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State Recognition Based on Hidden Markov Model

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Abstract

This paper puts towards the improvement of the HMM algorithm, then proposed the HMM state identification model of the electronic equipment. It is verified by examples of the experiment, which results show that the HMM state recognition effect is better, recognition rate can reach 94%.Finally, and the experimental results were analyzed, and found the number of hidden states and have bigger influence on the model of training samples.

***Keywords**: Hidden Markov Model, State Recognition, Random process*

1. Introduction

Fault prediction is an important part of the CBM, so fault prediction related technology research and development for the state maintenance and other advanced maintenance concept according to provide effective theory, can do advance warning before failure, effectively avoid some catastrophic failures. And it can reduce the complicated system or equipment maintenance support cost, so the relevant technology of the fault prediction research received extensive attention of the industry.

Fault prediction technology compared with the fault diagnosis technology is a new research field, as the key technology of status maintenance, fault prediction is put forward in 1927 by their tits and Yule, and for failure prediction of the related technology research laid a good foundation. For the fault prediction of electronic equipment related technology research is gradually attaches great importance to by the countries, the U.S. army in helicopter applied health and use of monitoring systems (HUMS) technology, space application on the plane condition monitoring system (the ACMS), the navy in the continuously explore comprehensive state evaluation system was put forward. The PHM technology has been studying at university of Maryland and other research institutions. Cai Jinyan and others are reliability model is established according to the state of degradation of the electronic equipment, also by accelerated test of electronic equipment fault prediction. Qiu Jing in national university of defense technology in recent years, mainly study the fault prediction of mechanical equipment of, through carries on the analysis of the fault mechanism and fault evolution experiments to achieve.

2. Theory of Based on HMM

HMM is a kind of probability model, which is to use the parameter to represent the random process, using hidden Markov chain. A Markov chain consists of a random process, used to describe the relationship between different states, usually state transition probability matrix is used to establish a connection. For the mutual transformation between states is done by the corresponding state transition probability matrix. And the state transition probability depends only on the current state of being, and other times it doesn't matter. A condition in which the system can only exist in different time and each

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state has a corresponding with the observed values. HMM between the different states of a random process description of random process, the condition number is limited. Another stochastic process is used to describe the relationship between the probability of each state and the corresponding observations. In the whole process, transfer between state and observation values are random, only through observations and observer to judge the system may state at this time, because the state of the system is hidden. Basic principle of HMM is shown in Figure 1.

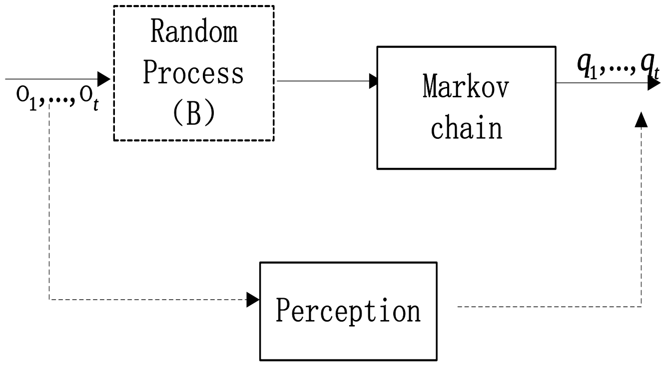

Figure 1. The Basic Principles of HMM

Estimate, decoding and HMM is mainly to solve three basic questions. For every problem the HMM will give an algorithm to solve, improved algorithm detailed below.

3. Improvement of HMM Algorithm

Not the improved HMM algorithm when the model training, can only enter an observation sequence. But in practice, usually more observation sequence problems, therefore to standard the HMM algorithm improvement are put forward.

Hypothesis is a collection L of observation sequence $O = \left\{ O^{(1)}, \ldots, O^{(L)} \right\}$ .Each observation sequence is $O^{(l)} = \left\{ o_1^{(l)}, \ldots, o_T^{(l)} \right\}$. With other observation sequence are independent of each other, then you can get more observation sequence $P\left(O \middle| \lambda\right)$.

$$P\left(O \middle| \lambda\right) = \sum_{l=1}^{L} \omega_l P\left(O^{(l)} \middle| \lambda\right) \tag{1}$$

$$\begin{cases} \omega_1 = \dfrac{1}{L} P\left(O^{(2)} \middle| O^{(1)}, \lambda\right) \cdots P\left(O^{(L)} \middle| O^{(L-1)} \cdots O^{(1)}, \lambda\right) \\ \omega_L = \dfrac{1}{L} P\left(O^{(1)} \middle| O^{(L)}, \lambda\right) \cdots P\left(O^{(L-1)} \middle| O^{(L)} O^{(L-2)} \cdots O^{(1)}, \lambda\right) \end{cases} \tag{2}$$

