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Fault Prediction of Electronic Equipment Based on Combination Prediction Model

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Abstract

Fault prediction is the precondition of Condition Based Maintenance (CBM), accurate prediction for equipment can not only make warning before failure occurs, but also reduce the cost of maintenance of complicated equipment and system. Therefore, it is of profound importance to make research on fault prediction of electronic equipment. This paper analyses some typical fault prediction method of electronic equipment, and presented improvement measures for the practical problems, finally proposed a combination of fault prediction model, and it was applied to the electronic equipment with complex structure verification.

Keywords: *Condition Based Maintenance, electronic equipment, combination fault prediction model, LSSVM, HMM, state recognition*

1. Introduction

Condition Based Maintenance (CBM), can be called predictive maintenance, is that the sensor or inside the equipment which will be installed in the test equipment on the outside of the equipment, in order to obtain accurate system running status information of the current time, and then evaluate current running state of equipment. By the method of predicting can understand the development of equipment failure, and before it happen significant performance degradation to implement the effective maintenance activities.

With the development of status maintenance technology, we put forward to the CBM with open system structure which can be divided into seven modules as shown in Figure 1.

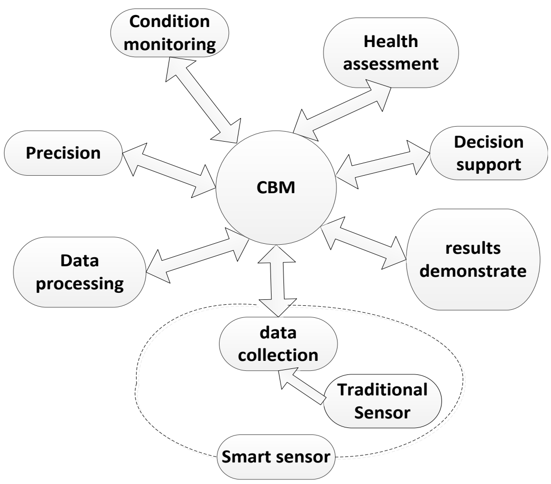

Figure 1. Composition of Non-destructive Testing Instrument

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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.

Due to the fault prediction technology is more and more attention, the prediction algorithm is also more and more, but how to according to actual condition to select the appropriate algorithm for fault prediction is the key problem, the appropriate algorithm can effectively improve the prediction precision. Failure prediction accuracy should be validated by real devices, but the actual equipment performance degradation and expectations are not necessarily the same, which makes the prediction results of verification cannot be achieved, in fault prediction research in the future how to verify the predicted results will become the difficulty of research.

According to the different principle, we always make to fault classification. For electronic equipment on the basis of fault occurrence, development process can be divided into sudden failure and progressive failure. Progressive failure is accumulated over time, electronic devices work in certain components or systems with the increase of working times finally exceed the limit of his scope of work and down. The progressive failure does not make the equipment component or system function complete loss, equipment can still work. In the electronic devices of this kind of failure occurrence proportion is stronger regularity.

2. Least Squares Support Vector Machine Fault Prediction Methods

Least Squares (LS) method is regarded as a fitting in the form of the mathematics. LS minimize the square sum of error determine the accord with the function of work with the data. Most is currently LS algorithm is used to implement the curve fitting and extrapolation, the algorithm is also applicable to solve the problem of linear and nonlinear mathematical model, so the LS method may be to realize fault prediction.

Support vector machine (SVM) classification problem is divided into for processing data of SVC (support vector classification), basic principle and used to solve the problem of predicting the SVR. SVR can better deal with high dimension and local minimum value, practical problems such as small sample. SVM in the face of a large amount of data is difficult to solve optimization problems. Therefore LSSVM was proposed to improve the shortcomings of the SVM, LSSVM turn the inequality constraint condition into the equation, the nonlinear regression problem is converted into linear regression problem, apply the error sum of squares to the objective function, then through the KKT (Karush-

Kuhn-Tucker) optimal conditions for the optimization problem of SVM into solving problem of linear equations, improves the training speed and convergence precision.

