Machine Performance Degradation Assessment based on PCA-FCMAC

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Abstract

A PCA-FCMAC (Principal Component Analysis-Fuzzy Cerebellar Model Articulation Controller) model is proposed for machine performance degradation assessment. In the model, the selected features from the sensor signals are first processed by PCA to eliminate the redundant information and then inputted into FCMAC. FCMAC is used to assess degradation states quantitatively based on its local generalization ability. The implementation of the model is presented. Then the application in a drilling machine to assess the states of the cutting tool shows the effectiveness of the model. The comparative analyses of the assessing results prove FCMAC work better than CMAC.

1. Introduction

Intelligent maintenance characterized by PAP(Predict and Prevent) is emerging as a trend of taking place of traditional FAF(Fail and Fix) maintenance. Deferent from fault diagnosis and traditional maintenance, intelligent maintenance focuses on the prediction and assessment of degradation states of machine [1]. Usually, the machine and components go through a series of degradation states before failure occurs. If the performance degradation behavior can be detected in time, the failure can be prevented.

The key challenge to implement IM is intelligent embedded prognostics algorithms for performance degradation assessment and prediction [2].Many efforts have been made to develop methods and tools for this purpose. Lee and Kramer [3] 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 had proven the feasibility of the proposed model. Lin [4] also used enhanced CMAC in performance analysis of rotating machinery. Zhang [5] suggested a modified CMAC algorithm for performance degradation assessment in self-maintenance machine. Yan [6] had used a logistic regression approach to assess performance degradation of an elevator door system. Casoetto [7] presented an autoregressive modeling and feature maps for multi-sensor process performance assessment. Qiu [8] gave a robust method for rolling bearing prognostics.

Among the methods mentioned above, CMAC is preferred because its extremely fast learning speed and easy implementation in software and hardware. Moreover, CMAC can assess performance degradation only based on the data of machine's normal state, which is critical when the historical running data under degradation and faulty states is not sufficient. To improve the accuracy of nonlinear function approximation, the higher-order CMAC(HCMAC) with B-spline receptive field function can be used as a replacement of common CMAC. But HCMAC is computationally complicated when the order of B-spline receptive field function is high. Furthermore, the convergent speed of HCMAC is not unstable as the model parameters alter [9]. To avoid these problems, this paper suggested a fuzzy CMAC(FCMAC) model for machine degradation assessment. The model adopts normal bell-shaped membership functions as the receptive field function and uses a special parallel fuzzy inference-like process to realize the function similar to HCMAC. The model inherits the advantages of fuzzy logic and local generalization capability of CMAC. The experiments proved the model can get much better results when used in the field of machine degradation assessment and prediction.

This paper is organized as follows. Section 2 presents the PCA-FCMAC model. Here PCA is proposed as a pre-processing method for reducing the number of the input of FCMAC. Section 3 discusses the experiments in assessing the states of the cutting tool in a drilling machine. Finally, a brief conclusion is given in Section 4.

2. PCA-FCMAC model

2.1 PCA-FCMAC Model

The proposed model is shown in Figure 1. The features extracted from the sensor signals, such as vibration, temperature, current or voltage, are firstly analyzed by PCA method. Then the principal components are inputted into FCMAC for machine performance assessment and prediction.

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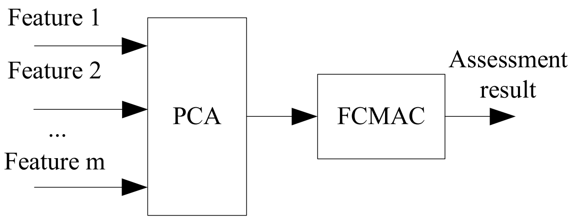

Fig. 1 PCA-FCMAC model

PCA is one of most general feature extraction methods. It reduces the dimensionality of the feature space by creating new features that are linear combinations of the original features [11. The PCA in the proposed model has following functions: First, It eliminates redundant information in performance features and retains the most important information in lower dimension. Second, it decreases the number of the inputs and the complexity of computation of FCMAC. Furthermore, The statistics characters of the main components of performance features can be visible in two or three dimensional space.

Suppose n observations for m features form a （n×m ） matrix, signed as $\mathbf{X} = [x_{ij}]$, j =1,2,…m, i =1,2,…n. Where x_{ij} has been standardized. After the PCA is performed, $\mathbf{X}$ can then be expressed as

$$\mathbf{X} = \mathbf{t}_1\mathbf{p}_1^T + \mathbf{t}_2\mathbf{p}_2^T + \cdots + \mathbf{t}_k\mathbf{p}_k^T + \cdots + \mathbf{t}_m\mathbf{p}_m^T \quad (1)$$

where $\mathbf{t}_j = \mathbf{X}\mathbf{p}_j$ is (n × 1) sore vector, namely the projection of the data onto the j-th principal component vector, $\mathbf{p}_j$ is the eigenvector of correlation matrix $\mathbf{C}$ ($\mathbf{C} = \mathbf{X}^T\mathbf{X}$) .An approximate model, comprising of the first k terms of (1), will capture most of the observed variance in $\mathbf{X}$ if the data are correlated.