Then the revaluation of the HMM formula was revised.

$$\overline{\pi} = \sum_{l=1}^{L} \frac{\alpha_1^{(l)}(i) \beta_1^{l}}{P\left(O^{(l)} \middle| \lambda\right)} \tag{3}$$

$$\overline{a}_{ij} = \frac{\sum_{l=1}^{L}\left[\frac{1}{P_l}\sum_{t=1}^{T_l-1}\alpha_t^{(l)}(i)a_{ij}b_j(o_{t+1}^{l})\beta_{t=1}^{(l)}(i)\right]}{\sum_{l=1}^{L}\left[\frac{1}{P_l}\sum_{t=1}^{T_l-1}\alpha_t^{(l)}(i)\beta_t^{(l)}(i)\right]} \tag{4}$$

$$\overline{b}_{jk} == \frac{\sum_{l=1}^{L}\left[\frac{1}{P_l}\sum_{t=1,o_t=v_k}^{T_l}\alpha_t^{(l)}(j)\beta_t^{(l)}(j)\right]}{\sum_{l=1}^{L}\left[\frac{1}{P_l}\sum_{t=1}^{T_l}\alpha_t^{(l)}(j)\beta_t^{(l)}(j)\right]} \tag{5}$$

The improved HMM algorithm steps is that.

(1)It is known that the model parameters $\lambda_0 = (A_0, B_0, \pi)$ and more observation sequence $O = \{O^{(1)}, \ldots, O^{(L)}\}$. The input these into model to get the model parameters π 、a_{ij} and b_{jk}. Again according to the forward and backward algorithm to calculate all the $\alpha_t^{(l)}(i)$ 、 $\beta_t^{(l)}(i)$.

(2)Using the revised revaluation formula(1)、(2)和(3),Restart the HMM new calculation model parameters $\overline{\pi}$ 、 $\overline{a}_{ij}$ 和 $\overline{b}_{jk}$. And the initial model parameters are replacing these.

(3)Repeat steps (1)、(2),Until $P(O|\lambda) = \prod_{l=1}^{L} P(O^{(l)}|\lambda)$ is to max. At the same time $\overline{\pi}$ 、$\overline{a}_{ij}$ 和 $\overline{b}_{jk}$ End of convergence is calculated. Get the final model parameters $\overline{\lambda}$.

It can prove that in the following. (1) revised model parameters to get a better explanation for more observation sequence; (2) in order to overcome the local minima problem, first of all need to design the reasonable structure of the model, the model structure and to solve the problem of the reality of the match, followed by a given model of different initial parameters, constantly training, when multiple training at the same time to achieve the same extreme value, can use it as a global optimal solution.

4. Model for State Recognition Based on Hidden Markov Model

4.1. Basic Structure of HMM

HMM can according to the probability that the signals to be observed method divided into continuous (CHMM) and a discrete (DHMM). For CHMM observations should be continuous, is generated by a Gaussian probability distribution function is assumed to simulate. But in the process of practical application, this assumption does not conform to the requirements. So it usually adapts to linear combination of multiple Gaussian probability distribution function, and applies it to the observation sequence simulation generated. DHMM observation probability matrix B is discrete. Its corresponding observation sequence is discrete. For electronic devices using sensors to collect the fault status signals are continuous. If the discretization to the collected signals, there will be some loss of useful signal, then the state recognition. So this article will use CHMM for electronic equipment fault state recognition.

HMM according to the different shapes of Markov chain to determine its structure, using matrix a description. Usually the HMM structure mainly can be divided into various state traversal and left and right two. Each state traversal type is A kind of state is likely to be transferred to any other state, reason of matrix A is not zero. Left and right type of the structure of the state in the HMM can only be moving from left to right, or keep the original state, need to comply with the constraint conditions $a_{ij} = 0,\ j < i$.

