Application of AI Techniques in Small Drill Condition Monitoring

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Abstract: - Determination of tool condition, specially emerging tool breakage is important in computer controlled manufacturing systems. The lifetime of large cutting tools can be forecasted but the failure of small sized tools is nearly unpredictable. A number of signatures accompanying excess wear or emerging failure are investigated. The application of multi sensor technique and the fusion of sensory signals by use of neural networks to the monitoring of small drills is described and the experimental results are discussed. Alternatively the application of rule based fuzzy system to classify the tool condition is outlined.

Key-Words: - Drill, Tool condition, Acoustic emission, Neural network, Fuzzy system

1 Introduction

Drilling operation represents approximately 40% of all machining operation. Therefore the role of monitoring tool condition became important, especially in case of small twisted drills with diameter in the 0,5-5 mm range.

Tönshoff et al. [16] demonstrated that effective machining time of the *CNC* milling centre could be increased from 10 to 65% with a reliable and flexible tool monitoring and control system. Several research works [11] predict that future manufacturing systems will have intelligent functions to enhance their own processes, and the ability to perform an effective, reliable, and superior manufacturing procedures. In the areas of process monitoring and control, these new systems will also have a higher process technology level.

2 Overview of cutting tool monitoring systems using AI techniques

In the last two decades a number of various techniques have been developed to detect excessive tool wear and predict emerging tool breakage [1],[7].

One of these techniques is based on the phenomena called acoustic emission. In order to improve correct detection rate it is usually combined with other sensory signals like feed and vibration pattern or energy.

Carrillo and Zadshakoyan [2] propose a fuzzy logic based system with the cutting force and thrust force as input to determine tool wear. The simulation show the systems effectiveness in inprocess tool wear in drilling operation.

Inasaki and Yonetsu [6] have found that the AE amplitude is independent of the machining parameters like the depth of cut and the feed per revolution but increases approximately linearly with the flank wear over the whole range of the cutting speed. The experiments showed an agreement between the estimated he flank wear and the optically measured values, with less than 15% deviation.

Kannetey-Asibu and Dornfeld[7] have discovered high correlation between the skew of the statistical distribution of the RMS value and the the tool wear when the flank wear reaches a certain value and crater wear developing. There is a considerable increase of the amplitude of the power at frequencies of 80 and 150 kHz with excessive tool wear. They proposed the fusion of sensory signals by the application of neural networks.

F. Erdélyi, C. Sántha[3] describe in their paper an experimental multi sensor tool monitoring system based on motor current and vibration. They combine the signatures by a fuzzy rule based system to monitor tool wear and breakage and at the same time to protect the tools from overload.

Li, and Wu used a two category linear classifier and sensor fusion for drill wear detection [10], [13]. They used the increase in percentage of the peak-to-peak amplitude of vertical acceleration and the the drilling thrust force. Two-category linear classifier was employed to distinguish the worn-out drills with a success rate better than 90% for one cutting process.

Average, peak, RMS values and the area of thrust and torque have been used as input features in a multi sensor monitoring system described by Liu and Anantharaman.

Wavelet transform can extract information in the time domain at different frequency bands. Both continuous and discrete wavelet transforms are used by Li for recognizing tool failure by measuring spindle and feed currents [9].

Wavelet transformations and neural networks are used by Tansel and his coauthors [15] in order to detect the failure of micro-drills. The translation coefficients represent the characteristics of micro-drilling signals with high accuracy and the coefficients of the normal micro-drills show the same patterns whereas the signatures of damaged micro-drills are easily distinguishable.

The technique described by El-Wardany and his coauthors [17] is based on vibration measurement and can detect the breakage of small drills and the wear of larger ones. The vibration is measured in both the transverse and the axial direction.

3 Monitoring of Drilling Operations

Drill wear can be classified in outer corner wear, flank wear, land wear, crater wear, two types of chisel edge wear and chipping on the cutting edges. Corner wear is the best performance index of drill life. As wear cannot be measured directly in the process, indirect measuring methods have to be applied. For this purpose process signatures like cutting and trust force, torsional vibration, acoustic emission, etc. can be used.

- deformation and sliding friction at the chip-tool surface
- sliding friction at the tool flank
- chip breaking and their impact on the cutting tool or workpiece
- normal and abnormal wear of the tool
- mechanical and thermal crack of the tool

There are two different types of acoustic emissions:

- the burst emission having low frequency components with high intensity connected to slip line formation and surface microcracks
- continuous emission characterized by low amplitude and high frequency related to internal mechanical activities.