The detailed process of PCA can be referred to [10]. There are many computation tools which can give the results of PCA easily if the matrix is given, such as the tools in Matlab.

2.2 Fuzzy CMAC (FCMAC) model

The structure of FCMAC is shown in Fig1. Similar to conventional CMAC, FCMAC performs two mappings: X →A→P, where X is the m-dimension input space. A is an n-dimension association cell vector which contains some non-zero elements. P is one-dimension output space.

Before further discussing, some terms are first defined and introduced:

i $(i = 1, \cdots, m)$ is the index of input dimension

x $(x = (x_1, \cdots, x_i, \cdots x_m))$ is the input vector

$x_{\min,i}$ is the minimum of x_i

$x_{\max,i}$ is the maximum of x_i

$R_i(x)$ is the resolution of dimension i

D_i is the width of quantization interval of dimension i

r is the effective radius of the receptive field function by using D_i as unit

$q_i(x)$ is the quantized position of input vector x

m, $x_{\min,i}$, $x_{\max,i}$, D_i, r is the parameters would be given first to determine the structure of FCMAC. If these parameters are give.

$$R_i(x) = floor(\frac{X_{\max,i} - X_{\min,i}}{D_i}) + 1 \quad (2)$$

$$q_i(x) = floor(\frac{x_i - X_{\min,i}}{D_i}) \quad (3)$$

The function floor(z) gets the integer which isn't larger than z.

We adopt normal bell-shaped membership functions as the receptive field functions, as shown in Fig 1.

$$u_j^i(x) = e^{-((x_i - m_j^i)/\sigma)^2} \quad (4)$$

Where m_j^i denotes the j-th mean on dimension i, which can be computed as

$$m_j^i = X_{\min,i} + (j - \frac{1}{2}) \times D_i \quad \text{where } j \in [-r+1, R_i + r] \quad (5)$$

The receptive field function $u_j^i(x)$ denotes the degree of x belonging to $[\lambda_{j-1}^i, \lambda_j^i)$ where $\lambda_{j-1}^i = (q_i(x) - 1) \times D_i$ $\lambda_j^i = q_i(x) \times D_i$

The variance σ of $u_j^i(x)$ in (4) can be decided on the idea that two adjacent fuzzy receptive field functions should have a proper overlapping region. As in Fig2 , assuming the intersecting point whose membership grade is β ($\beta \in (0,1]$). Then σ can be derived from (7) according to the value of β in (6)

$$\beta = \exp(-(\frac{(m_1 + m_2)/2 - m_1}{\sigma})^2) \quad (6)$$

$$\sigma = \sqrt{\frac{((m_2 - m_1)/2)^2}{abs(\ln(\beta))}} = \frac{D_i}{2\sqrt{abs(\ln(\beta))}} \quad (7)$$

The decision of β can refer the following principle. The higher the β is, the smoother the bell-shaped receptive field function is.