The initial probability should satisfy $\pi_i = \begin{cases} 1 & i = 1 \\ 0 & i > 1 \end{cases}$

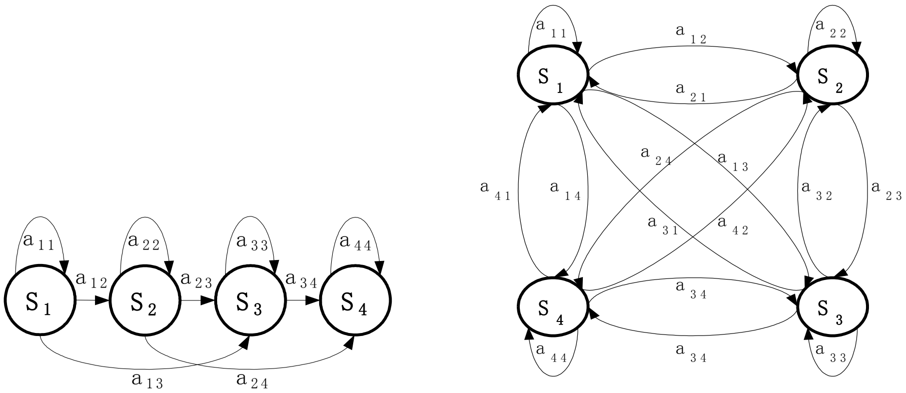

Figure 2. Left-Right Type and Ergodic Type of HMM

4.2. Build Model of HMM for Electronic Equipment

On electronic equipment cannot be directly observed equipment failure prediction of the state, because its status is hidden. It can only be acquired through signal characteristics to speculate that the equipment status and the signal feature is obtained with a state of the corresponding to each other. Therefore, the electronic equipment state HMM is used to describe is the most appropriate.

For electronic equipment, its working status from normal to complete failure is a process of gradual deterioration, not only use two kinds of normal and fault is described. The device function in the process of gradual deterioration will experience a variety of intermediate state; available degradation state 1, such as degradation state 2 is described. But the state of degradation and cannot be observed directly, through the fault signal characteristics to judge. With the accumulation of time, the function of the electronic equipment degradation degree increases gradually, and from the normal to the fault of the irreversible transformation, so the state transition of the electronic equipment in left - right, as shown in Figure 3. .Where $a_{ij}\left(i,\ j = 0,1,2,3\right)$ is for different state transition probability values, $O_k\left(k = 0,1,2,3\right)$ is for different states of observation sequence.

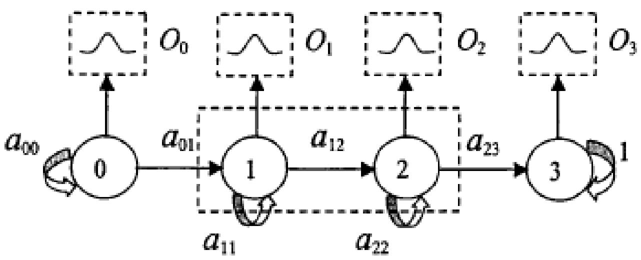

Figure 3. The HMM Basic Block Diagram of the Electronic Device

4.3. Model for State Recognition

State identification model of the electronic equipment can be divided into the following four steps.

(1)Data collection. It is through the sensor signal for electronic equipment.

(2)Data processing. First of all to obtain the status of the signal preprocessing, reserve the useful information signal. Feature extraction by LDA. The sample data is divided into training and testing samples, and the observation sequence of the HMM model.

(3)Model training. First set the initial model parameters, the training sequences in the input model, the state again through continuous training model and the model parameters. Finally the state model is HMM1, HMM2·HMMn.

(4)State recognition. It is used to identify the status of data of observation sequence. Input to the trained each state model, each model calculate the probability of the observation sequence. According to the maximum likelihood probability value to judge the current observation sequence represents the state of equipment.

4.4. State Recognition Based on HMM

(1)The data collection

It uses a band-pass filter, through the state set and simulation analysis, which received 10 kinds of state of the 10 d voltage characteristic vector 50 each group.

(2)The data processing

Through the simulation analysis of the collected data cannot all showed the characteristics of the circuit is in state, so if the collected information directly in the input model for training can make relatively slow training speed, and increases the complexity of the model. So LDA was carried out on the collected data dimension reduction, the results are shown in Figure 4.