5 Fusion of Sensory Signals

The structure of general purpose monitoring system is given in Fig. 1. The process signatures are captured by a set of appropriate sensors of different art, located at suitable position to provide the best signal/noise ratio. The preprocessors are responsible to amplify, filter and generate characteristic values from the various signals. The feature generator establishes the so-called feature vector, where the different components are either digital or analogue values and fully represent the current state or object or process to be monitored. The classifier uses this data to determine the class to which the condition of the object or process in question belongs to. Based on the classification results decision is taken: the appropriate action is initiated.

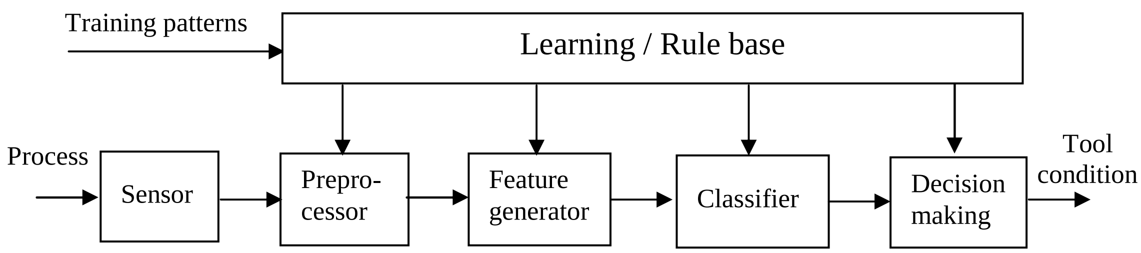

Fig. 1. Structure of a tool monitoring system

4 AE Signal in Machining

Acoustic emission (AE) is generated by the deformation and fracture in metalworking process. It is an elastic stress wave produced by the sudden release of the strain energy in the material. The various sources of acoustic emission in machining are listed below:

- plastic deformation and shear of work material

For the fusion of sensory signals neural networks or rule-based fuzzy systems are the obvious solutions. In our experimental system we have tested both of them.

The neural network structure used in our investigations was a multilayer feed-forward neural network that uses the backpropagation learning algorithm. Its structure is given in Fig.3. The input layer has one node for each feature

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extracted from the raw signature. In the output layer, the number of perceptrons is determined by the number of possible classes and their coding.

For instance one output node is needed for a twoclass problem if output value +1 corresponds to the first class and output value -1 to the second class. In problems that involve a larger number of classes one output node will be assigned to each class or a binary coding will be applied.

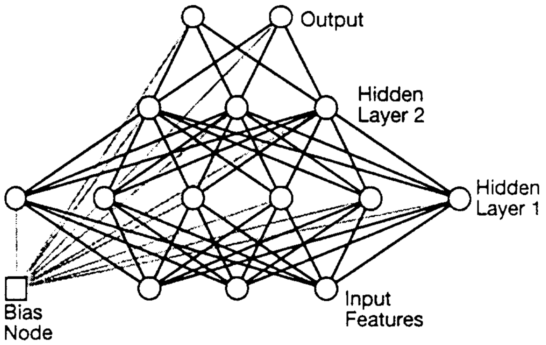

Fig. 2. The structure of an artificial neural network

The neural network described above represents a complex non-linear function. The learning algorithm adjusts the parameters of the non-linear function, by modifying the weights of the connections, until the classification error is minimised. There are two important situations in which a neural network is particularly useful. The first case is when non-linear decision function is needed to separate two classes of data from each other. The second case is when the data neglects the normality conditions.

The other approach to detect tool emerging drill failure was based on fuzzy logic. In order to produce comparable result to the neural network approach as input signal again AE vibration and force was used. The features generated from the raw signal were the rms value of the power in different frequency bands.

In establishing the fuzzy system was the determination of the membership functions. These are given in Fig. 3. bellow.

