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PCA-CMAC based machine performance degradation assessment

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Abstract: A principal component analysis-cerebellar model articulation controller (PCA-CMAC) model is proposed for machine performance degradation assessment. PCA is used to feature selection, which eliminates the redundant information among the features from the sensor signals and reduces the dimension of the input to CMAC. CMAC is used to assess degradation states quantitatively based on its local generalization ability. The implementation of the model is presented and the model is applied in a drilling machine to assess the states of the cutting tool. The results show that the model can assess the wear states quantitatively based on the normal state of the cutting tool. The influence of the quantization parameter g and the generalization parameter r in the CMAC model on the assessment results is analyzed. If g is larger, the generalization ability is better, but the difference of degradation states is not obvious. If r is smaller, the different states are distinct, but memory requirements for storing the weights are larger. The principle for selecting two parameters is that the memory storing the weights should be small while the degradation states should be easily distinguished.

Key words: principal component analysis; cerebellar model articulation controller (CMAC); performance degradation assessment

In recent years, intelligent maintenance of machines has been emerging as a replacement for preventive maintenance and reactive maintenance. Different from fault diagnosis, intelligent maintenance focuses on the prediction and assessment of degradation states of a machine. Usually, the machine and components go through a series of degradation states before failure occurs[1]. If the performance degradation behavior can be detected in time, the failure can be prevented. Then the machine can be running in zero-breakdown condition.

Many efforts have been made to develop methods and tools to predict and assess machine performance degradation. Lee[2] first proposed a pattern discrimination model based on the cerebellar model articulation controller (CMAC) neural network. Experimental results on the stepping motor and the robot have proven the feasibility of the proposed model. Lin and Wang[3] also used enhanced CMAC in performance analysis of rotating machinery. Zhang et al.[4] suggested a modified CMAC algorithm for performance degradation assessment in self-maintenance machines. Yan and Muammer[5] used a logistic regression approach to assess performance degradation of an elevator door system. Dae and Lee[6] presented the ART2 (adaptive resonance theory 2) method that could easily create new classes for new states and the adaptive ability for changed running conditions was improved.

In general, if the data can be collected in normal state, degradation states with different severities and all kinds of fault states, the assessment of performance degradation can be looked on as pattern recognition or classification. So many methods such as time-frequency analysis, fuzzy logic, vector machine support, etc. can also be used. But in fact, historical running data under degradation and faulty states are difficult to acquire. Especially for some new products, the data is too impossible to classify different states. Therefore, developing the method of assessing performance degradation based on the normal state is critical. Among the methods mentioned above, the CMAC is preferred because it can meet this need. But the mapping process in the CMAC becomes complex and the physical memory needed for storing the weights is too large to implement if the number of the inputs to the CMAC is very large. The proper number of the inputs to the CMAC is between 1 and 5. This limits the practical application of the CMAC.

In this paper, principal component analysis (PCA) is proposed as a pre-processing method for reducing

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the number of the inputs to the CMAC. The PCA-CMAC model is applied to assess performance degradation just based on the data in normal conditions. First, PCA plays the roles of feature selection and data-dimension reduction. Then, the CMAC is used to assess degradation quantitatively. To show the effectiveness of the model, an experiment in assessing the states of the cutting tool in a drilling machine has been performed.

1 PCA-CMAC Model

PCA is one of the most general feature extraction methods. It has been widely used in feature extraction from complex and high dimensional data in many fields, such as signal processing, image processing and pattern recognition. It reduces the dimensionality of the feature space by creating new features that are linear combinations of the original features. As a result, information storage, processing, and transmission can become easier and more efficient[7].

The proposed model is shown in Fig. 1. The features extracted from the sensor signals, such as vibration, temperature, current or voltage, are firstly analyzed by the PCA method. Suppose that n observations for m features form an $n \times m$ matrix, signed as $\boldsymbol{X} = (x_{ij})$, $j = 1, 2, \ldots, m$; $i = 1, 2, \ldots, n$. The PCA is processed as follows[8]:

1) The data is standardized.

$$x_{ij} = \frac{x_{ij} - x_{j,\,\mathrm{mean}}}{\sigma(x_j)} \tag{1}$$

where $x_{j,\,\mathrm{mean}}$ and $\sigma(x_j)$ are the mean and the standard deviation of the j-th feature, respectively.

