Online health degradation monitoring of machining tools based on growing self-organizing maps and support vector machines

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***Abstract*—This article presents a method for online health monitoring of machining tools using massive sensor signals. The features of the signals were extracted from three domains. With the intent at reducing the data, the vital features are selected with the use of Pearson correlation coefficient (PCC) analysis. Then fusion of the significant features of the signals is made with the use of the Growing Self-Organizing Map(GSOM) to get the Minimum Quantization Error (MQE), which is proved to have a similar trend with tool flank wear. On the basis of MQE, the state of machining tool is identified by Particle Swarm Optimization-Support Vector Machine (PSO-SVM). The experimental results verify the effectiveness and feasibility of the proposed methodology, as well as the superiority to Back-Propagation (BP) method and Adaptive Network-based Fuzzy Inference System (ANFIS).**

Keywords- health monitoring; fusion; GSOM;PSO-SVM

I. INTRODUCTION

With the increasing competition of manufacturing industry, an enterprise must continuously improve the quality of products and the efficiency of production. In manufacturing processes, the catastrophic failure of machining tools will affect the manufacturing productivity and the product quality. Hence, monitoring the health condition of machining tools is necessary[1].

Nowadays online health monitoring technology of machining tools has attracted more and more attention. Researchers have used monitoring data collected from different sensors installed on computerized numerical control (CNC) machine to realize the health monitoring of machining tool [2]. Compared to a single type of sensor, multi-sensor information fusion may get more specific and accurate inferences for the health monitoring of the machining tool. Fortunately, recent technological advances in the field of information and communication , massive sensor data might be quite convenient to be obtained and transferred after long time operation of CNC machine. To accurately and timely identify the health condition of machining tool, the new challenge is how to implement the multi-sensor information fusion in big data environment.

In this paper, we propose a method for online health monitoring of machining tool using massive sensor data. Firstly, massive sensor signals are collected from machining center of an experimental setup. Secondly, the features are extracted from three domains and selected by Pearson correlation coefficient analysis. Thirdly, the GSOM is used to fuse features to get the MQE, which is proved to have a similar trend with tool flank wear. At last, on the basis of MQE, the state of machining tool is identified by PSO-SVM.

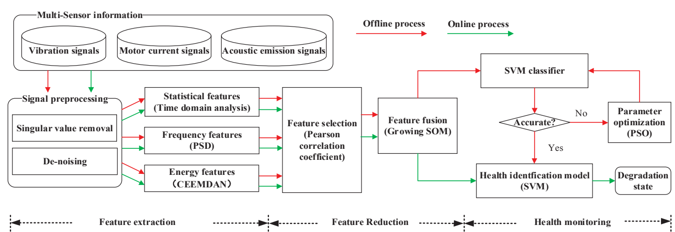

Figure 1. An online health monitoring schema for machining tools.

The rest of the paper is organized as follows: Section II describes a methodology for machining tools includes feature extraction and reduction methods, health monitoring model based on PSO and SVM. A case study for the proposed methods employed in practical system is implemented in Section III and The results and discussion are made in Section IV. Finally, the paper is concluded in Section V.

II. METHODOLOGY

A. Feature extraction

Feature extraction means extracting valuable feature variables from the original data as much as possible. Statistics features in time domain, frequency domain and time-frequency domain is usually efficient for condition monitoring .

1) Time domain features

Nine time domain features are extracted and equations are shown in Table I.