2.1. Least Squares Support Vector Machine Fault Prediction Model

LSSVM prediction model is established, the first turn on the training data input in the model, determined by corresponding relations between input and output of the phase space reconstruction, the prediction model was established, then input model to predict the test data, so as to realize the prediction of some point in the future, below is the LSSVM learning samples.

$$\begin{cases} X = \begin{bmatrix} x_1 & x_2 & \cdots & x_m \\ x_2 & x_3 & \cdots & x_{m+1} \\ \vdots & \vdots & \cdots & \vdots \\ x_{n-m} & x_{n-m+1} & \cdots & x_{n-1} \end{bmatrix} \\ Y = \begin{bmatrix} x_{m+1} \\ x_{m+2} \\ \vdots \\ x_n \end{bmatrix} \end{cases} \tag{1}$$

From the type (1) may find in the input and output is one-to-one mapping. Where, $f : R^m \to Rm$. The m is the embedding dimension, which determinate according to the Final Prediction Error (FPE) criteria is as follows.

$$FPE(k) = \frac{n+k}{n-k}\sigma_k^2 \tag{2}$$

Where, $\sigma_k^2 = \frac{1}{n-k}\sum_{j=k+1}^{n}\left[y_i - \left(\sum_{j=1}^{n-k}\left(\alpha_i - \alpha_i^*\right)k\left(x_j, x_i\right) + b\right)\right]^2$

It can be seen that $FPE(k)$ is changing with k. When $FPE(k)$ obtain the minimum value, the optimal solution m is the best embedding dimension $m = k_{opt}$.

Get trained LSSVM model, LSSVM regression function is as follow.

$$y_t = \sum_{i=1}^{n-m}\alpha_i K\left(x_i, x_t\right) + b \tag{3}$$

Step 1 prediction.

$$y_{n+1} = \sum_{i=1}^{n-m}\alpha_i K\left(x_i, x_{n-m+1}\right) + b \tag{4}$$

At the same time also can get $x_{n-m+2} = \left\{x_{n-m+2}, x_{n-m+3}, \cdots, x_n, \hat{x}_{n+1}\right\}$.

Step 2 prediction.

$$y_{n+2} = \sum_{i=1}^{n-m}\alpha_i K\left(x_i, x_{n-m+2}\right) + b \tag{5}$$

And so on, the k step of LSSVM prediction model is .

$$y_{n+k} = \sum_{i=1}^{n-m}\alpha_i K\left(x_i, x_{n-m+k}\right) + b \tag{6}$$

Where, $x_{n-m+k} = \left\{x_{n-m+k}, \cdots, \hat{x}_{n+1}, \cdots, \hat{x}_{n+k-1}\right\}$.

2.2. Least Squares Support Vector Machine Fault Prediction Process

LSSVM prediction process is shown in Figure 2.

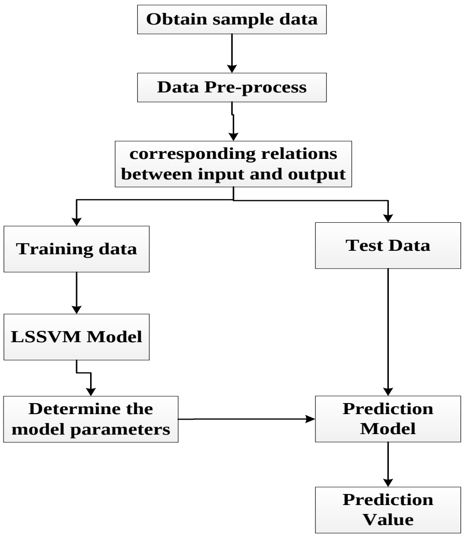

Figure 2. Fault Prediction Process based on LSSVM

Based on LSSVM failure prediction steps are as follows.

(1) Determine the characteristic parameters and data processing. For a given prediction system were analyzed, and find out reflect characteristic parameters of the system state changes to obtain sample data; On the sample data preprocessing, model training and test data needed for; In order to avoid the influence of the sample data of magnitude, can first of all sample data normalization processing.

(2) Determine the model parameters. First of all, according to the need to choose the appropriate LSSVM prediction model, and then enter the learning samples LSSVM, according to the formula of the embedding dimension, mapping relation model is obtained by studying input and output.

(3) Model training. The sample data is divided into training data and the test data, the training data input model for training.

(4) Predictions. The test sample input model to prediction, the output value is predicted.

(5) Evaluation prediction model. To evaluate results than those obtained by the analysis, if can't achieve the ideal prediction results, the training again, until they get the prediction results are satisfactory. In this paper, the evaluation index for the absolute error and relative error.