2) Calculate $m \times m$ correlation matrix $\boldsymbol{C}$, which is symmetrical and positive definite.

$$\boldsymbol{C} = \boldsymbol{X}^{\mathrm{T}}\boldsymbol{X} \tag{2}$$

3) The eigenvalue λ_j and the eigenvector $\boldsymbol{p}_j$ of $\boldsymbol{C}$ are computed in decreasing order of magnitude ($\lambda_1 > \lambda_2 > \ldots > \lambda_m$). The original data can then be expressed in terms of the eigenvalues and eigenvectors, which define the principal component directions:

$$\boldsymbol{X} = \boldsymbol{t}_1\boldsymbol{p}_1^{\mathrm{T}} + \boldsymbol{t}_2\boldsymbol{p}_2^{\mathrm{T}} + \ldots + \boldsymbol{t}_k\boldsymbol{p}_k^{\mathrm{T}} + \ldots + \boldsymbol{t}_m\boldsymbol{p}_m^{\mathrm{T}} \tag{3}$$

where $\boldsymbol{t}_j = \boldsymbol{X}\boldsymbol{p}_j$ is an $n \times 1$ sore vector, namely the projection of the data onto the j-th principal component vector. An approximate model, comprising of the first k terms of Eq. (3), will capture most of the observed variance in $\boldsymbol{X}$ if the data are correlated. The percentage that the information in $\boldsymbol{X}$ can be expressed as the first k terms of principals is

$$Q = \frac{\lambda_1 + \lambda_2 + \ldots + \lambda_k}{\sum_{j=1}^{m} \lambda_j} \tag{4}$$

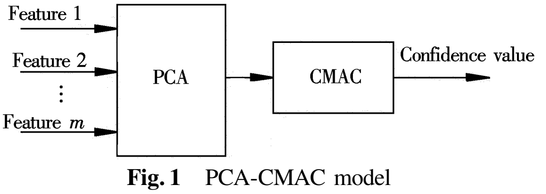

Fig. 1 PCA-CMAC model

The PCA in the proposed model has the following functions:

1) It eliminates redundant information in performance features and retains the most important information in lower dimensions.

2) It decreases the complexity of computation in the CMAC.

3) The statistical characteristics of the main components of performance features can be visible in two- or three-dimensional space.

The CMAC neural network is employed to evaluate variant degradation states. The main advantages of the CMAC against MLP, RBF and other neural networks are its local generalization, extremely fast learning speed and easy implementation in software and hardware. The CMAC can be considered as an associative memory network, which performs two mappings: $\boldsymbol{S} \to \boldsymbol{A} \to \boldsymbol{P}$, where $\boldsymbol{S}$ is the m-dimensional input space, $\boldsymbol{A}$ is an n-dimensional association cell vector which contains g non-zero elements, g is the generalization parameter, and $\boldsymbol{P}$ is one-dimensional output space.

Before the mapping, each input variable s_i ($i = 1, 2, \ldots, m$) in $\boldsymbol{S}$ should be quantized as

$$\bar{s}_i = \frac{s_i - s_{i,\,\min}}{r_i} \tag{5}$$

where $s_{i,\,\min}$ is the minimum of s_i, and r_i is the quantization parameter of s_i (r_i is also called the resolution). The mapping address of s_i will be determined according to its quantization value.

Then, the first mapping combines each mapping address and projects the point $\boldsymbol{S}_k$ in the input space into a binary associative vector $\boldsymbol{A}_k$. The elements in $\boldsymbol{A}_k$ are defined as

$$a_{k,j} = \begin{cases} 1 & \text{if the } j\text{-th element is activated} \\ & \text{by the } k\text{-th sample} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where $1 \leqslant j \leqslant n$.

The second mapping calculates the output of the network as a scalar product of $\boldsymbol{A}_k$ and the weight vector $\boldsymbol{W}$, as shown in Eq. (7).

$$Y_{r,k} = \boldsymbol{A}_k^{\mathrm{T}} \cdot \boldsymbol{W} = \sum_{j=1}^{N} a_{k,j} w_j \tag{7}$$

The weights are updated as

$$w_j(t+1) = w_j(t) + \Delta w_j(t) = w_j(t) + \frac{\beta a_{k,j}}{g}\left(Y_{d,k} - \sum_{j=1}^{N} a_{k,j} w_j(t)\right) \tag{8}$$

where $Y_{r,k}$ is the real output at the k-th sample, w_j is the j-th element in the weight vector $\boldsymbol{W}$, t is the t-th cycle, β is the learning rate, and $Y_{d,k}$ is the desired output at the k-th sample. The initial value of w_j can be set to zero. The initial value of β should be in $(0,2)$ and β can be reduced with the learning cycle increasing.