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TABLE I. STATISTICAL FEATURES FOR MONITORING

Feature	Equation	Feature	Equation
Mean value(MV)	$x_1=\sum_{i=1}^{N} y(i)/N$	Skewness factor (SF)	$x_6=\frac{\sum_{i=1}^{N}(y(i)-x_1)^3}{(N-1)x_2^3}$
Mean square error (MSE)	$x_2=\sqrt{\sum_{i=1}^{N}(y(i)-x_1)^2/N}$	Kurtosis factor (KF)	$x_7=\frac{\sum_{i=1}^{N}(y(i)-x_1)^4}{(N-1)x_2^4}$
Square mean root (SMR)	$x_3=\left(\sum_{i=1}^{N}\lvert y(i)\rvert/N\right)^2$	Crest factor (CF)	$x_8=x_5/x_4$
Root mean square (RMS)	$x_4=\sqrt{\sum_{i=1}^{N}(y(i))^2/N}$	Margin factor (MF)	$x_9=x_5/x_3$
Maximum absolute value (MA)	$x_5=\max\lvert y(i)\rvert$		

2) Power spectrum analysis

Power spectrum analysis is widely used to extract features from vibration signal in frequency domain. The power spectrum of vibration signal reflects the frequency components and their energy, so the features in frequency domain can be well described. The equations are represented in Table II.

TABLE II. FREQUENCY FEATURES FOR MONITORING

Feature	Equation
Frequency center (FC)	$\mathrm{FC}=\frac{\int_0^{+\infty} f*S(f)df}{\int_0^{+\infty} S(f)df}$
Mean square frequency(MSF)	$\mathrm{MSF}=\frac{\int_0^{+\infty} f^2S(f)df}{\int_0^{+\infty} S(f)df}$
Root mean square frequency (RMSF)	$\mathrm{RMSF}=\sqrt{MSF}$
Variance of frequency (VF)	$\mathrm{VF}=\frac{\int_0^{+\infty}(\mathrm{f}-\mathrm{FC})\mathrm{S}(\mathrm{f})\mathrm{df}}{\int_0^{+\infty} S(f)df}$
Root variance of frequency (RVF)	$\mathrm{RVF}=\sqrt{VF}$

3) Energy feature extraction using CEEMDAN algorithm

As for time-frequency domain, it provides another perspective that is not found otherwise in the statistical domain to tool wear condition. Complete Ensemble Empirical Mode Decomposition with Adopt Noise (CEEMDAN) algorithm is widely used to decompose the signal completely[3].

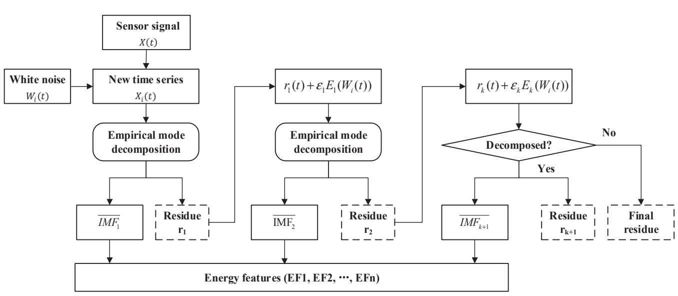

Figure 2. Flow chart of CEEMDAN algorithm.

B. Feature reduction using Pearson correlation coefficient and GSOM

1) Pearson correlation coefficient analysis

Most of features extracted cannot represent the raw signals for machining tool health condition detection. Feature selection technique can effectively lower the dimension of feature space. PCC is a statistical measure of independence of two or more random variables. So PCC is adopted to select the features which have strong correlation with tool flank wear in this paper. This can remove most of valueless features and improve the reliability of fusion result. Pearson correlation coefficient is defined as:

$$\mathrm{R(X,Y)}=\frac{\mathrm{Cov}(X,Y)}{\sqrt{D(X)D(Y)}} \tag{1}$$

where X is tool flank wear and Y is extracted feature,Cov(X,Y) is the covariance of X and Y,D(X) is the variance of X, D(Y) is the variance of Y.

