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A Hybrid Pattern Recognition Architecture for Cutting Tool Condition Monitoring

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1. Introduction

One of the important developments in modern manufacturing industry has been the trend towards cost savings through staff reductions whilst simultaneously improving the product quality. Traditional tool change strategies are based on very conservative estimates of tool life from past tool data and this leads to a higher tool change frequency and higher production costs. Intelligent sensor based manufacturing provides a solution to this problem by coupling various transducers with intelligent data processing techniques to deliver improved information relating to tool condition. This makes optimization and control of the machining process possible.

Many researchers have published results in the area of automatic tool condition monitoring. The research work of Scheffer C. etc. showed that proper features for a wear monitoring model could be generated from the cutting force signal, after investigating numerous features. An approach was developed to use feed force measurements to obtain information about tool wear in lathe turning (Balazinski M. etc.). An analytical method was developed for the use of three mutually perpendicular components of the cutting forces and vibration signature measurements (Dimla D. E. etc.). A tool condition monitoring system was then established for cutting tool-state classification (Dimla D. E. etc.). In another study, the input features were derived from measurements of acoustic emission during machining and topography of the machined surfaces (Wilkinson P. Etc.). Li, X etc. showed that the frequency distribution of vibration changes as the tool wears (Li X. etc.). Tool breakage and wear conditions were monitored in real time according to the measured spindle and feed motor currents, respectively (LI X. L. Etc.).

Advanced signal processing techniques and artificial intelligence play a key role in the development of tool condition monitoring systems. Sensor fusion is also found attractive since loss of sensitivity of one of the sensors can be compensated by other sensors. A new on-line fuzzy neural network (FNN) model with four parts was developed (Chungchoo C. etc.). They have the functions of classifying tool wear by using fuzzy logic; normalizing the inputs; using modified least-square back propagation neural network to estimate flank and crater wear. A new approach for online and indirect tool wear estimation in turning using neural networks was developed, using a physical process model describing the influence of cutting conditions on measured process parameters (Sick B.). Two methods using Hidden

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Markov models, as well as several other methods that directly use force and power data were used to establish the health of a drilling tool (Ertunc H. M.).

In this study, a new fuzzy neural hybrid pattern recognition algorithm was developed to accomplish multi-sensor information integration and tool wear states classification. The technique shows some remarkable characteristics by imitating the thinking and judging modes of human being. It has shown that definite mathematical relationships between tool wear states and sensor information are not necessarily needed and that the effects caused by experimental noise can also be decreased greatly. The monitoring system that has been developed 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 Fig. 1. The power consumption, cutting force (in three perpendicular directions), acoustic emission (AE) and vibration sensors chosen were found to provide healthy time domain signals for tool condition monitoring.

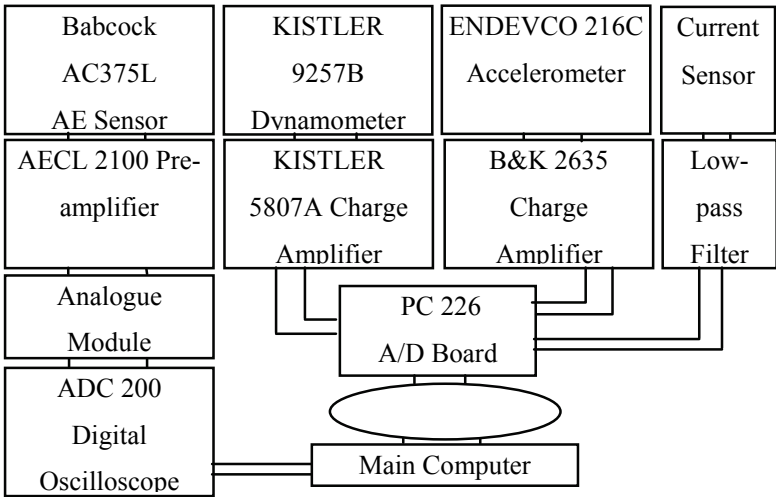
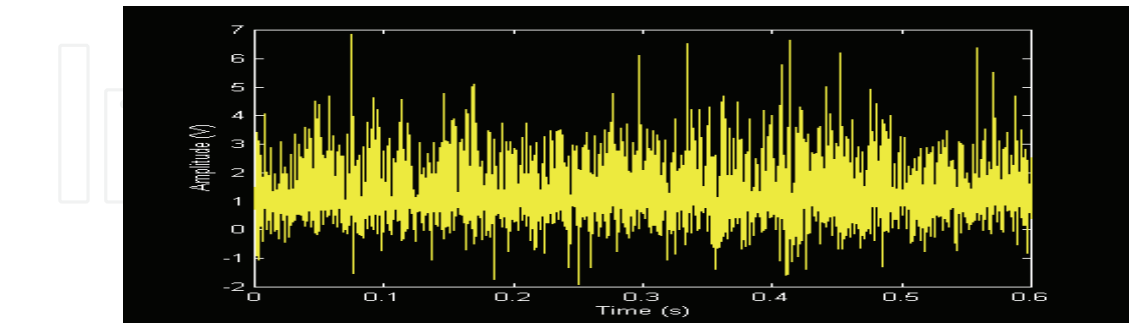