The mapping built into the CMAC assures local generalization, that is to say similar inputs create similar outputs while different inputs create nearly independent outputs. This generalization ability of the CMAC makes it very suitable for performance degradation assessment. The CMAC can be trained only using the data in the normal state. If the input deflects from the input in normal conditions, the output of the CMAC will deflect from the desired output in the normal state. Moreover, the degree of deflection in the output can reflect the degree of deflection in the input. This characteristic is due to the mapping mechanism in the CMAC, so other neural networks cannot achieve it. This good generalization ability is a significant reason that the CMAC can be used as a powerful tool for machine performance assessment.

2 Performance Assessment of Cutting Tool

The proposed model is applied to evaluate the wearing state of a cutting tool in a drilling machine. The cutting tool goes from brand new to worn after 132 holes have been drilled. The vertical vibration signal on the spindle in the stationary cutting process is sampled. The machining and sampling parameters are as follows: feed rate is 250 mm/min; cutting velocity is 1 200 r/min; the depth of hole is 12. 6 mm; sampling rate is 15 kHz; filter frequency is 6 kHz (low pass).

Through fast Fourier transform (FFT) of the measured vibration signals, two characteristic frequencies are found. One is low frequency, between 600 and 800 Hz, and the other is high frequency, between 3 800 and 4 000 Hz. The following features are extracted as the performance features of the cutting tool. f_1 is the root mean square value (in time domain); f_2 is the mean amplitude in the first characteristic frequency; f_3 is the mean amplitude in the second characteristic frequency; f_4 is the maximum amplitude in frequency domain; f_5 is the maximum power amplitude; f_6 is the frequency with the maximum power amplitude in the first characteristic frequency; f_7 is the frequency with the maximum power amplitude in the second characteristic frequency.

To reduce the unfavorable influence of outliers, the following method is used to eliminate some outliers. Suppose that Z is the series composed of f_1. $\bar{Z}$ is the series after Z is processed by one order exponent smoothing. $\bar{Z}_t = \alpha Z_t + (1-\alpha)\bar{Z}_{t-1}$, $\alpha = 0.7$. σ^2 is the variance of all elements of Z. If $\bar{Z}_t - k\sigma < Z_{t+1} < \bar{Z}_t + k\sigma$ ($k = 6$ here), Z_{t+1} is thought of as a normal sample point, otherwise Z_{t+1} is an outlier and eliminated. Then 125 holes are finally obtained. The performance of the cutting tool is good during when 1 to 30 holes are drilled, and degradation occurs because of the wear after the 30-th hole. Suppose $\boldsymbol{F} = \{f_1, f_2, \ldots, f_7\}$ is a 30 × 7 data set which represents the normal state of the cutting tool. Through principal component analysis to $\boldsymbol{F}$, the principal components (PCs) and the space composed of PCs can be obtained. The first three PCs are retained because they have contained 91. 17% of the information of $\boldsymbol{F}$.

For assessing the performance of the cutting tool, the data representing different states are projected onto the PC space. The PCs will change with a trend when the wear becomes more and more serious. The three PCs are shown in Fig. 2. " * "s represent the 1st to 30th holes; "o"s represent the 31st to 75th holes and " + "s represent the 76th to 125th holes.

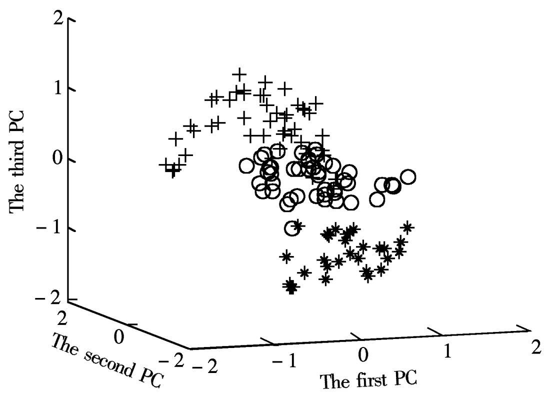

Fig. 2 Three principal components

Supposing when the cutting tool in the normal state, the desired output of the CMAC is equal to 1. The three PCs in normal state are used to train the CMAC. When the PCs in other cases are inputted into the CMAC, the outputs of the CMAC show the chan -

ging condition of the cutting tool. If the output of the CMAC is close to 1, the cutting tool is still in a normal state. With the wear becoming more and more serious, the output of the CMAC will deflect from 1 further and further. This means that performance degradation is becoming more and more serious. The minimum output of the CMAC is 0 when the input deflects from that of normal states completely. Fig. 3 shows the assessment results of the CMAC. The output of the CMAC can be taken as the confidence value of the cutting tool, which decreases during the drilling process. The confidence value is about 0. 9 after 70 holes have been drilled and about 0. 8 after 120 cycles. What 0. 9 or 0. 8 means, dull or worn out, should be decided according to a practical drilling process and the experience of operators or experts.