2) Feature fusion using Growing Self-Organizing Map

After feature selection, GSOM is used to extract the degradation indicator. GSOM is proposed based on Self-Organizing Map (SOM). Comparing with SOM, units in GSOM are increased when a new input cannot find a best matching unit (BMU) if the distance from it exceeds the threshold[4]. As a result of that the features selected by PCC are variable because of the working condition, GSOM is more appropriate in this methodology. The steps of GSOM are described as follows:

(1) Initialize the network parameters;

(2) Input training sample D^n , determine the distance threshold $d_{\max}$;

(3) Randomly select $\mathrm{x(t)}\in D^n$,determine the BMU by $o_{i(x)}(\mathrm{x})=\min\{\lVert x-\omega_i\rVert\}$;

(4) Increasing process. if $o_{i(x)}(\mathrm{x})>d_{\max}$, increase the number of units by 1,or go to (6);

(5) Set the feedforward connection weight(FCW) value of the new unit as $\mathrm{x(t)}^T$. Calculate the distance between it and all the other units, define units set N1 by $d_i<n_1*d_{\max}$,which is shown in Figure 3(a), N2 by $d_i<n_2*d_{\max}\,(n_1<n_2)$,which is shown in Figure3(b), if the connection between the new unit and units in N1 intersect the connection between units in N2, do not establish neighborhood relationships ,which is shown in Figure 3(c).

(6) Calculate the FCW value: $\omega_{i(x)j}=\exp\left\{-\frac{d_{i(x)j}^2}{2\sigma^2}\right\}(j=1,2\ldots N)$.

(7) Calculate the FCW weight value as given.

$$\begin{cases}\Delta\omega_i(t)=\alpha(t)\omega_{i(x)j}(t)\left(x-\omega_j(t)\right)\\ \omega_j(t+1)=\omega_j(t)+\Delta\omega_i(t)\quad(j=1,2\ldots N)\end{cases} \tag{2}$$

(8) End, or go to (2) if there is new input sample.

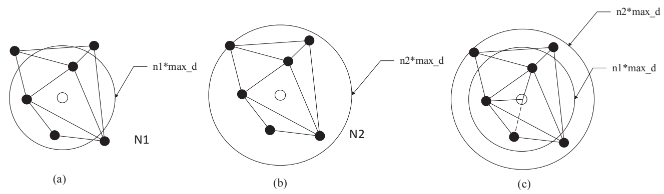

Figure 3. Increasing process of GSOM algorithm

The GSOM is trained with normal condition data firstly. Then comparing the features vector corresponding to the measurement with the weight vectors of all map units[5]. The distance between the measurement data and BMU actually indicates how far the input data deviate from the region of normal operation. The distance is called MQE which is defined as:

$$\mathrm{MQE} = \left\| \mathrm{x} - \omega_{BMU} \right\| \tag{3}$$

where x is the input feature vector, ω_{BMU} is the weight value of BMU.

MQE can be considered as fused degradation indicator due to its trend can actually depict the machining tool health condition. Integrating PCC and GSOM, initial features will be fused into only one degradation indicator.

C. *Health degradation identification model using SVM and PSO*

1) *Support Vector Machine*

The degradation indictor MQE should be classified by SVM appropriately to represent the health condition of machining tool. SVM has been widely applied in classification and recognition problems due to its versatility**Error! Reference source not found.**. Generally, SVM algorithm can be used to divide data into two classes. Given a set of training examples, SVM algorithm establishes the hyperplane and find the maximum gap between the two classes. The hyperplane contains a subset of points of the two classes called support vectors.

Assuming a linear separable training set $(x_i, y_i), \mathrm{i}=1,\ldots,1, x_i \in R^d; y \in \{-1,+1\}$, y is the category identification, d is the dimension of input vector. Then the hyperplane problem transforms into the following optimization problem:

$$\begin{aligned} &\min \frac{1}{2} \| \omega \|^2 + C \sum_{i=1}^{l} \xi_i \\ &\text{s.t.} \quad y_i \left[(\omega * x_i) + b \right] \geq 1 - \xi_i, \mathrm{i}=1,\ldots 1 \end{aligned} \tag{4}$$

where C is a penalty parameter. The classification function is given as:

$$\mathrm{f(x)} = \mathrm{sgn} \left\{ \sum_{i=1}^{l} \alpha_i y_i K(x_i, x) + b \right\} \tag{5}$$

where α_i is the Lagrange multiplier, $K(x_i, x)$ is kernel function RBF and given as:

$$K(x_i, x) = \exp\left(\frac{-\left\| x_i - x \right\|^2}{2\sigma^2} \right) \tag{6}$$