Fig. 1. The tool condition monitoring system

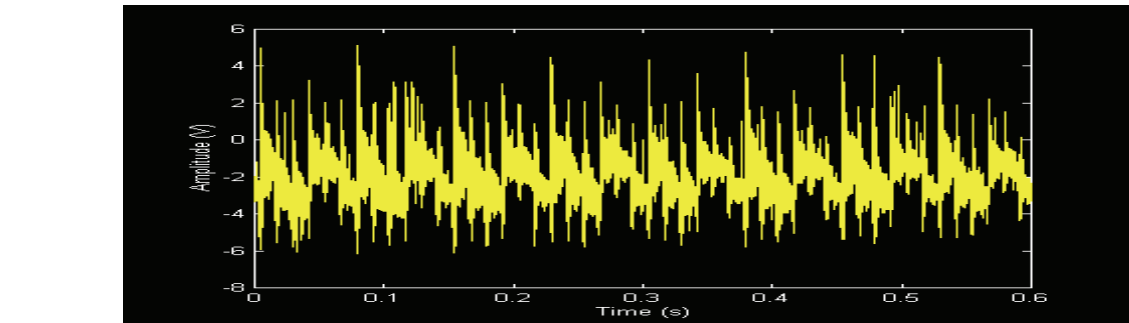
The experiments were carried out on a Cincinnati Milacron Sabre 500 machining centre. Like many other modern machine tools, it delivers a motor current signal that is proportional too torque, which at a constant spindle speed, corresponds to the actual power consumption. A KISTLER 9257B force dynamometer was used to measure cutting forces in three mutually perpendicular directions. The dynamometer has a measuring range of 5000 (N) in each direction, linearity of 1%, stiffness of 350 N/μm in the Z direction and 1000N/μm in the X and Y directions and a resonant frequency of 4kHz.

The acoustic emission (AE) measuring apparatus includes an AE sensor and a signal processing device. The AE sensor has a measuring frequency range of 100KHz - 2MHz. The 60dB pre-amplifier connects the AE sensor to the AE output instrument and has a 113KHz - 1.1 MHz built-in filter. An analogue module receives the input from the pre-amplifier and provides outputs of both amplified AE analogue signals and AE RMS signals. An accelerometer was mounted in the feed direction. The sensor has a frequency response of 5 - 33 kHz, mounted resonant frequency 50 kHz. Fig.2 shows the power consumption, cutting

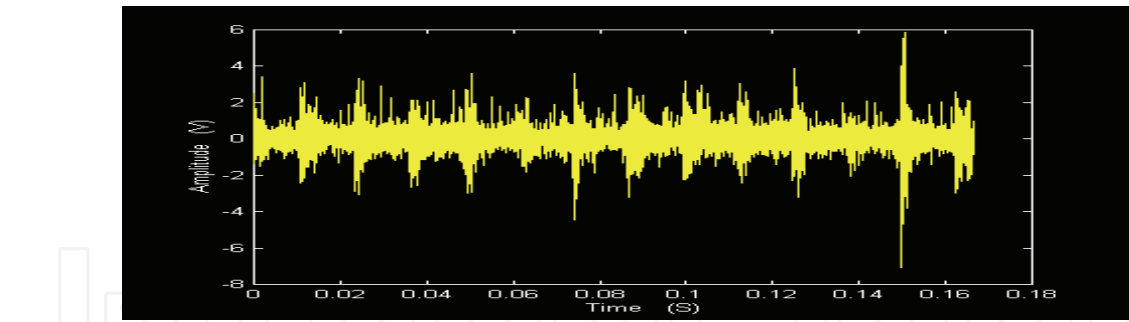
force (in the cutting direction), vibration and acoustic emission signals collected in milling process. The entry and exit of an insert in relation to the workpiece can be easily recognized. From those healthy signals many tool wear relevant features can be extracted for the future pattern recognition process.