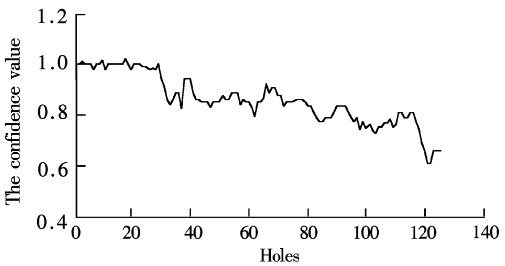

Fig. 3 Assessment results of the CMAC

There are two parameters which play important roles in adjusting the structure and performance of the CMAC. One is the quantization parameter r of each input variable(in Eq. (5)) and the other is the generalization parameter g (in Eq. (8)). These two parameters must be selected properly. Fig. 3 shows the outputs of the CMAC with $r = 0.25$ and $g = 32$. If g is becoming larger, the generalization ability is better. So the curve is smoother, but at the same time, the difference of the outputs at different states is not obvious. If g is too much smaller, all the outputs will be zeros except in the normal state, so variant degradation states will not be distinguished. In the same way, if r is becoming smaller, the different states are easily distinct while the needed memory cells where the weights are stored become very large. In general, the selection of r and g should satisfy two basic rules. First, the memory storing the weights should be small. Secondly, the degradation states should be easily distinguished. $g = 32$ and $r = 0.25$ are proper in this study.

Although the outputs of the CMAC are changing when g or r is changed, the trends showing the performance degradation are similar. Some threshold values can be obtained from the experience of the operators or experts, so alarms can be created when the performance is decreased to be smaller than these thresholds. Moreover, the quantization parameters of the input variables are the same in this study. But in fact, they can be set to different values according to the sensitivities to the performance of the cutting tool. If the performance of the cutting tool is more sensitive to one feature than others, the quantization parameter of this feature can be set to a smaller value than quantization parameters of other features.

3 Conclusions

The application of the proposed PCA-CMAC model for assessing the states of cutting tools in the drilling machines proves that it is feasible. This model is generic and can be used in performance degradation assessment for other machines. If we fix sensors in different parts of a machine, the performance degradation of the machine can be evaluated by this model. The advantages of the model can be concluded as follows:

1) It can assess the degradation state based only on the data in the normal state, which is important when the data in abnormal states are difficult to collect for some high-performance machines or new machines.

2) The degree of the performance degradation can be evaluated by the output of the CMAC quantitatively.

3) It can fuse multiple feature information.

4) The sensitivity of each feature to machine performance can be adjusted by the resolution (the quantization parameter) of this feature.

5) It can be on-line updated because of fast convergence speed of the CMAC.

In this paper, the application of the PCA-CMAC in the cutting tool is a simple example. How to use this model in machines more generally and how to properly determine the quantization parameter of each feature according to its sensitivity to machine performance need further investigation.

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基于 PCA-CMAC 的设备性能退化评估

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摘要:提出了一种用于设备性能退化评估的 PCA-CMAC(主成分分析-小脑模型节点控制器)模型. 该模型利用 PCA 进行特征提取,去除多个传感器信号特征的冗余信息,并且减少 CMAC 的输入维数;利用 CMAC 的局部泛化能力定量地评估设备的性能退化. 给出了模型的实现过程,并将模型应用于钻削过程刀具状态的评估,试验结果证明该模型能基于刀具的正常状态,对刀具的磨损状态进行定量的评估. 分析了 CMAC 中泛化参数 g 和量化参数 r 对评估结果的影响,g 越大,CMAC 的泛化能力越好,但各退化状态之间的区别越不明显;r 越小,各退化状态之间越容易区分,但所需的权存储空间越大. 2 个参数的基本选择原则是 CMAC 的权存储空间应尽量小,与此同时,各退化状态之间应容易区分.

关键词:主成分分析;小脑模型节点控制器;性能退化评估
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