An intelligent pattern recognition algorithm and its application in cutting tool condition monitoring process

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Abstract

An intelligent tool wear monitoring system for metal cutting process will be introduced in this paper. The system is equipped with four kinds of sensors, signal transforming and collecting apparatus and a micro computer. A knowledge based intelligent pattern recognition algorithm has been developed. The fuzzy driven neural network can carry out the integration and fusion of multi-sensor information. The weighted approaching degree can measure the difference of signal features accurately and ANNs successfully recognize the tool wear states. The algorithm has strong learning and noise suppression ability. This leads to successful tool wear classification under a range of machining conditions.

Keywords

Condition monitoring, feature extraction, fuzzy logic, neural network, pattern recognition, sensor fusion

1 INTRODUCTION

Metal cutting operations constitute a large percentage of the manufacturing activity. One of the most important objective of metal cutting research is to develop techniques that enable optimal utilization of machine tools, improved production efficiency, high machining accuracy and reduced machine downtime and tooling costs. Tool condition monitoring is certainly the important monitoring requirement of unintended machining operations. Such a monitoring system can be realized by the efforts and progresses in the following research issues: the selection of suitable sensors and data acquisition system to collect healthy signals from the machining process; the development and selection of appropriate signal features that are

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sensitive to tool wear and insensitive to experimental noise; the development of signal classification procedures for reliable identification of tool wear states.

Many tool wear sensing methods have been suggested, but only some of these are suitable for industrial application. It was found that both the normal cutting force coefficient and the friction coefficient can be well represented as functions of tool wear (Lin and Yang, 1995). Experiments showed that the axial feed force is influenced much more by tool wear than the tangential cutting force (Rutelli and Cuppini, 1988; Yie and Zhang, 1990). Some characteristic parameters such as the derivative of force wave form, power and auto-correlation coefficient of force signals were also found to reflect tool wear (Lister and Barrow, 1986). Diei and Dornfeld (1987) found that acoustic emission (AE) root mean square (RMS) showed an increasing trend with the growth of flank wear. The spectra of AE signals were also used to detect tool wear and breakage. The results showed progressive tool wear to be associated with increasing AE power within the 400-700 kHz range (Giusti and Santochi, 1984; Uehara, 1973). In turning operations, a mathematical formula was established to show the relationship between spindle motor current and tool flank wear (Liao, 1986). Spectral cascades in the lower frequency range 0-1kHz of vibration signal were used to identify the various stages of tool wear (Jiang and Zhang, 1987). It was also found that the total amount of vibration energy in the frequency range of 4-8 kHz increased as the tool wear increased (Taglia and Fortunato, 1976).

It has been widely accepted now that under varying machining conditions, the information required to make reliable decisions on the tool wear state can hardly be available by using single sensor information. Sensor fusion is attractive since loss of sensitivity of one of the sensors can be compensated by other sensors. Grieshaber et al (1987) designed a discriminate function technique to combine force signal with acoustic emission information to monitor cutting tool condition. S. Rangwala et al (1987) proved neural networks to be suitable for integrating information from acoustic emission and cutting force sensors to predict tool wear in turning operation. The sensor signal patterns and the tool wear states were successfully associated. Choi et al (1990) developed a neural network-based real-time tool wear monitoring system. P.G.Li et al (1988) used fuzzy pattern recognition algorithm to monitor drilling tool wear. The thrust and torque are selected as the features relevant to drill wear and the relationship between these features and drill wear was found from fuzzy manipulation.

In this study, a fuzzy driven neural network based pattern recognition algorithm was developed to accomplish multi-sensor information integration and tool wear states classification. By imitating the thinking and judging modes of human being, the technique shows some remarkable characteristics. Definite mathematical relations between tool wear states and sensor information are not necessarily needed. The effects caused by experimental noise can also be decreased greatly. The established monitoring system provided accurate and reliable tool wear classification results over a range of cutting conditions.

2 TOOL CONDITION MONITORING SYSTEM

The tool wear monitoring system is composed of four types of sensors, signal amplifying and collecting devices and the main computer, as shown in figure.1.