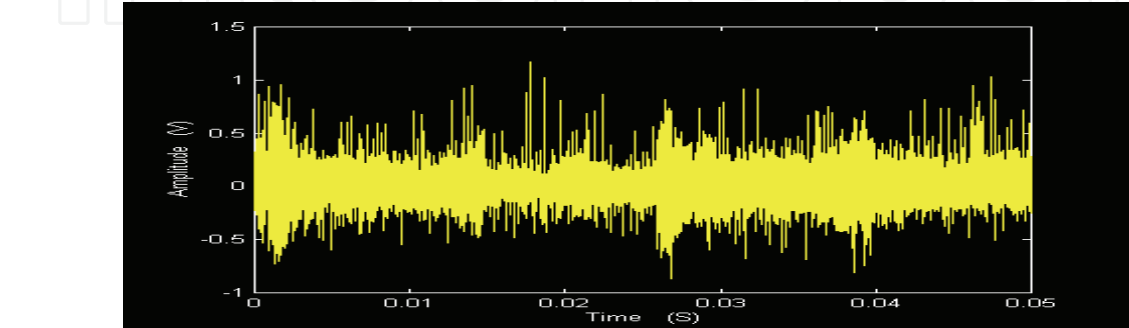
(a)The power consumption signal



(b)The cutting force signal



(c)The vibration signal



(d)The Acoustic emission signal

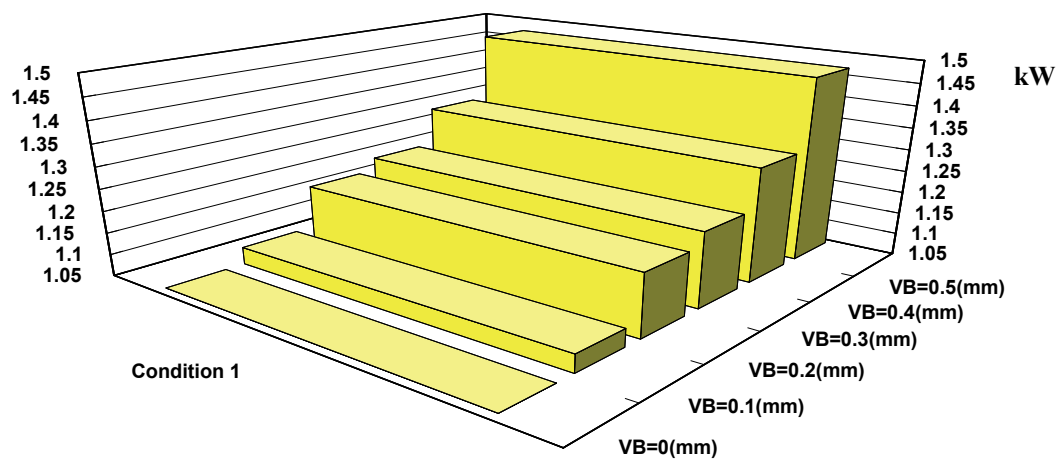
Fig. 2. Tool condition monitoring sensor signals

3. Feature extraction

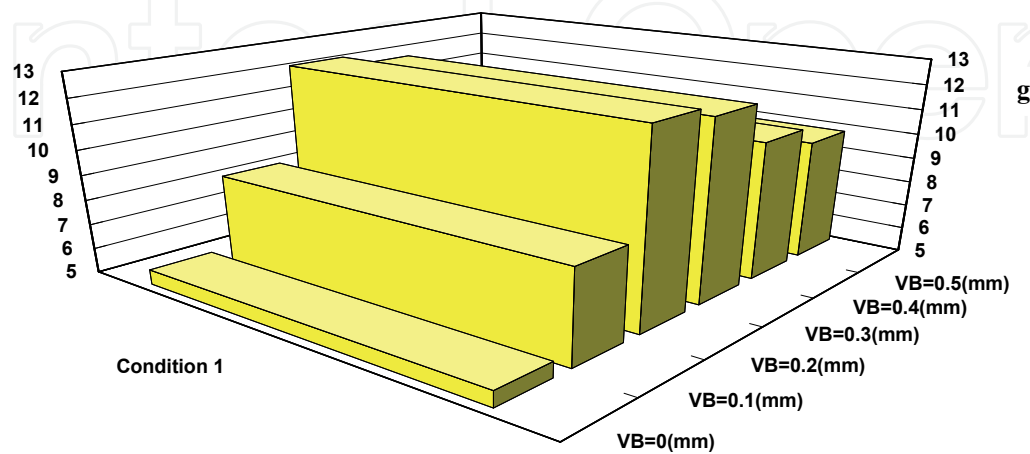
The original signals have large dimensions and can not be directly used to estimate tool wear value. The purpose of feature extraction is to greatly reduce the dimension of the raw signal but at the same time maintain the tool condition relevant information in the extracted features. This step is the foundation for the pattern recognition process.