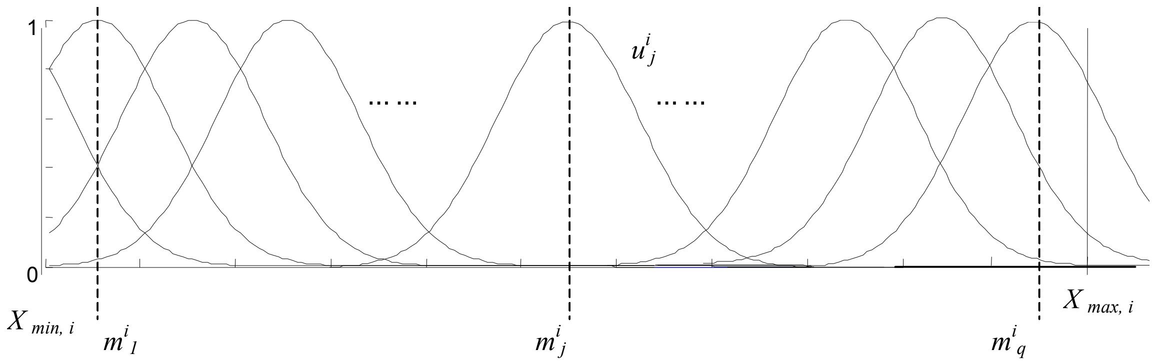

Fig 2 Fuzzy receptive function

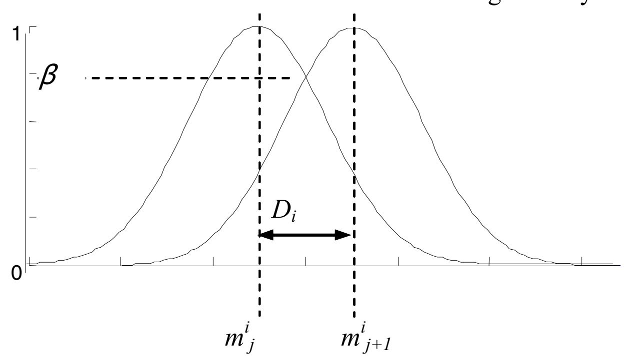

Fig 3 The decision principle of β

If the input of FCMAC is larger than 1(m>1), we must decide the composition rules of multidimensional fuzzy receptive field functions. Suppose the active receptive field location of dimension i is Li, like the mapping in CMAC, the general locations activated by m dimension can be written as

$$L = L_1 \oplus L_2 \oplus \cdots \oplus L_m \quad (8)$$

where $L_i = [q_i(x) - r, \cdots, q_i(x), \cdots q_i(x) + r]'$, each column $L_i (i = 1, 2, \cdots, m)$ contains $2r+1$ elements. The sign $\oplus$ means an addressing scheme of FCMAC. We adopt the main diagonal addressing scheme here. So L is a column matrix with $2r+1$ elements corresponding to the indices of the receptive field functions with nonzero membership grade.

The grades of receptive field function for each location index can also be expressed as the matrix

$$R(x) = R^1(x_1) \otimes R^2(x_2) \otimes \cdots \otimes R^m(x_m)] \quad (9)$$

where

$$R^i(x_i) = \left\{ u^i_j(x_i) \mid j = q_i(x) - r, \cdots, q_i(x), \cdots q_i(x) + r \right\}$$

The sign $\otimes$ means the multiplication operation. It should be mentioned that the multiplication is performed on the elements whose receptive field locations are composed by main diagonal addressing scheme.

Finally, the firing strength α can be derived by the mapping

$$\alpha = F(L, R) = \{\alpha_1, \alpha_2, \cdots, \alpha_j, \cdots, \alpha_{N_L}\} \quad (10)$$

Where N_L is the number of the weight W. The association vector α has $2r+1$ nonzero elements, whose indices are in L and whose grades are in R. The final output of FCMAC is

$$O_r = \frac{\sum_{k=1}^{N_L} \alpha_k w_k}{\sum_{k=1}^{N_L} \alpha_k} \quad (11)$$

The adjusting of W is follow as

$$\Delta w_k = \frac{\eta (O_d - O_r) \alpha_k}{\sum_{k=1}^{N_L} \alpha_k} \quad (12)$$

Where η is the learning rate, O_d is the desired output.

The more detailed process of FCMAC can be referred to [9][11]. FCMAC inherits the advantage of local generalization ability of CMAC. The local generalization means similar inputs create similar outputs while different inputs create nearly independent outputs, which is the key reason why FCMAC is suitable for degradation assessment. At the same time, FCMAC can approximate nonlinear function more smoothly because of fuzzy inference, so it has better performance than CMAC.

3. The performance assessment of the cutting tool

The proposed model is applied to evaluate the wearing state of a cutting tool in a drilling machine. The vertical vibration signal on the spindle in stationary cutting process is sampled. The machining and sampling parameters are as follows:

Feed rate: 250mm/pm
Cutting velocity: 1200 r/pm
Depth of hole: 12.6 mm
Sampling rate: 15 kHz
Filter: 6 kHz (Low pass)

Through FFT (Fast Fourier Transform) of the measured vibration signals, two characteristic frequencies are found. One is low frequency between 600-800Hz and another is high frequency between 3800-4000Hz.

Following features are extracted as the performance features of the cutting tool.

Mean1: the mean amplitude in the first characteristic frequency

Mean2: the mean amplitude in the second characteristic frequency

Max-fft: the maximum amplitude in frequency domain

Max2: the maximum power amplitude

Z1: the frequency with the maximum power amplitude in the first characteristic frequency

Z2: the frequency with the maximum power amplitude in the second characteristic frequency

The cutting tool is from brand new to worn after 125 holes have been drilled. The performance of the cutting tool is good during 1-30 holes are drilled, and degradation happens because of wear after the 30-th hole. Suppose $\mathbf{F} = [Mean1, Mean2, Max\text{-fft}, Max2, Z1, Z2]$ is a 125×6 data set. Through principal component analysis to F, the Principal Components (PCs) and the space composed of PCs can be obtained. The first three PCs are retained because they have contained the 90.24% information of F. The three PCs are shown in Figure 4. '*'s represent the 1-30th holes; 'o's represent the 31-75th holes and '+'s represent the 75-125th holes. From the figure2, it can be seen the projection of main PCs has changed when the wear becomes more and more serious.