Fig.1 The tool condition monitoring system

3 FUZZY NEURAL NETWORK BASED PATTERN RECOGNITION

Tool condition monitoring is a pattern recognition process in which the characteristics of the tool to be monitored are compared with those of the standard models. A fuzzy neural network based pattern recognition algorithm has been developed from this study. The tool wear classification process is composed of the following parts: feature extraction, determination of the membership functions, calculation of the fuzzy similarity, learning and tool wear classification.

4 FEATURE EXTRACTION

Features extracted from the time domain and frequency domain for the further pattern recognition are as follows. Power consumption signal : mean value; AE-RMS signal: mean value, skew and kurtosis; Cutting force, AE and vibration : mean value, standard deviation and the mean power in 10 frequency ranges. As an example, figure.2 shows several features in time and frequency domain (under cutting condition 1*). It can be seen that both the amplitude and the distribution pattern can represent the development of tool flank wear (VB).

(a) Mean value of the power consumption signal

(b) Standard deviation of the vibration signal

(c) Spectra of the AE signal

(d) Spectra of cutting force (F_x) signal

Fig.2 Some sensor signal features

5 MEMBERSHIP FUNCTIONS OF THE FEATURES

The features of sensor signals can reflect the tool wear states. For the standard models (cutting tool with standard flank wear values), the j -th feature of the i -th model can be considered as a fuzzy set A_{ij} . Theoretical analysis and experimental results show that these features can be regarded as modified normal distribution fuzzy sets. The membership function of the fuzzy set A_{ij} can be represented as:

$$\begin{aligned}
 A_{ij}(x) &= 1 - \frac{1}{2\sigma_{ij}^2}(x - a_{ij})^2 & a_{ij} - \sqrt{2}\sigma_{ij} < x < a_{ij} \\
 &= 1 & a_{ij} \leq x \leq b_{ij} \\
 &= 1 - \frac{1}{2\sigma_{ij}^2}(x - b_{ij})^2 & b_{ij} < x < b_{ij} + \sqrt{2}\sigma_{ij} \\
 &= 0 & \text{for other values of } X
 \end{aligned} \tag{1}$$

where a is the mean value and σ is the standard deviation. In order to determine the values of the coefficients in the formula, several groups of inserts possessing

standard wear values were used in milling operations. K groups of specimens were drawn for the j-th feature, then for each group the mean value $\bar{x}_{ijt}$ and the standard deviation σ_{ijt} can be calculated ($t=1,2,\dots,k$). So a_{ij} and b_{ij} can be set as the maximum and minimum values of $\bar{x}_{ijt}$ and σ_{ijt}^2 can take the mean value of σ_{ijt}^2 . For a certain group of inserts with unknown wear value, its j-th feature can also be regarded as a normal distribution fuzzy set. It has the following membership function:

$$B_j(x) = 1 - \frac{(x - x_j)^2}{2\sigma_j^2} \quad x_j - \sqrt{2}\sigma_j \leq x \leq x_j + \sqrt{2}\sigma_j \quad (2)$$

$$= 0 \quad \text{for all others}$$

6 THE SIMILARITY OF FUZZY SETS

Fuzzy approaching degree and fuzzy distance can be used as the quantitative indexes to represent the similarity of two fuzzy sets (A and B).

6.1 Approaching degree

Assume that $\mathcal{F}(X)$ is the fuzzy power set of a universal set X and the map, $N: \mathcal{F}(X) \times \mathcal{F}(X) \rightarrow [0,1]$ satisfies: (a). $\forall A \in \mathcal{F}(X)$, $N(A, A) = 1$; (b). $\forall A, B \in \mathcal{F}(X)$, $N(A, B) = N(B, A)$; (c). if $A, B, C \in \mathcal{F}(X)$ satisfies $|A(x) - C(x)| \geq |A(x) - B(x)|$ ($\forall x \in X$) then $N(A, C) \leq N(A, B)$. So the map N is the approaching degree in $\mathcal{F}(X)$ and $N(A, B)$ is called the approaching degree of A and B. It can be calculated by using different methods. Here the inner and outer products are used. Assume that $A, B \in \mathcal{F}(X)$, so $A \bullet B = \vee \{A(x) \wedge B(x): x \in X\}$ is defined as the inner product of A and B and $A \oplus B = \wedge \{A(x) \vee B(x): x \in X\}$ is defined as the outer product of A and B. Finally, in the map $N: \mathcal{F}(X) \times \mathcal{F}(X) \rightarrow [0, 1]$, $N(A, B)$ is the approaching degree of A and B.