In the time domain the mean value and the standard deviation are simple but effective features. Power spectrum density (PSD) analysis in the frequency domain can provide very useful information and experimental results show that for force, AE and vibration signals, the spectrum distribution changes with tool wear.

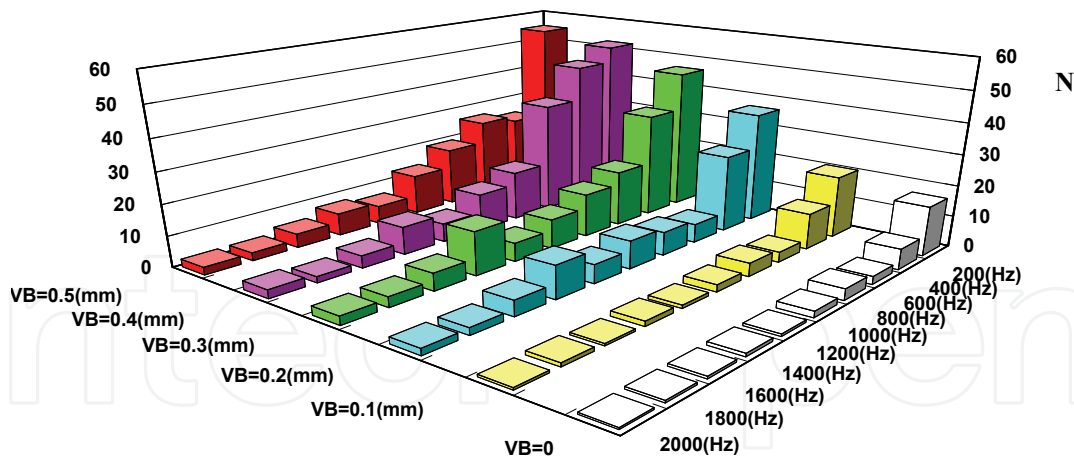
A typical group of features extracted from the time domain and frequency domain for the further pattern recognition are as follows. Power consumption signal: mean value; AE-RMS signal: mean value, skew and kurtosis; Cutting force, AE and vibration : mean value, standard deviation and the mean power in 10 frequency ranges. Fig. 3 shows several features (under cutting condition 1*) in time and frequency doorman. It can be seen that both the amplitude and the distribution pattern represent the development of tool flank wear (VB).



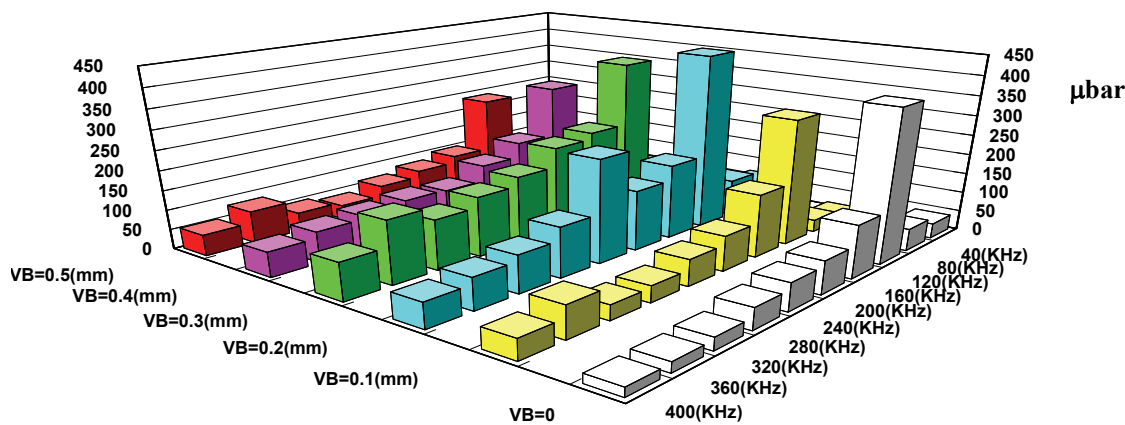
(a) Mean value of the power consumption signal



(b) Standard deviation of the vibration signal



(c)Frequency spectra of cutting force (F_x) signal



(d) Frequency spectra of the AE signal

Fig. 3. Features extracted from different sensor signals

4. Fuzzy driven neural network

4.1 Fuzzy membership function

The features of sensor signals can reflect the tool wear states. Theoretical analysis and experimental results show that these features can be regarded as normal distribution fuzzy sets. The membership function of the fuzzy set A_i can be represented as:

$$A_i(x) = 1 - \frac{(x - a_i)^2}{2\sigma_i^2} \quad a_i - \sqrt{2}\sigma_i \leq x \leq a_i + \sqrt{2}\sigma_i$$
$$= 0, \quad \text{for all others} \tag{1}$$

where a and σ are mean value and standard deviation.