Absolute Error(AE):

$$AE = \left|\hat{x}_i - x_i\right|, i = 1,2,...n \tag{7}$$

Relative Error(RE):

$$RE = \frac{\hat{x}_i - x_i}{x_i}, i = 1,2,...,n \tag{8}$$

3. State Recognition based on Hidden Markov Model

3.1. Feature Extraction Based on LDA

Feature extraction is the key to the electronic equipment fault prediction technology. To choose the appropriate feature extraction method can improve the accuracy of the prediction to a great extent. Normally obtained from the sensor of the electronic equipment fault state data there are some information is not available, so make sure you try on the feature extraction, the raw data from the extracted information effectively, and to retain as much as possible failure analysis, failure prediction of fault characteristic information you need. In this paper, the feature extraction method is adopted by Linear Discriminant Analysis (LDA).

LDA is able to classify samples well a supervised learning method, is widely used in face recognition, and the technology is relatively mature, this method has been applied to the data analysis and pattern recognition, etc. LDA by Fisher criterion, by choosing a maximum vector, as the best projection direction, then the sample projection, such divergence within the minimum class divergence between maximum, thus makes the separation of different categories of samples as soon as possible after projection, preliminary classification effect. LDA as a broad feature extraction technology, not only the realization of effective dimensionality reduction, and at the same time also can get the best classification effect, the features of the used for state recognition more representative, in view of these advantages as a feature extraction method of this paper.

3.2. Theory Based on the of HMM

HMM is a kind of probability model, is to use the parameter to represent the stochastic process, developed by 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 state 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 the system can only exist in different time. And each 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. The improved HMM algorithm steps are as follows.

3.3 The Algorithm of Improved HMM

When the model training, not-improved HMM algorithm can only enter an observation sequence, but in practice, often will encounter more observation sequence problem, so the standard HMM algorithm improvement are put forward.

A collection of observation sequence is $O = \left\{ O^{(1)}, ..., O^{(L)} \right\}$. Each observation sequence with other observation sequence is independent of each other. It can get more observation sequence $P\left(O|\lambda\right)$.

$$P\left(O|\lambda\right) = \sum_{l=1}^{L} \omega_l P\left(O^{(l)}|\lambda\right) \tag{9}$$

$$\begin{cases} \omega_1 = \dfrac{1}{L} P\left(O^{(2)}\middle|O^{(1)},\lambda\right) \cdots P\left(O^{(L)}\middle|O^{(L-1)} \cdots O^{(1)},\lambda\right) \\ \omega_L = \dfrac{1}{L} P\left(O^{(1)}\middle|O^{(L)},\lambda\right) \cdots P\left(O^{(L-1)}\middle|O^{(L)}O^{(L-2)} \cdots O^{(1)},\lambda\right) \end{cases} \tag{10}$$

Then the revaluation of the HMM formula was revised.

$$\bar{\pi} = \sum_{l=1}^{L} \frac{\alpha_1^{(l)}(i)\beta_1^l}{P\left(O^{(l)}|\lambda\right)} \tag{11}$$

$$\bar{a}_{ij} = \frac{\sum_{l=1}^{L}\left[\frac{1}{P_l}\sum_{t=1}^{T_l-1}\alpha_t^{(l)}(i)a_{ij}b_j(o_{t+1}^l)\beta_{t=1}^{(l)}(i)\right]}{\sum_{l=1}^{L}\left[\frac{1}{P_l}\sum_{t=1}^{T_l-1}\alpha_t^{(l)}(i)\beta_t^{(l)}(i)\right]} \tag{12}$$

$$\bar{b}_{jk} == \frac{\sum_{l=1}^{L}\left[\frac{1}{P_l}\sum_{t=1,o_t=v_k}^{T_l}\alpha_t^{(l)}(j)\beta_t^{(l)}(j)\right]}{\sum_{l=1}^{L}\left[\frac{1}{P_l}\sum_{t=1}^{T_l}\alpha_t^{(l)}(j)\beta_t^{(l)}(j)\right]} \tag{13}$$

It can prove that:

(1)The 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. Combination Prediction Model in the Application of the Electronic Equipment

4.1 Electronic Equipment Structure

For an electronic device, its internal structure is very complex, often can be seen as an electronic equipment by a large number of modules with different functions according to certain structure, each module is composed of a large number of circuit according to certain structure, once the equipment failure, where it is difficult to find fault in a short time, can't timely troubleshooting, such damage to the electronic equipment is immeasurable. Fault prediction can solve this problem, through the different positioning of the sensor in the electronic equipment to monitor equipment operation signal, when the electronic equipment failure or performance degradation, the sensor will detect changes of signal, the fault prediction by monitoring the signal collected, before its complete failure or performance obvious degradation on the maintenance, reduce the loss. In which each module has the following characteristics: the module is the part of the electronic equipment, able to remove and replace from equipment. Each module should have specific function. Between modules are connected and used for signal monitoring interface.