$$N(A, B) = (A \bullet B) \wedge (A \oplus B)^c \quad (3)$$

6.2 Fuzzy distance

If $A \in \mathcal{F}(X)$, when $X = \{x_1, x_2, \dots, x_n\}$, the membership value of $A((A(x_1), A(x_2), \dots, A(x_n)))$ can be explained as the points in the n-

dimensional Euclidean space. So the distance between two fuzzy sets can be defined like what the distance in Euclidean space is defined. When $X = [a, b]$, $A(x)$ is a limited function on $[a, b]$, the distance between two fuzzy sets can be defined as following:

Suppose $M_p : \mathcal{F}(X) \times \mathcal{F}(X) \rightarrow [0, +\infty)$ (p is a positive real number)

$\forall (A, B) \in \mathcal{F}(X) \times \mathcal{F}(X)$, when $X = \{x_1, x_2, \dots, x_n\}$,

$$M_p(A, B) = \left[\sum_{i=1}^n |A(x_i) - B(x_i)|^p \right]^{1/p} \quad (4)$$

when $X = [a, b]$,

$$M_p(A, B) = \left[\int_a^b |A(x) - B(x)|^p dx \right]^{1/p} \quad (5)$$

M_p is fuzzy distance on $\mathcal{F}(X)$, $M_p(A, B)$ is the fuzzy distance between fuzzy set A and B . In general situation, p can take the value of 1.

6.3 Two dimensional weighted approaching degree

In the conventional fuzzy pattern recognition process, the approaching degree or fuzzy distance between corresponding features of the object to be recognized and different models are first calculated. Combining these results can determine the fuzzy similarity between the object and different models. The object should be classified to one of the models that has the highest approaching degree or shortest fuzzy distance with it. Because most features have vague boundaries so using fuzzy membership function to represent their characteristics and fuzzy distance to describe the similarity of corresponding features are quite appropriate. Fuzzy pattern recognition techniques are thus quite reliable and robust. They can be further improved by developing a method that can assign suitable weights to different features to reflect their specific influences in the pattern recognition process. The two fuzzy similarity measures can also be combined to describe the closeness of fuzzy sets more comprehensively.

Approaching degree and fuzzy distance reflects the closeness of two fuzzy sets from different angles. For two intersecting membership function, approaching degree reflects the geometric position of the intersecting point and the fuzzy distance shows the area of the intersecting space. Approaching degree and fuzzy distance between different sensor signal features also have changing importance in the practical pattern recognition process. In this study, artificial neural networks (ANNs) is employed to integrate approaching degree and fuzzy distance and assign them with suitable weights to provide a two dimensional weighted approaching degree. This makes more accurate and reliable tool wear classification possible.

7 FUZZY DRIVEN NEURAL NETWORK

ANNs has the ability to classify inputs. The weights between neurons are adjusted automatically in the learning process to minimize the difference between the desired and actual outputs. ANNs can continuously classify and also update classifications. In this study, ANNs is connected with fuzzy logic system to establish a fuzzy driven neural network pattern recognition algorithm. Its principle is shown in the following figure.

Fig.3 The fuzzy driven neural network

Here a back propagation ANN is used to carry out multi-sensor information integration and tool wear classification. The approaching degree and fuzzy distance calculation results are the input of the ANNs. The associated weights can be updated as: $w_i(new) = w_i(old) + \alpha \delta x_i$. Here α , δ , x_i are learning constant, associated error measure and input to the i-th neuron. In this updating process, the ANN recognizes the patterns of the features corresponding to certain tool wear state. So in practical machining process, the feature pattern can be accurately classified to that of one of the models. In fact ANNs combine approaching degree and fuzzy distance and assign each feature a proper synthesized weight and the output of the ANNs are two dimensional weighted approaching degrees. This enables the classification process be more reliable.