4.2 Fuzzy approaching degree

Fuzzy approaching degree is an index that represents the fuzzy distance between two fuzzy sets (A and B). Assume that $\mathfrak{Z}(X)$ is the fuzzy power set of a universal set X and the map,

$N: \mathfrak{F}(X) \times \mathfrak{F}(X) \rightarrow [0,1]$ satisfies: (1). $\forall A \in \mathfrak{F}(X), N(A, A) = 1$ (2). $\forall A, B \in \mathfrak{F}(X), N(A, B) = N(B, A)$ (3). If $A, B, C \in \mathfrak{F}(X)$ satisfies $|A(x) - C(x)| \geq |A(x) - B(x)| \quad (\forall x \in X)$ then $N(A, C) \leq N(A, B)$, so the map N is the approaching degree in $\mathfrak{F}(X)$ and $N(A, B)$ is called the approaching degree of A and B . Approaching degree can be calculated by using different methods. Here the inner and outer products are used.

If $A, B \in \mathfrak{F}(X), A \bullet B = \bigvee \{A(x) \wedge B(x) : x \in X\}$ is defined as the inner product of A and B and $A \oplus B = \bigwedge \{A(x) \vee B(x) : x \in X\}$ is defined as the outer product of A and B . Finally, in the map $N: \mathfrak{F}(X) \times \mathfrak{F}(X) \rightarrow [0, 1], N(A, B)$ is the approaching degree of A and B .

$$N(A, B) = (A \bullet B) \wedge (A \oplus B)^c \quad (2)$$

Using conventional fuzzy pattern recognition methods, the fuzzy approaching degrees between corresponding features of the object to be recognized and different models are calculated to determine the fuzzy similarity between a given object and different models. The method can be further improved by assigning suitable weights to different features in order to reflect their specific influences in the pattern recognition process. ANNs have the ability to continuously classify the inputs and also update classifications. In this study, ANNs are connected with a fuzzy logic system to establish a fuzzy driven neural network pattern recognition system and its principle is shown by Fig. 4.

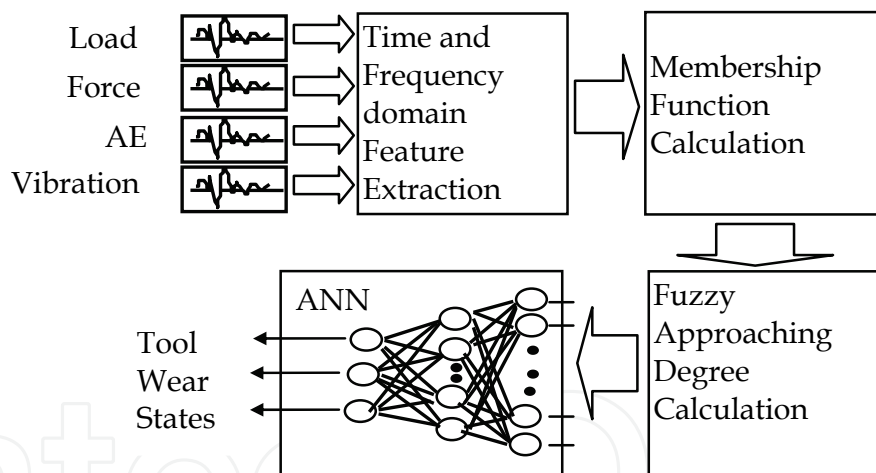


Fig. 4. The fuzzy driven neural network

Here a back propagation ANN is used to carry out tool wear classification. The approaching degree calculation results are the input of the ANN. 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. In fact the ANN assigns each feature a proper synthesized weight and the outputs of the ANN are weighted approaching degrees. This enables the tool wear classification process be more reliable.

Altogether six standard tool wear values were selected as standard wear values, 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. Cutting tools with standard wear values are used in milling operations and multi-channel sensor signals were collected. So, for all the models, the membership functions of all their features can be calculated and then stored in a library in the computer. ANNs can then be trained to recognize different tool wear states, under each specific cutting condition.

After the training the constructed frame and associated weights of the ANN can reflect the distinct importance of each individual feature for each model under specific cutting conditions. These feature weights will change, under different cutting conditions, to truly represent the practical situation. 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.