4.2 Combination Prediction Model

At present for fault prediction research mainly focus on a single prediction methods, although you can get a certain degree of prediction results, but does not achieve ideal prediction effect, so a lot of experts and scholars began to combination prediction method is proposed. Based on the combination of different prediction algorithm to achieve future trend prediction of equipment or system, can not only make full use of the advantages of each algorithm, also can make up for the inadequacy of the algorithm, greatly reduce the computation complexity, improve the operation efficiency, and higher prediction precision. For small changes or slow change of equipment or system failure can present the ideal prediction results, facilitate the timely processing of maintenance support work, reduces the failure rate of equipment.

4.3 Established Combination Prediction Model

This paper puts forward the LSSVM based on CBM and HMM combination prediction method. Make full use of the LSSVM solve the small sample data, computing speed and good prediction effect, HMM data structure is rigorous, reliable performance, state the advantages of high accuracy, combining both realize fault state prediction. Fault prediction state of the electronic equipment using LSSVM, get the future state of the predicted value, for electronic equipment, it is not enough to get predictions future time, according to the predicted value is unable to accurately judge the equipment in fault condition or performance degradation state, because the state of the equipment is hidden, it can't carry on the reasonable repair, will miss the reasonable repair time may cause inevitable failure. So you need to use HMM can be solved by the decoding function of predicting the future state, the LSSVM predictive value input HMM can estimate the equipment in the state or condition of degradation path. It will be the future of the equipment status, can be more intuitive understanding of the equipment is going to experience the state of the, doing well the preparation work of maintenance activities. Through the combination of fault prediction method proposed in this paper can achieve the purpose of directly predict the state of electronic equipment.

Based on the LSSVM method with the combination of HMM, a combination prediction model is set up, implement fault state prediction of electronic equipment, mainly divided into three steps:

Step 1: data collection. Choose suitable monitoring signals, by setting the monitoring signal, sensor layout in the acquisition of equipment status, to obtain the status of the signal preprocessing and LDA feature extraction, the composite model of the data that need and it can be divided into training data and testing data;

Step 2: fault prediction. Will return to training, training data input to the LSSVM model to determine the model parameters, after the training, through a few state observation data to predict the future state of equipment, to get prediction future state;

Step 3: state recognition. First will get the equipment state of each training data into the HMM model, get the HMM model of equipment status, then the predicted values of sequence of LSSVM input to the trained HMM model is used to identify the state, the probability of each model to calculate the predicted sequence respectively, according to the maximum likelihood probability value to judge the current prediction sequence represents the equipment degradation state.

4.4 Combination Prediction Model in the Application of the Electronic Equipment

Suppose the actual circuit diagram of the electronic equipment structure with hybrid structure as shown in Figure 3. Circuit diagram of all resistors, capacitors, tolerance is within 5%, through the study of the sensitivity analysis of the circuit, found that the change of the C3 to affected by the waveform of the output voltage V (out), this paper only consider the change of C3 to the electronic equipment, the influence of other component parameters change within 5%.

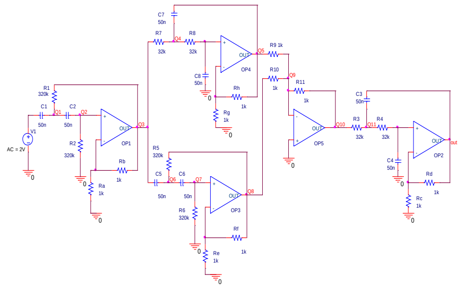

Figure 3. The Actual Circuit Diagram of Electronic Equipment

C3 tolerance range respectively is [5,7.5]%, [7.5,10]%, [10,12.5]%, [12.5,15]%, [15,17.5]%, [17.5,20]%, [20,22.5]%, [22.5,25]%, which to simulate the state of degradation process of the electronic equipment, plus normal set up nine state. Each state 50 times the MC analysis.