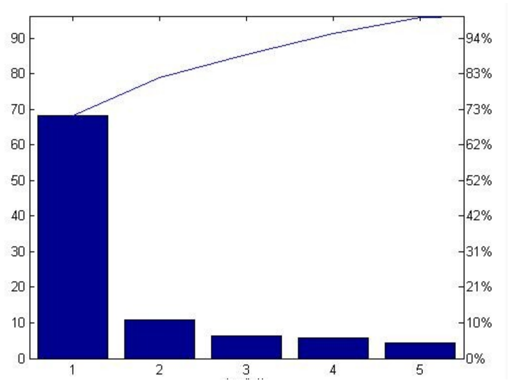

Figure 4. The Contribution Rate of LDA Dimensionality Reduction for Each Property

It can be seen from the Figure 4 by LDA to deal with the first five attributes the cumulative contribution rate can reach 95%, so the 10 d voltage characteristic vector can be reduced to 5 d input sample data as a model. The data grouping is as follows.

- There are ten kinds of state, each state 50 sets of data, each group of data through the LDA processing characteristics of voltage vector for 5 d.
- 30 group as the training sample, 20 groups of test samples.
- From 30 samples randomly from 5 groups constitute a HMM model of the observation sequence, can obtain 30 groups of observation sequence. The same set of test samples from 20 groups of observation sequence can be obtained.

(3)Model Training

Then each state observation sequence input for training model, training iteration Figure to state is obtained. Ordinate for logarithmic likelihood probability value is as shown in Figure 5 and Figure 6.

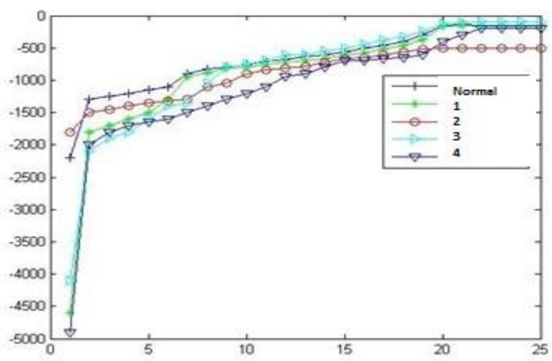

Figure 5. HMM Iterative Process of Training in the First Five States

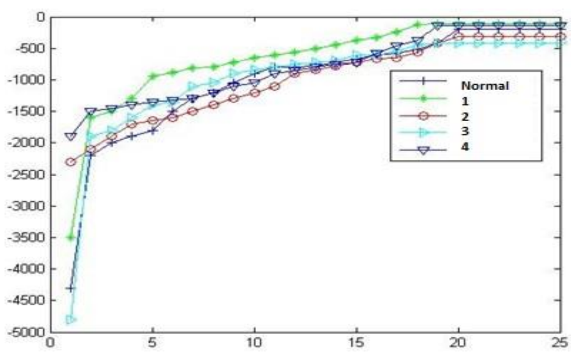

Figure 6. HMM Iterative Process of Training in the Last Five States

Figure 5 and Figure 6 for the HMM model in the simulation results in the process of training. In the process of training with the increase of iteration steps, the logarithmic likelihood probability of each state values are set at the iteration steps before reached the convergence, and converges faster. This proves that the HMM learning ability is very strong.

(4)State Recognition

Through the study of the training of the training sample gotten kinds of state of the HMM model, received 10 HMM model. Will be 20 groups of test is used to identify the status of the input observation sequence in the HMM model. Application can be seen that the HMM state recognition effect is good, even if some state recognition errors in judgment, but are the current should state judgment for the next one or two degradation under state. Think in terms of maintenance, this judgment is the result of the repairs to the system in advance, can also reduce the maintenance cost, and ensure the safe operation of the system.

Ten kinds of state recognition rate are in the following table.

Table 1. Recognition Rate of 10 Kinds of State

Normal	Degradation state 1	Degradation state 2	Degradation state 3	Degradation state 4
100%	95%	90%	95%	100%
Degradation state 5	Degradation state 6	Degradation state 7	Degradation state 8	Failure
85%	95%	90%	90%	100%

Through the Table 1 can see clearly the 10 kinds of state recognition rate, the average recognition rate reached 94%, the effect is better.

(5)Results analysis

1. The number of state in a Markov chain is a very important in the HMM model parameters, is used to describe the transfer between different states, so its value has a great influence on the performance of the model. In this paper, in order to study the effect of a few values are different on the model, set up 2 ~ 10 different state values, for each state numerical tested 10 times respectively, on average, the final result of the results are as follows.