5. Algebraic neurofuzzy networks

A neural fuzzy system has both the transparent representation of a fuzzy system and the learning ability of neural networks. It processes information using fuzzy reasoning techniques, but it can be trained using neural type learning algorithms because it also has a multi-layer ANN structure. The combination of the rule based representation and adaptive numeric processing can lead to a robust modeling system. Various applications of fuzzy neural integrated systems may be cited (Blanz W. E. etc.) (Brown M. etc.) (Fukuda T. etc.). Many neurofuzzy systems use B-spline or Gaussian basis functions (Brown etc.). Gaussian representation is potentially more flexible, but it is harder to generate appropriate fuzzy algorithms. Adaptive B-spline based neurofuzzy system uses algebraic operators and B-spline fuzzy membership functions to simplify the overall system, produces more transparent models. It is also possible to use learning algorithms to extract neurofuzzy models directly from the input data.

5.1 B-spline fuzzy sets

As mentioned before, signal features can be treated as fuzzy sets, which can then be represented by fuzzy membership functions. Here, B-spline basis functions, piecewise polynomials of order k , are used to represent fuzzy membership functions. Fig. 5 shows the B-spline basis function of order 3. When the order k is changed, they can represent membership functions of different shapes.

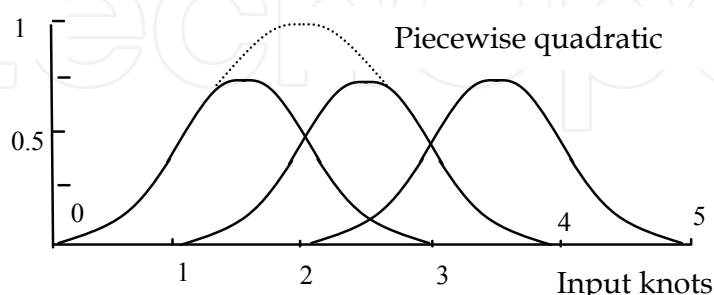


Fig. 5. B-spline fuzzy membership function

The order and the knot vector determine the smoothness and shape of the basis functions. The knots partition the input space into a series of intervals on which the basis functions are defined. Multivariate B-spline basis functions are formed by taking tensor production of n

univariate basis functions, where only one univariate function is defined on each input axis. The multivariate basis functions are then defined on a lattice, which is generated from the projection of all the individual knot vectors parallel to the remaining input axes.

5.2 Fuzzy knowledge representation

The relation between signal features and tool wear values can be expressed by the description: if the power consumption is large and cutting force is medium and ... then the tool wear value is large. This can be represented:

$$r_{ij} : \text{IF}(x_1 = A_1^i \text{ AND } x_2 = A_2^i \text{ AND } \dots \text{ AND } x_n = A_n^i) \text{ THEN } (y = B^j), (c_{ij}) \quad (3)$$

where x_k and y are the input and output, r_{ij} is the fuzzy rule and c_{ij} is the rule confidence.

A_k^i is the univariate linguistic term and B^j is the output linguistic term.

The union (fuzzy OR) of a group of fuzzy rules is called a fuzzy algorithm in which the knowledge of a fuzzy system is stored. So the set of all the confidences c_{ij} (rule confidence matrix) illustrates the complex relation between the input and the output of the system. To fulfill the fuzzy rule set, functions must be chosen to implement the fuzzy logic functions, AND, OR, IF (), THEN (), etc. Recent research shows that the algebraic operators, sum and product, can produce smoother output than the traditional truncation operators, min and max [12].

5.3 The B-spline neurofuzzy system

The process of calculating the output of a fuzzy system includes fuzzification, inference and defuzzification. This involves representing the crisp input as fuzzy sets, pattern matching this with the rules stored in the rule base, combining each rule and mapping the resulting sets to crisp output. Here, B-splines are used to implement the fuzzy membership functions. Singleton fuzzy sets are used to represent the crisp input. Algebraic operators are chosen to accomplish the fuzzy logic functions and the defuzzification is realized by using a centre of gravity algorithm, and the rule confidences are normalized. Thus the output of the neurofuzzy system can be given by:

$$y(X) = \sum_i \mu_{A^i}(X) w_i \quad (4)$$

Where $\mu_{A^i}(X)$ is the i -th fuzzy membership function of a multivariate input X and w_i is the weight. The structure of the neurofuzzy system is shown in Fig. 6.

In Fig. 6, the multivariate fuzzy input sets (termed as basis functions) are defined on a lattice in the input space. The weight of a basis function is an estimate of the value of the network's output; given that the input lies within the set.