2) *Particle Swarm Optimization*

PSO is widely used to optimize the parameters in SVM algorithm. PSO is developed from artificial life and evolutionary theory. In this algorithm, particles are composed of cells called position and a particle in the swarm represents a potential solution**Error! Reference source not found.**. Assuming searching in a n dimension space, a swarm is formed by m particles, then the ith particle can be described as $X_k^i = (x_1^i, x_2^i, \ldots x_n^i), \mathbf{i}=1,\ldots \mathrm{m}$, X_k^i is also called its position. According to objective function $\mathrm{f}(X_i)$, the adaptability value f_k^i can be calculated. The flying velocity of ith particle is defined as $V_k^i = (v_1^i, v_2^i, \ldots v_n^i)$, the optimal position searched by the ith particle currently is $P_k^i = (p_1^i, p_2^i, \ldots p_n^i)$, the optimal position searched by the whole swarm is $P_k^g = (p_1^g, v_2^g, \ldots v_n^g)$. In the PSO algorithm, a swarm is randomly generated and each particle is given a randomly velocity, then the following iterations are used to update the velocity and position of every particle:

$$V_{k+1}^i = w_k V_k^i + c_1 \phi_1 \left(P_k^i - X_k^i \right) + c_2 \phi_2 \left(P_k^g - X_k^i \right) \tag{7}$$

$$X_{k+1}^i = X_k^i + V_{k+1}^i \tag{8}$$

where $w_k \geq 0$ is inertia factor, C_1 and C_2 is learning factor, usually $c_1 = c_2 = 2$, $\phi_1, \phi_2 \in [0,1]$, is random number.

III. EXPERIMENTAL STUDY

A. *Experimental setup*

The experimental scheme as shown in Figure4 is the milling tool wear test jointly implemented by UC Berkeley and NASA, and the six sensor signals are collected from the Matsuura machining center MC-510V.

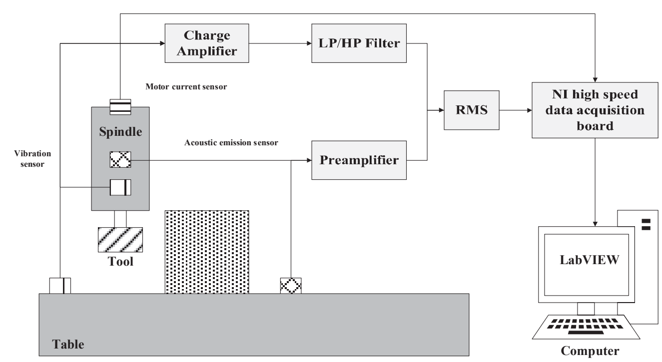

Figure 4. Experimental setup.

The experiments were done a second time with the same parameters with a second set of inserts. The experimental conditions of cases to be discussed were set in Table III below. It shows fours cases with different depth of cut, feed, and processing time. Case A1, A2 and Case B1, B2 represent two different working conditions.

TABLE III. EXPERIMENTAL CONDITIONS

Case	Depth of cut(mm)	Feed(mm/rev)	Time(min)	Material

A1	0.75	0.25	45	steel
A2	0.75	0.25	19	steel
B1	0.75	0.5	24	steel
B2	0.75	0.5	12	steel

B. *Sensor signal collection and preprocessing*

We first analyzed the data from case A1, and adopted the strategy consist of feature extraction and feature fusion to other cases. Then same strategy was used with the data from A2 to verify the model. As for B1 and B2, the signals were considered as the online data and was dealt with the verified strategy and model.