We only use three PCs in normal state to train FCMAC. When the cutting tool in the normal state, the desired output of FCMAC is 1. The three PCs composed the input of FCMAC and they have the same parameters as follows: D_i =0.25 ($i=1,2,3$); r =8* D_i =2; $\beta = 0.6$; $\sigma = 0.175$; η=0.5 . After these parameters are given, FCMCA can be trained according to the description of 2.2. The initial weights are all set to zero, and the procedure is as follows:

Step 1. For each dimension $i = 1,2,3$, $x_{\min,i}$, $x_{\max,i}$ can be gotten from the data set, then $R_i(x)$ can be computed by (2).

Step 2. For each dimension of each training sample, compute $q_i(x)$ ($i=1,2,3$).

Step 3. Let $j = q_i(x) - r, \cdots, q_i(x), \cdots q_i(x) + r$, compute m_j^i by (5) and $u_j^i(x)$ by (4).

Step 4. Get L by (8)

Step 5. Get $R(x)$ by (9)

Step 6. Determine α by (10)

Step 7. Compute O_r by (11)

Step 8. Adjusting W by (12)

Step 9. For next training sample, do step2-step8 until all samples are trained.

Step 10. Compute the training error of all samples, if the error is smaller than the required threshold value, the training is finished. Otherwise, repeat step 7-step10.

Based on the generalization ability of FCMCA, when the PCs in other cases are inputted into FCMAC, the outputs of FCMAC show the changing condition of the cutting tool. If the output of 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 CMAC will deflect from 1 further and further. This means performance degradation is becoming more and more serious.

Figure 5 shows the compared assessment results of CMAC and FCMAC. It can be seen the FCMAC can get smoother results because its receptive field functions adopt normal bell-shaped membership function.

Just like CMAC, there are two parameters which play important roles in adjusting the structure and performance of FCMAC. One is the quantization resolution D_i of each input variable (in(2)) and the other is the effective radius

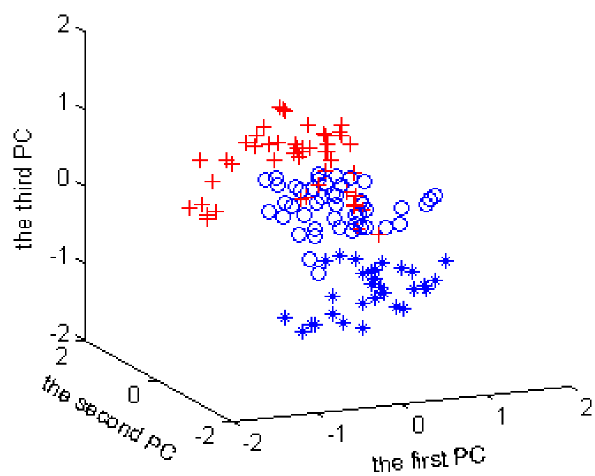

Fig.4 The three PCs of the holes

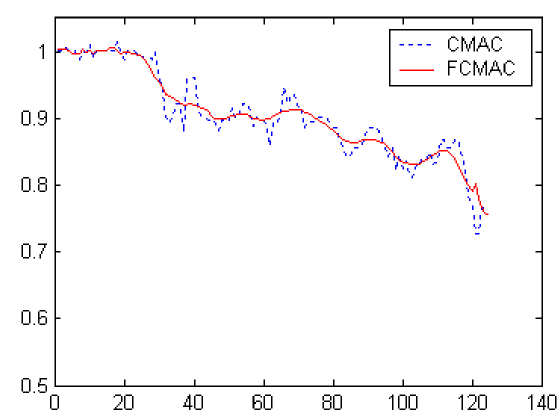

Fig. 5 The assessing results of CMAC and FCMAC

of the receptive field function r (in (5)). These two parameters must be selected properly. The selecting guide can be referred to [12]. Of course, although the assessing results are changing when D_i or r is changed, the trends showing the performance degradation are similar.

4. Conclusion

We proposed a PCA-FCMAC model for assessing the machine degradation assessment in intelligent maintenance. The model can fuse multiple sensor features and give a quantitative evaluation on degradation degree by the output of FCMAC. More importantly, it can be trained only used the data in the normal state, which is can't be achieved by other neural networks. The sample for assessing the wearing states of the cutting tool is simple, the complex application and the improved learning algorithm for FCMAC need to be further studied.

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