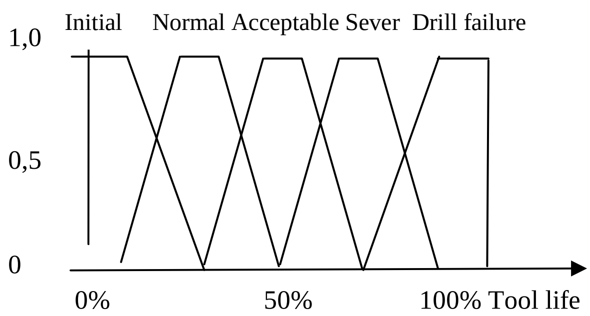

Fig. 3. Fuzzy membership function for the tool condition

In our case for monitoring the drill condition the following features have been used:

- rms value of the power in the band 0-300Hz
- rms value of the power in the band 300-600Hz
- rms value of the power in the band 600-1000Hz
- rms of the power in the band 1000-1500Hz
- rms of the power in the band 1000-1500Hz
- rms of the power in the band 1500-2000Hz

6 Experimental Results

The experimental drill monitoring system was set up on a manually operated conventional milling machine.

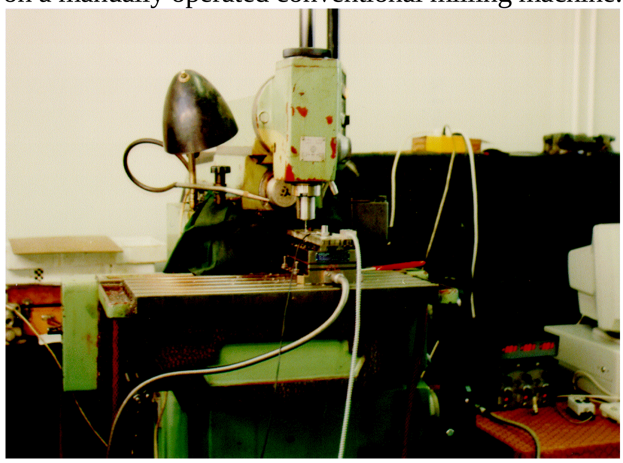

Fig. 4. Experimental set-up of the drilling process

The acoustic emission and the vibration were measured by an AKL 85 and a KD 91 broadband sensor attached to the workpiece close (50 mm) to the actual cutting zone.

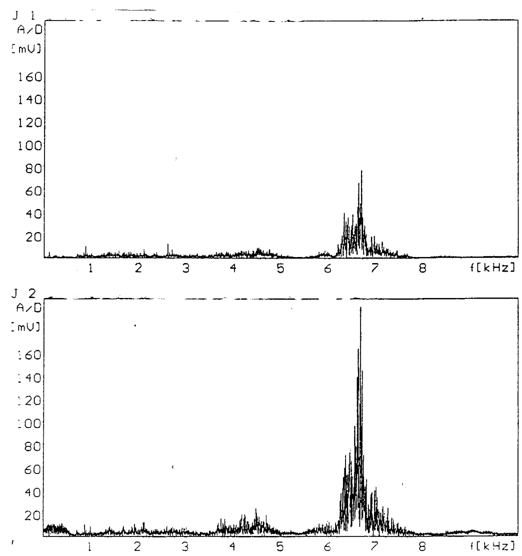

Fig. 5. AE spectrum of sharp and worn 1.5mm diamool conditionseter twist drill (material KO36 feed 25mm/min, 2500 rev/min)

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For measuring the feed force a Kistler dynamometer was used. Both signals were again amplified by charge amplifiers.

Sensor Combination	Correct Recognition Rate
RMS AE + Force	94%
RMS AE + Vibration	72%
Vibration + Force	85%

Table 1. Correct recognition rate of the multilayer feedforward network

Sensor Combination	Correct Recognition Rate
RMS AE + Force	96%
RMS AE + Vibration	75%
Vibration + Force	89%

Table 2. Correct recognition rate of the single category based classifier

Number of Input Features	Correct Recognition Rate
2	94%
4	96%
6	96%
8	82%

Table 3. The influence of the number of input features on the correct recognition rate is given in case of a single category based classifier.

Tool condition	Recognition Rate
Initial	61%
Normal	89%
Acceptable	81
Sever	76%
Tool failure	100%

Table 4. Recognition rate using fuzzy reasoning

7 Conclusion

The real time drill wear/failure monitoring described has the subsequent main properties:

- By applying a neural network in combination with an AR time series model a considerable improvement in the correct tool condition recognition rate can be achieved.
- Tool wear detection based on AE RMS + Force signal is independent of the technological parameters and not influenced by the changes of the machining conditions.
- It was recognised that for tool wear detection a relatively small neural network works well.
- The single category based classifier has the advantage over the multilayer feedforward network the in can learn unsupervised which is advantageous in an industrial environment.

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