The signal from case A1 was acquired and shown as Figure 5. It illustrated three machining tool states for each sensor. As we can see in Figure 5, at the sampling points 0~700, the machining tool even did not contact with workpieces, was idle phase. At the sampling points 700~4500, the machining tool started to contact with workpieces, was contact phase. At the sample points 4500~9000, the machining tool had contacted with workpieces completely, was stable phase. Therefore, the signals at Sampling points of stable phase was selected to be discussed.

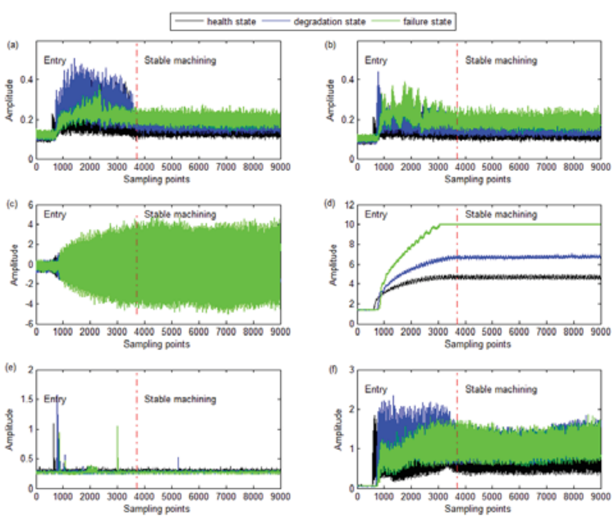

Figure 5. Signals of one running sample for six sensors: (a) Acoustic emission sensor on spindle, (b) Acoustic emission sensor on table, (c) AC Spindle motor current sensor, (d) DC Spindle motor current sensor, (e) Vibration sensor on spindle, (f) Vibration sensor on table.

The null value was removed and replaced by MV from the signal for the preliminary processing. Then the singular value is removed from the data by three sigma theorem.

IV. USING THE TEMPLATE

Statistic features extraction from time domain are depicted in Figure 6, then the features with appropriate trend will be selected by PCC. The features with thick line behaved a rising trend gradually. The statistic features from acoustic emission sensor on table contain more useful information. Similarly in Figure 7, features from frequency domain by power spectrum are shown.

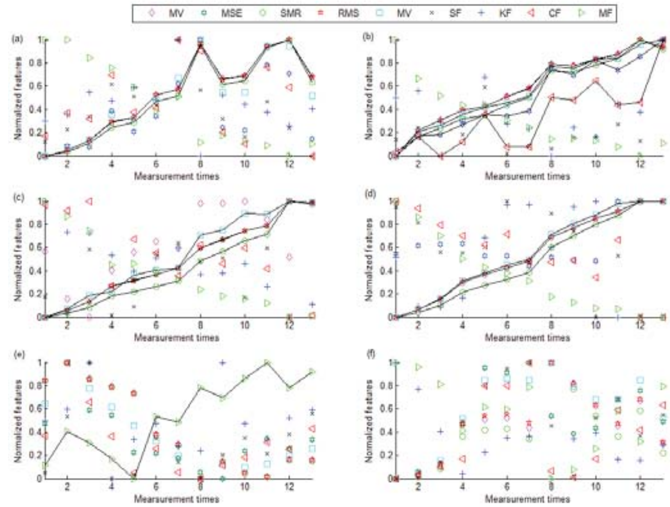

Figure 6. Features in time domain for six sensors.