8 LEARNING PROCESS

Six standard tool wear values were selected as the models for the future pattern recognition, ranging from new to severe wear where the width of the flank wear area increased from 0 to 0.5 mm in steps of 0.1 mm. Three standard flank wear

value, 0, 0.2 mm and 0.5 mm are used to represent new tool, normal tool and worn tool. For each tool with the standard wear value, the membership functions of all its features can be calculated and then stored in a library in the computer. The training process of the ANNs is as the following: first, for every model, 10 groups of sensor signals are collected from the practical machining process. So 10 groups of membership functions of all the features for each model can be determined. These are called sub-membership functions. They can be considered as sub-models of each model having the same standard tool wear values. Then the approaching degree and fuzzy distance between the corresponding features of these sub-models and six models are calculated. The results can be used as the training inputs of the ANNs. The ANNs then integrate the input and provide the two dimensional weighted approaching degree. The training targets can be determined like this: the weighted approaching degree between each model and its own sub-models should be 1 and the value between a model and other model's sub-models can be calculated by decreasing the value from 1 to zero linearly according to the difference of the actual tool wear value. After the training the constructed frame and associated weights of the ANNs can reflect the distinct importance of each individual feature for each model under specific cutting conditions. So the future tool wear classification results can be reliable and accurate. The determination of the membership functions of all the features for each model and the construction of ANNs for classification mark the end of the learning stage.

9 TOOL WEAR CLASSIFICATION

In the practical tool condition monitoring process, the tool with unknown wear value is the object and it will be recognized as “new tool”, “normal tool” or “worn tool”. The membership functions of all the features of the object can be determined first. The approaching degree and fuzzy distance of the corresponding features of the standard model and the object to be recognized can then be calculated and become the inquiry input of the ANNs. One of a pre-trained ANNs is then chosen to calculate the two dimensional weighted approaching degree. Finally the tool wear state should be classified to the model that has the highest weighted approaching degree with the tool being monitored.

In a verifying experiment, fifteen tools with unknown flank wear value were used in milling operations. Figure.4 shows the classification results under cutting condition 1*. It can be seen that all the tools were classified correctly with the confidence of higher than 80%. Experiments under other cutting conditions showed the similar results.

10 CONCLUSIONS

An intelligent tool condition monitoring system has been established. Tool wear classification is realized by applying fuzzy driven neural network based pattern recognition algorithm. On the basis of this investigation, the following conclusions can be made.

- (1) Power consumption, vibration, AE and cutting force sensors are applicable for monitoring tool wear in metal cutting process. The healthy signals picked up by these sensors describe tool condition comprehensively.
- (2) Many features extracted from time and frequency domains are found to be relevant to the changes of tool wear state. This makes accurate and reliable pattern recognition possible.
- (3) The combination of ANN and fuzzy logic system integrates the strong learning and classification ability of the former and the superb flexibility of the latter to express the distribution characteristics of signal features with vague boundaries. This methodology indirectly solves the weight assignment problem of the conventional fuzzy pattern recognition system and let it have greater representative power, higher training speed and be more robust.
- (4) The introduction of the two dimensional weighted approaching degree can make the pattern recognition process more reliable. The fuzzy driven neural network effectively fuses multi-sensor information and successfully recognizes the tool wear states.
- (5) Armed with the advanced pattern recognition methodology, the established intelligent tool condition monitoring system has the advantages of being suitable for different machining conditions, robust to noise and tolerant to faults.
- (6) Future work should be focused on developing data processing methods that produce feature vectors which describe tool condition more accurately, improving the fuzzy distances calculation methods and optimizing the ANNs structure.

* Cutting condition 1(for milling operation): cutting speed - 600 rev/min, feed rate - 1 mm/rev, cutting depth - 0.6 mm, workpiece material - EN1A, cutting inserts - Stellram SDHT1204 AE TN-42.

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