety condition of high-speed train brake pipe is divided into four types: normal condition (S_0), brake pipe leakage fault (S_1), blocking fault of brake pipe (S_2), compressor fault (S_3); these are HMM models' sets of states; O_0, O_1, O_2, O_3 respectively represent the observation sequence corresponding to each of four safety conditions. The sets of states correspond to the observation sequence; a_{ij} $(i, j = 0, 1, 2)$ is the element in the state transition probability matrix. This model can reflect the transition between the safety state of the brake pipe of the high-speed train. The HMM model is shown in Figure 2.

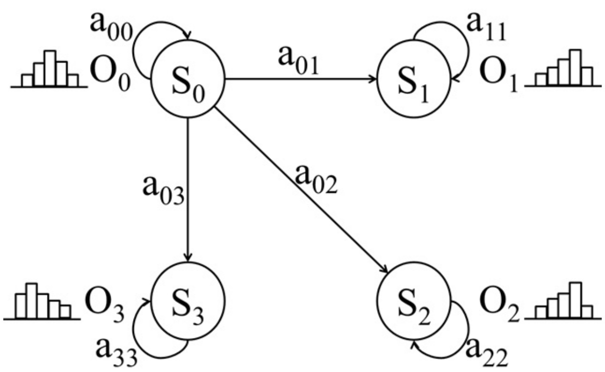

Figure 2. HMM model

When modeling, four types of hidden states were used to represent the four safety conditions of the high-speed train brake pipe; the observation sequence of the HMM model was the pressure data of the high-speed train brake pipe; the initial state probability distribution, the state transition probability matrix of initial model, and the probability distribution of the initial observations were acquired by using the rand function in MATLAB, and through normalization.

After selecting 800 high-speed train air pressure data as the training samples, the EM algorithm was used to train the initial HMM model. After the completion of the initial training of HMM, four different HMM diagnosis models were obtained: normal HMM model, brake pipe leakage fault model, blocking fault brake pipe model, and compressor fault HMM model. The training curve of HMM model is shown in Figure 3. In the process of training the HMM model, the logarithm value of the maximum likelihood probability $\ln P(O|\lambda)$ did not stop increasing with the growth of the iterations until the range of error reached the requirement of a convergence.

Figure 3 shows the HMM training curves in normal condition, brake pipe leakage fault condition, brake pipe blocking fault condition, the compressor fault condition, and all conditions reach convergence in 16 times iteration, also with fast speed.

4.2. Brake pipe safety condition diagnosis. Through the last step the training of HMM model was completed, and four different HMM diagnosis models were obtained, and then the pre-treated test samples were taken into different HMM diagnosis models to gain the logarithm of the maximum likelihood probability, which can show the fitting degree between the test sample and four kinds of HMM diagnosis models. The larger the $\ln P(O|\lambda)$ shows, the higher the degree is, which means the test sample belongs to the recessive condition (fault type) corresponding to the HMM diagnosis model.