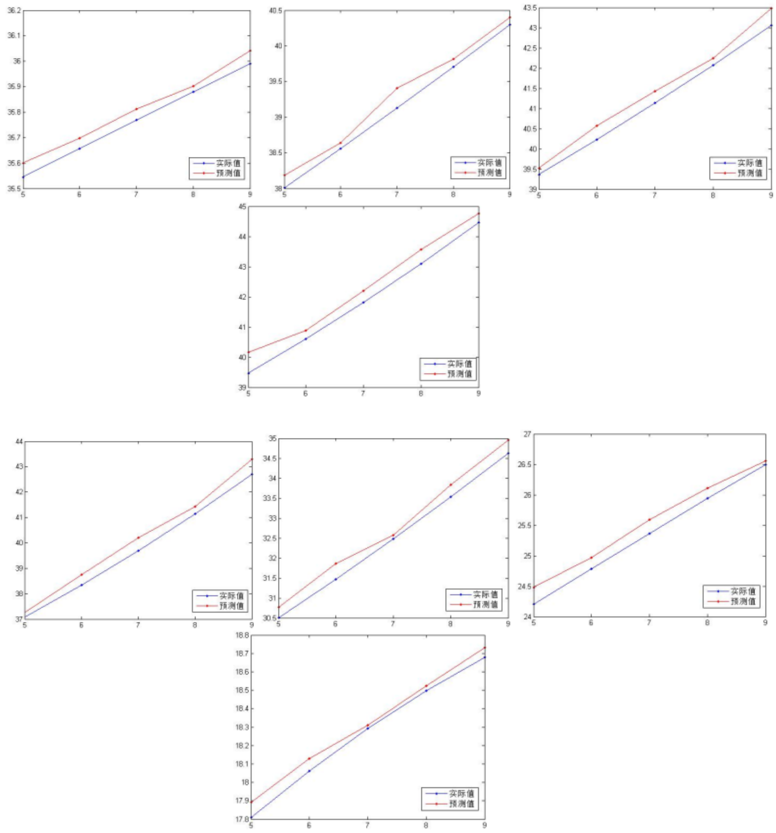

Figure 4. Comparison of the Actual and Prediction Curves of Each State

It is found C3 changes on the influence of the circuit is the largest between 25 kHz to 110 kHz. So each state which is 25KHz、50KHz、60KHz、70KHz、80KHz、90KHz、100KHz、110KHz take corresponding voltage value forms a set of 8 dimensional feature vectors. Then each state has a set of eigenvectors 50, 30 group as the training sample, 20 groups as test samples.

Eight of dimension feature vector nine states is average, get nine state LSSVM training samples, model parameter setting and the training process as described above. As shown in Figure 4, which is obtained by LSSVM prediction under the different frequency of the predicted and actual values are close to, get good prediction effect. Through the different training samples, the final state can be obtained 20 groups from state 5 to state 9 predictive vectors.

See the foregoing model training and observation sequence composition, each training sample set of 8 d eigenvector by LDA form 4 d eigenvector dimension reduction. Will get the status of the LSSVM prediction state 5 to 9 8 d predictive vector by LDA same mapping space is reduced to 4 dimensional feature vector, vector for each state at the same time take 5 groups at random prediction constitute an observation sequence, a total of 15 set of predicted observation sequence for HMM state recognition. As shown in Table 1, each state recognition rate are 93.3%, 86.7%, 100%, 93.3%, 100%, the average state recognition rate is 94.7%, state identification precision is higher.

Table 1. Recognition Results of Each State

States	5	6	7	8	9
5	14	1	0	0	0
6	0	13	1	1	0
7	0	0	15	0	0
8	0	0	0	14	1
9	0	0	0	0	15

5. Conclusion

For the complex structure of the electronic equipment and the existing single fault prediction methods cannot state projections for electronic equipment directly. This paper introduces the LSSVM and HMM working principle and working process of LSSVM with HMM combination prediction model is put forward, analysis the advantage of the combination model and applied to a mixed structure of electronic devices. The predicted results by using LSSVM by HMM recognition directly get the prediction of the equipment state, and state of high prediction precision can be achieved by using the combination of both.

6. Acknowledgements

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7. References

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