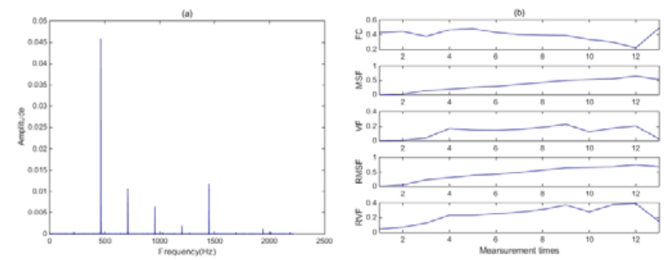

Figure 7. (a) Power spectrum for Vibration sensor on table ,(b) features from frequency domain by power spectrum.

In time-frequency domain, for each sensor, we obtained 11 IMFs by CEEMDAN algorithm. Figure 8(a) shows the waveform of IMFs decomposed by CEEMDAN for the acoustic emission sensor on Figure 8(b) shows the energy features(EF) of IMFs Correspondingly.

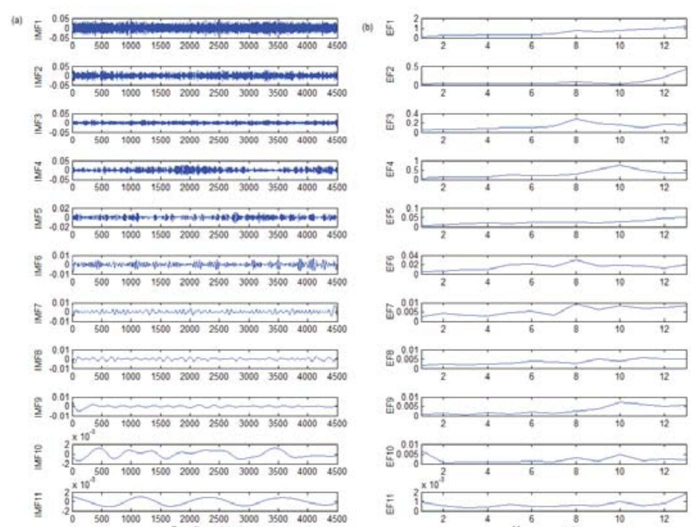

Figure 8. (a)Waveform of IMFs based on CEEMDAN for the acoustic emission sensor on table, (b) Energy features of IMFs for the acoustic emission sensor on table.

For the features extracted from each sensor, nine are from time domain, and eleven are from time-frequency domain. In addition, ten features were extracted by power spectrum from two vibration sensors. Next, a total of 130 features were preliminarily selected by Pearson correlation coefficient analysis. we kept the features with the correlation coefficient more than 0.8, which means a strong correlation with tool flank wear. 30 features were retained, and the specific features after PCC analysis is shown in Figure 9.

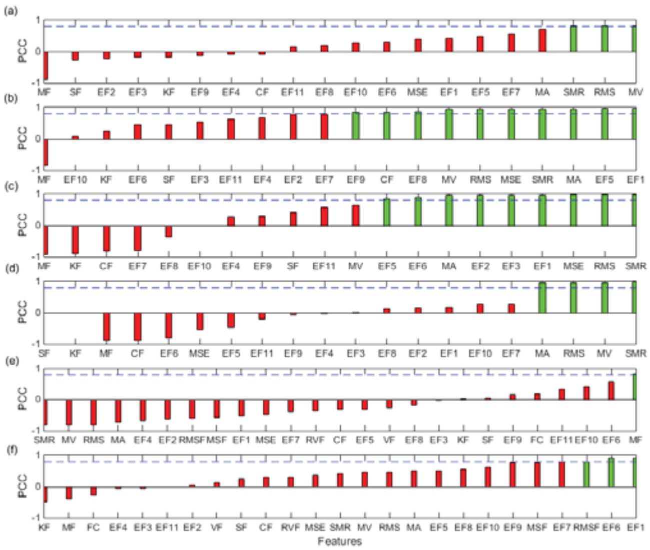

Figure 9. Pearson correlation coefficient analysis for six sensors.