A weight can be fuzzified to produce a rule confidence vector which can then be defuzzified to produce the original weight. The output of the network is linearly dependent on the weight set. This network structure allows an efficient linear learning strategy, Conjugate Gradient, to be used to adapt the weights for optimal performance.

The neurofuzzy system can be a powerful tool for cutting tool condition monitoring. In the training process, for all the signal features of each model (cutting tool with standard wear

value), a group of feature values are put into the neurofuzzy network as the training input. A fuzzy rule base is then established to describe the mapping between the systems input and output states. So in the practical condition monitoring process, it can recognize the incoming feature pattern and associate the pattern with different models with corresponding classification confidence.

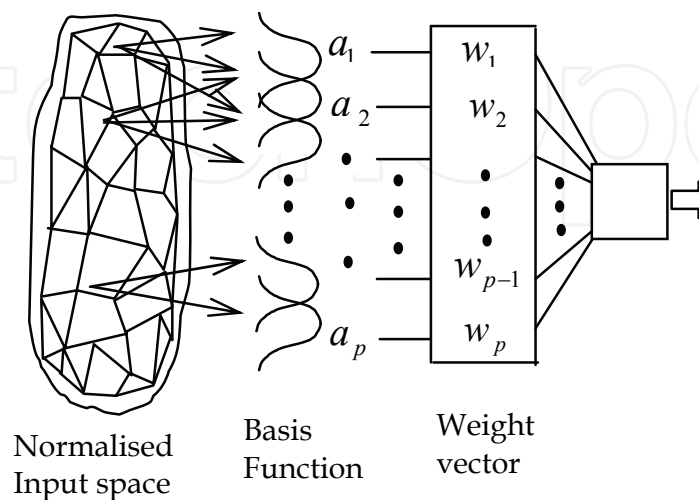


Fig. 6. Algebraic neurofuzzy network

6. Fusion on two levels

Tool wear is a very complex process and it is unlikely that tool condition monitoring could be reliably accomplished by using only one sensor and conventional signal processing strategies. Modern condition monitoring systems are based on the integration of multi-sensor information and the development of reliable intelligent signal classification routines. To make the tool condition monitoring system more reliable, fusion on two levels is employed in this study. The first level is sensor fusion. The monitoring system is equipped with four kinds of sensors and multi-sensor signal features are fused by the intelligent data processing process. Different sensor signals can reflect the tool wear state from different aspects. Their functions are independent and mutually complementary. For example, the dynamometer, accelerometer and AE sensor work respectively in the frequency ranges from several hertz to 1 MHz and higher. The fused information describes the tool wear process more comprehensively.

The second fusion is on a higher level: the fusion of two pattern recognition algorithms. As stated before, both the fuzzy driven neural network and the algebraic neurofuzzy network can carry out intelligent pattern recognition. These methods are the modified and improved versions of the traditional fuzzy logic and neural network pattern recognition processes and experimental results have shown that they have better or at least the same good performance. But because of the extreme complexity of the tool wear mechanism, these algorithms still may not be completely reliable in a few exceptional cases.

It should be noticed that the two proposed algorithms have different characteristics and they can describe the tool wear process from different view points. The calculation of normal distribution type fuzzy membership functions is a statistical calculation process and this makes the results of the fuzzy driven neural network quite reliable. But in some cases

the confidence of the classification may not be as high as it should. The algebraic neurofuzzy network works in a different way. It uses B-splines to represent the membership functions of the input sets and the relation between the signal features and the tool wear values are represented by a fuzzy rule base and the rule confidence matrix. This algorithm is quite accurate for most circumstances but exceptionally, where the rule base is not perfectly complete, the system may refuse to classify some individual objects. The authors of this paper argue that by combining the two algorithms to establish a fused pattern recognition process the tool wear classification results can be more reliable and this idea is supported by large amounts of experiment results.

7. Fuzzy neural hybrid pattern recognition system

The fuzzy neural hybrid pattern recognition system is established by the integration of the fuzzy driven neural network and the algebraic neurofuzzy network. The multi-sensor signals collected from the machining process are first processed to extract tool wear relevant features. Then the membership functions of the features and the fuzzy approaching degrees between the corresponding features of the object and different models can be calculated.

These features that have unstable value or only small change of value of approaching degree for different models should be removed. This step can filter out the redundant features and decrease the training time of the network greatly. The parameters of the determined membership functions can also help the neurofuzzy network to choose correct knots on each input axis.