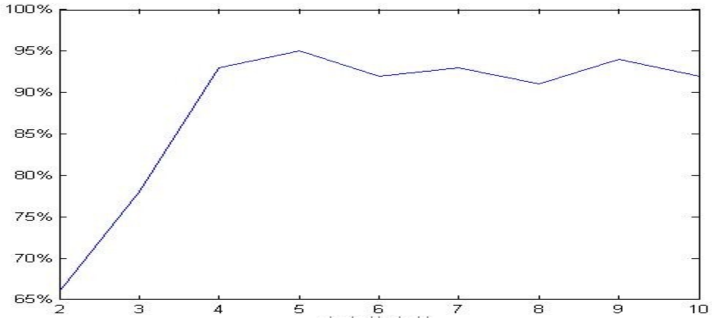

Figure 7. The Recognition Rate of the Different Number of States

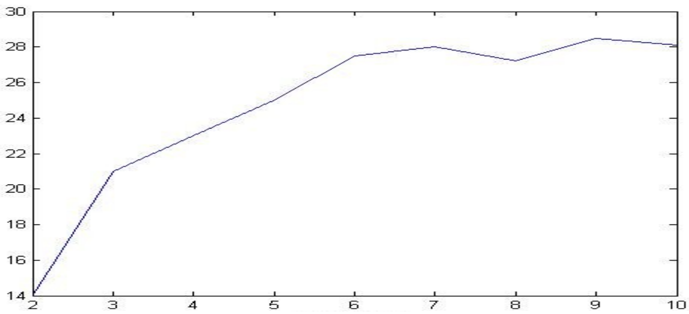

Figure 8. The Time-Consuming Training of Different Number of States

(1) From Figure 7 and Figure 8 you can see that the number of hidden states, the more the greater the recognition rate and the training time consuming. But when the number of hidden states increased to a certain number, the recognition rate and the training time consuming fluctuation is not big, so to determine the best number of hidden states is 5.

(2) The training sample size matters to the results of the model of training, also directly affect the result of the state recognition. By changing the proportion of the training sample for state recognition, the same for each state 10 times test average. The result is shown in Figure 9 and Figure 10.

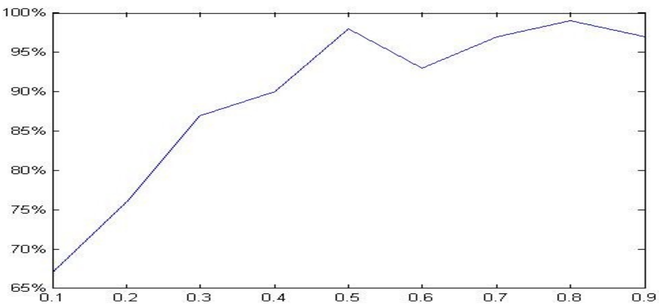

Figure 9. The Recognition Rate of Training Samples in Different Ratio

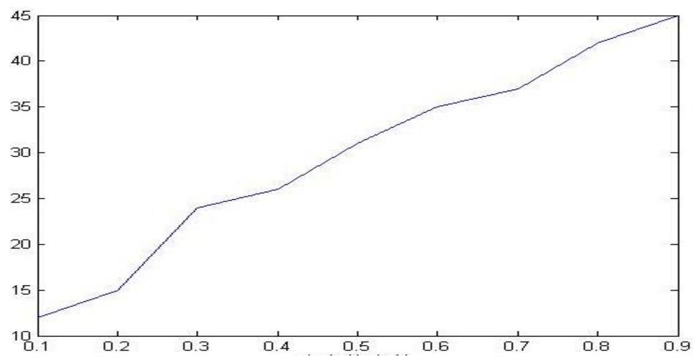

Figure 10. The Time-Consuming Training of Training Samples in Different Ratio

It Can be seen from the Figure 9 when the training sample is seldom, model recognition effect is better also. When the training sample proportion gradually increases, the recognition rate increased significantly, and finally, no matter how much samples to increase recognition rate would also have minor changes from within a certain range.

Figure 10 shows that the training sample proportion increasing model when increasing the consumption of time, so as long as choosing the appropriate proportion of the training sample can achieve good training results.

5. Conclusion

This paper puts towards the improvement of the HMM algorithm, then proposed the HMM state identification model of the electronic equipment, and is verified by examples of experiment. The results show that the HMM state recognition effect is better, and recognition rate can reach 94%. Finally, the experimental results were analyzed, and found the number of hidden states and have bigger influence on the model of training samples. It is obtained through the simulation experiment of the optimal number of hidden states to 5, the effect of the training sample proportion accounted for 50%.

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