To fuse the 30 features, the MQE indicator was calculated by GSOM algorithm. GSOM fused the training data from Case A1 and Case B1. As shown in Figure 10, MQE has a similar trend with tool flank wear. Thus, it is a good indicator to classify the heath condition of Machining tool even with different GSOM structures.

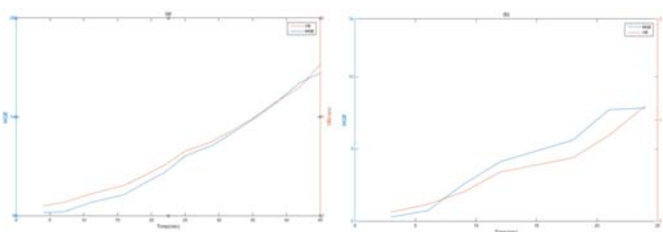

Figure 10. MQE value compared to tool flank wear (a) caseA1 (b) case B1.

According to the standard parameters of milling machine, the tool state is divided into three types by the tool wear: health state(tool flank wear less than 0.2 mm) , degradation state(tool flank wear more than 0.2 mm and less than 0.7 mm) ,failure state(tool flank wear more than 0.7mm). The PSO-SVM classifier was trained and optimized respectively by the data from Case A1 and Case B1. Then the online data from Case A2 and Case B2 was processed and input to the classifier to identify the condition of machining tool. The classification results are shown in Figure 11. It is indicated a perfect performance on online health monitoring. To prove the feasibility and superiority of proposed methodology, other machine learning algorithms were applied to this experimental cases. ANFIS algorithm have been verified to effectively recognize and predict the condition of machining tool. In addition, BP algorithm is the most widely used neural network. Table IV shows the classification precision of each method applied to these cases. Furthermore, the dimension of selected features after PCC analysis was different from Case A1 to Case B1, and only GSOM algorithm can deal with the variable features while the features are fixed in other algorithms.

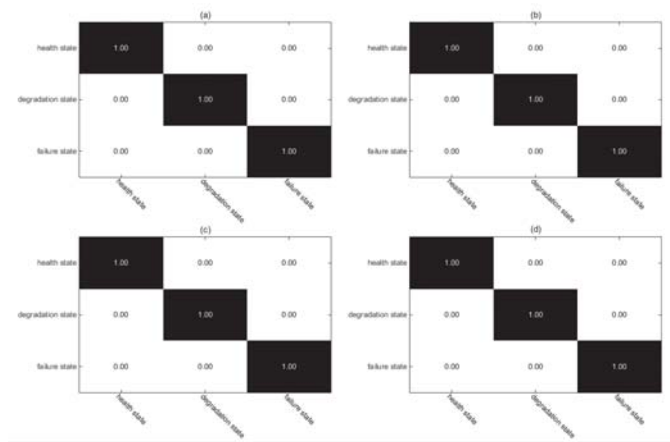

Figure 11. Classification results of PSO-SVM (a) Case A1 for training,(b) Case A2 for testing,(c) Case B1 for training,(d) Case B2 for testing.

TABLE IV. TABLE TYPE STYLES

Method	**Classification precision (%)**			
	Case A1	***Case A2***	***Case B1***	***Case B2***
Proposed method	100.00	100.00	100.00	100.00
ANFIS	84.60	85.71	85.71	80.00
BP	84.60	85.71	85.71	80.00

V. CONCLUSIONS

In this paper, a new methodology for structural health monitoring has been proposed. We can conclude the main findings of this paper as follows.

(1) Selecting crucial features by Pearson correlation coefficient analysis to avoid the problem of dimensionality, using the GSOM to fuse the crucial features to get the MQE, which is proved to have a similar trend with tool flank wear.

(2) On the basis of MQE, the state of machining tool is identified by PSO-SVM with the RBF kernel. The experimental results verify the effectiveness and feasibility of the proposed methodology, as well as the superiority to ANFIS and BP method.

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