Both the two systems provide the similarities between the object and different models and classify the object to the most similar model with a certain confidence value. These two confidence values are not necessarily equal, but combining them provides a more reliable and accurate result. A threshold is set by considering the difference between the classification confidence values and tool wear values of the two classification results. Should the two pattern recognition processes give different results, the system averages the results when the difference is within threshold and refuses to do the classification if the threshold is exceeded. The failure of the classification shows the incoming data is too noisy or the networks have not been fully trained and need to be improved. By doing this, the reliability of the classification process is improved.

Signals collected under 220 representative cutting conditions have been processed to verify the proposed fuzzy neural hybrid system (Experiments were partly carried out in the Advanced Manufacturing Lab. of Southampton Institute, U.K.). The system showed very good classification accuracy and reliability. Following is an example, fifteen tools with unknown flank wear value were used in milling operations and Fig.7 shows the classification results. It can be seen that all the tools were classified correctly with the confidence of higher than 80%. Experiments under other representative cutting conditions showed the similar results.

8. Conclusion

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

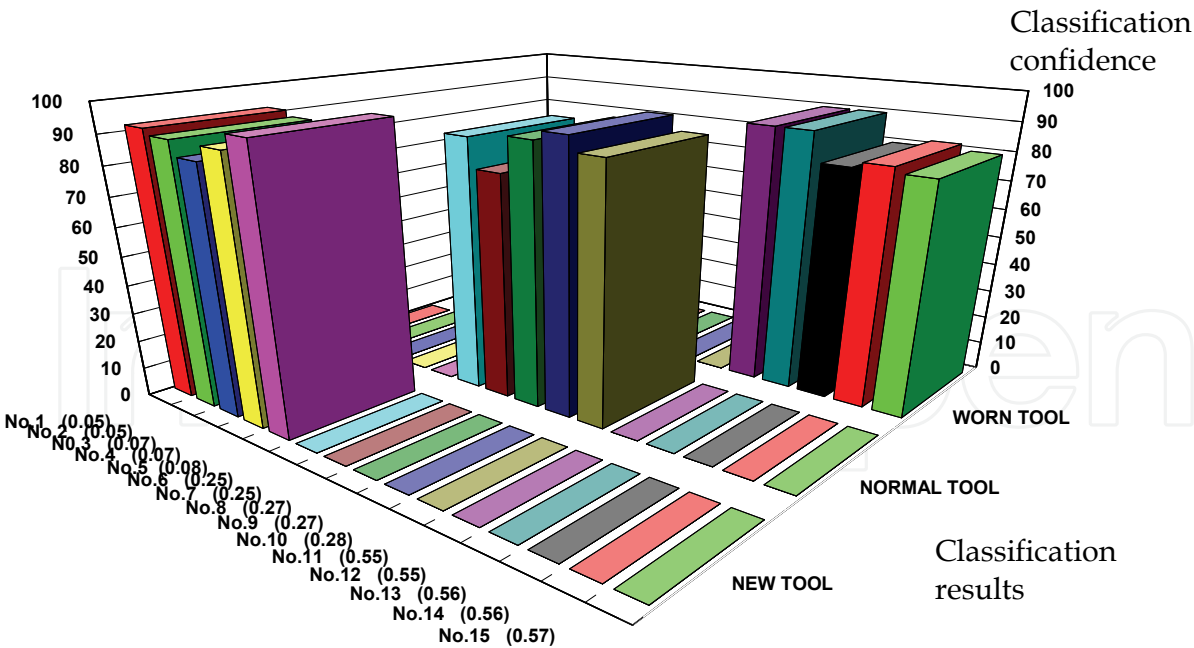


Fig. 7. A group of tool wear states classification results

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 ANNs 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 the resulting fuzzy driven neural network is more accurate and reliable.
4. B-splines that are defined on a lattice-type structure mean that a fuzzy representation of the network can be generated. The Fuzzy rule base established can well describe the mapping between the systems input and output states. A smoother defuzzification surface can be obtained by the use of algebraic operators. The developed neurofuzzy networks have a simplified structure and produces better and more transparent models than a general fuzzy system.
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.

* 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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A wealth of advanced pattern recognition algorithms are emerging from the interdiscipline between technologies of effective visual features and the human-brain cognition process. Effective visual features are made possible through the rapid developments in appropriate sensor equipments, novel filter designs, and viable information processing architectures. While the understanding of human-brain cognition process broadens the way in which the computer can perform pattern recognition tasks. The present book is intended to collect representative researches around the globe focusing on low-level vision, filter design, features and image descriptors, data mining and analysis, and biologically inspired algorithms. The 27 chapters covered in this book disclose recent advances and new ideas in promoting the techniques, technology and applications of pattern recognition.

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