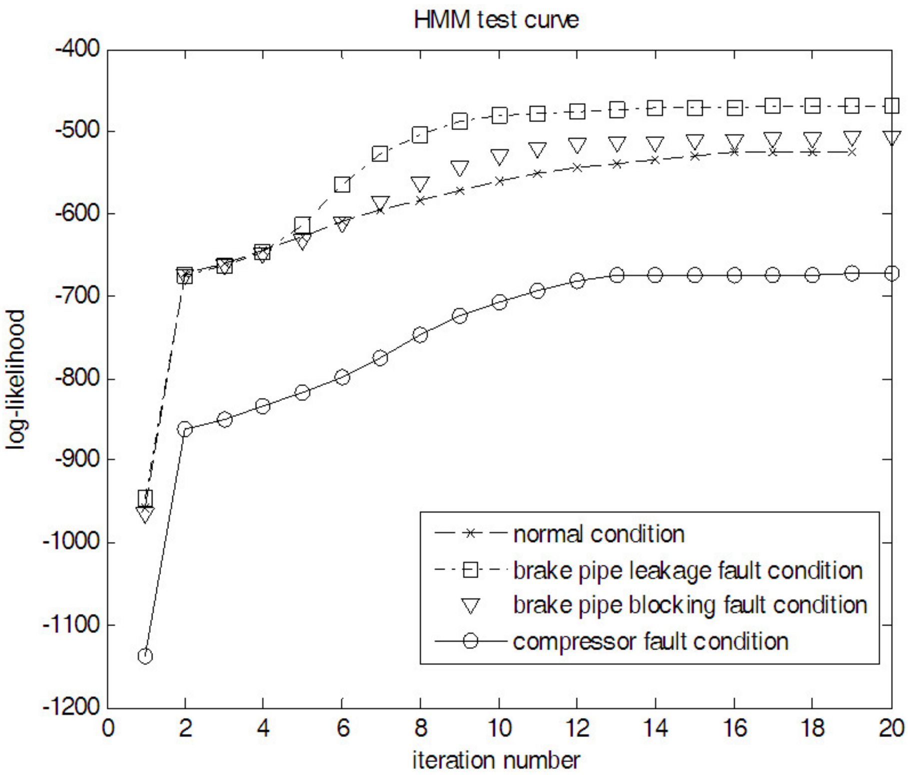

Figure 3. HMM model training curve

Table 1. Diagnosis results

Fault type	*HMM1* (λ_1)	*HMM2* (λ_2)	*HMM3* (λ_3)	*HMM4* (λ_4)	*Recognition result*
Normal condition	-23.4948	$-\infty$	-611.9262	-216.7603	λ_1
Brake pipe leakage fault condition	$-\infty$	-21.3004	$-\infty$	-212.7994	λ_2
Brake pipe blocking fault condition	-239.1502	$-\infty$	-25.0400	$-\infty$	λ_3
Compressor fault condition	$-\infty$	-878.3588	$-\infty$	-28.7002	λ_4

High-speed train brake pipe diagnosis results are shown in Table 1; through maximum likelihood probability, it can accurately diagnose if the high-speed train brake pipe is in normal or fault condition. In case of fault condition, the fault type can also be distinguished, and also the degree of the fault and the logarithm value of maximum likelihood probability are positively correlated. Taking the brake pipe leakage fault condition as an example, the observation sequence was brought into HMM1 (normal condition model), HMM2 (brake pipe leakage fault model), HMM3 (brake pipe blocking fault model), HMM4 (compressor fault model) respectively, and the likelihood probability are $-\infty$, -21.3004, $-\infty$, -212.7994. The likelihood probability that was put into HMM2 is of the largest number, which suggests that the condition that system was in is brake pipe leakage fault condition.

In order to test the accuracy of the high-speed train brake pipe safety condition diagnosis method, 200 were randomly selected from the observation data, and tested. The results of the experiment are shown in Table 2. In the table you can see that HMM1 has a higher recognition rate of 100%; HMM4 has a lower recognition rate of 86%, but

TABLE 2. Statistical diagnosis of different failure modes

Type	*HMM1*	*HMM2*	*HMM3*	*HMM4*	*Recognition rate*
Normal condition	*50*	*0*	*0*	*0*	*100%*
Brake pipe leakage fault condition	*0*	*44*	*0*	*6*	*88%*
Brake pipe blocking fault condition	*1*	*0*	*49*	*0*	*98%*
Compressor fault condition	*0*	*7*	*0*	*43*	*86%*
The average recognition rate					*93%*

the average recognition rate is 93%. All these statistics indicate that it works well in the diagnosis of the high-speed train safety condition.

5. **Conclusions.** At present, although HMM has been widely applied in many fields and has developed well in such fields as speech recognition, biological medicine, and signal processing, it has seldom been applied in high-speed train. In this paper, facing the problem of the high-speed train brake pipe safety condition, the authors use the dynamic time-series model HMM, and give the specific procedures in practice, also with a good result. The results show that the HMM model can be applied to high-speed train, and the method can diagnose the safety condition of the brake pipe of the high-speed train. Because the method mentioned in this paper uses the dynamic time-series model HMM, it is very suitable for diagnosing a large number of data and non-stationary data. The method has a good prospect in the application of high-speed train.

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