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NEURAL NETWORK BASED SIGNAL PROCESSING SCHEME FOR AUTOMATIC TOOL WEAR RECOGNITION

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ABSTRACT

Monitoring of components in the manufacturing plants involves the automatic detection and identification of failure events. One of the important machine monitoring problems is the monitoring of tool wear in automatic metal drilling systems. The purpose of tool wear detection systems is to actually track down the wearing process of the machining tool, allowing the estimation of the quality of parts being machined by tool and prediction of the useful life of tools. Conventional methods of detecting the tool wear from processing the sensor measured signals have led to tool wear detection systems which perform well for a given set of machining parameters, but are not capable of meeting performance requirements in real manufacturing operations, where the machining parameters are more varied. This paper reports a automatic tool wear recognition scheme based on neural network technology. This technolgy provides an improved tool wear recognition alternative because of potential of neural networks to operate in real time mode and to handle data that may be distorted and noisy.

1. INTRODUCTION

Automatic machine monitoring systems have generated great deal of interest in recent years, because of the rapid increase in the number of large, fully automated manufacturing systems. Mechanical system monitoring will increase productivity of manufacturing systems by minimising system down time while maintaining a high standard of manufacturing quality. One of the important machine monitoring problem in many industrial applications is the monitoring of tool wear in automatic metal drilling systems. Detection of tool wear can be used to actually track down the wearing process of machining tool. Tracking the machine tool wear can allow estimation of quality of parts being machined by tool, and prediction of useful life of tools, which varies significantly even under similar cutting conditions. Prediction of useful life of a tool is essential in fully automated manufacturing systems with high quality machining requirements.

In the past several decades, the research emphasis in tool wear monitoring has been on developing accurate structural models of mechanical deformations resulting from tool use [1]. This modelling work involves use of signals from a variety of sensors, including accelerometers for acoustic emissions [2], dynamometers for force and torque measurements [3], acoustic vibrations [4], and current probes for power/current measurements of feed motors [2]. The success of any monitoring scheme depends on accuracy of the sensor signal measurements to a great extent and affects directly the ability to detect and identify faults [5]. Given that a properly calibrated instrumentation exists, measurements are accurate when the sensor mounting does not limit the frequency and dynamic ranges of the sensor, sensor properties does not affect the dynamic characteristics of the object, and when measurements are always collected at the same locations [6]. The tool wear signals typically have low signal to noise ratio (< 3 dB) because of a variety of noise sources on the drilling machine. The presence of noise complicates the monitoring task in two forms : by masking the true signal and by increasing the measured tool wear signal beyond the monitoring criteria, when in fact the percentage of wear is minimum. Hence monitoring systems use various signal processing schemes, where low SNR tool wear signals are subjected to various signal enhancement and noise reduction algorithms. For a cost-effective implementation, many of the earlier monitoring systems were designed with tool wear classification schemes employing noisy signals without preprocessing, or applying a simple low pass filter to the signal to average out the corrupting noise sources. While relatively easy to implement, these techniques have proven to be generally ineffective at reducing the noise and tend to remove information necessary for proper tool wear classification.

2. REVIEW OF CONVENTIONAL TOOL WEAR UNDERSTANDING METHODS

The measured tool wear signal consists of comprises of actual signal mixed with noise. The original tool wear signal (without noise) consists of two main components: a slowly varying response of the work piece material to quasi-periodic excitations, and randomly occurring transients. The slowly varying response component of the signal contains information about the wear of the tool as well as the continuous plastic deformation and shear of the work material. Depending on the sensor used, the slowly varying signal has a spectral shape corresponding to different levels of tool wear [7].

The randomly occurring transients in the observed tool wear signal are a result of discrete mechanical damage to the tool. Example of this type of wear include chipping of the tool, sudden fractures within the tool, or catastrophic breakage of the entire tool. The number of occurences of transients within an interval of time, as well as as their frequency response correlate with the wear of the tool and, therefore, can also be used to determine the tool's condition. In the work reported we used this method for determining the wear in the tool.

The presence of noise in the tool wear signal is due to many reasons. The dominant component of noise is generated by the moving parts of the mechanical systems of the drilling machine including gears and rotation of spindle bearings causing machine vibration and adding extraneous acoustic energy in the lower frequencies. Another source of noise, due to electrical systems of the machine, manifests itself as a low-frequency line noise, heat, and high frequency vibrations of the machine. Also, noise is introduced by high power spraying of the tooling surface with various spraying fluids (lubricants, coolants, air). Since most of the interfering noise is in lower frequencies, it is more appropriate to process high frequency signals such as those measured by acoustic emission errors [8].

A number of schemes have been proposed using slowly varying component of tool wear signal, based on ARMA model of spectral shape of the tool wear [2], and those based on deconvolution techniques [7, 9] Few of the schemes have also reported processing of transients by using time-frequency techniques [10, 11]. Some of them have also adrressed the noise problem with slowly varying component of the signal as in [12]. Also statistical pattern recognition approach, knowledge based approach and a hypid pattern recognition-knowledge based approach has found wide acceptance, recently, as the systems can be built with human expertise embedded in them. For example, the rules that the human tool wear experts use may include knowledge about combinations of machining parameters (e.g., work-piece and tool types, coolants used, feed rate, and spindle rate) that would be difficult to incorporate in decision-making process of a statistical technique.

It is possible to improve tool wear recognition under realistic indusrial environment with low SNR tool wear signals, by using robust signal enhancement and noise reduction algorithms instead of expensive instrumentation setups. Neural network based techniques provide attractive alternative to the conventional signal processing schemes because of the potential of neural networks to operate in real time mode and to handle data that may be distorted or noisy.

3. NEURAL NETWORK METHODOLOGY

Neural networks may be designed to classify input patterns in predefined classes or to create categories that group patterns according to their similarity. The most important characteristic of neural networks is their ability to model processes and systems from actual data. The neural network is supplied with data and then trained to mimic the input-output relationship of the process or system. Neural networks also have the ability to respond in real time to the changing system state descriptions provided by continuous sensor inputs. For complex systems involving many sensors and possible fault types, real-time response is a difficult challenge to human operators, neural network technology may provide a viable alternative to the solution to this problem.

For the analysis of tool wear signals, neural network may be used as a classifying tool. To perform classification, it is necessary to attach to each tool wear signal a label that describes the degree of wear. The input to the network is tool wear signal collected from sensor, and the output is class label signifying the degree of tool wear. The network is trained to identify a set of patterns, representing healthy tool, or a varying degree of tool wear. In the work reported her, tool wear signals are collected when system is operating under identified state, and the tool wear signals are mapped to the corresponding malfunctions.

4. PROPOSED SCHEME

In the scheme proposed here, automatic tool wear detection system comprises of three different functional modules. Figure 1 shows the block schematic of the system comprising of pre-processing module, feature-extraction module and classification module. Even though, use of neural network as a classifier has been very popular for various recognition tasks, we attempted using neural network for each of the module here, as neural networks can be trained to pre-process the noisy spectral signatures, can extract the the required features from a large preprocessed data set, by using appropiate combination of input, output and hidden layers, and can recognize the degree of tool wear by attaching a label to it in the pattern classifier module.

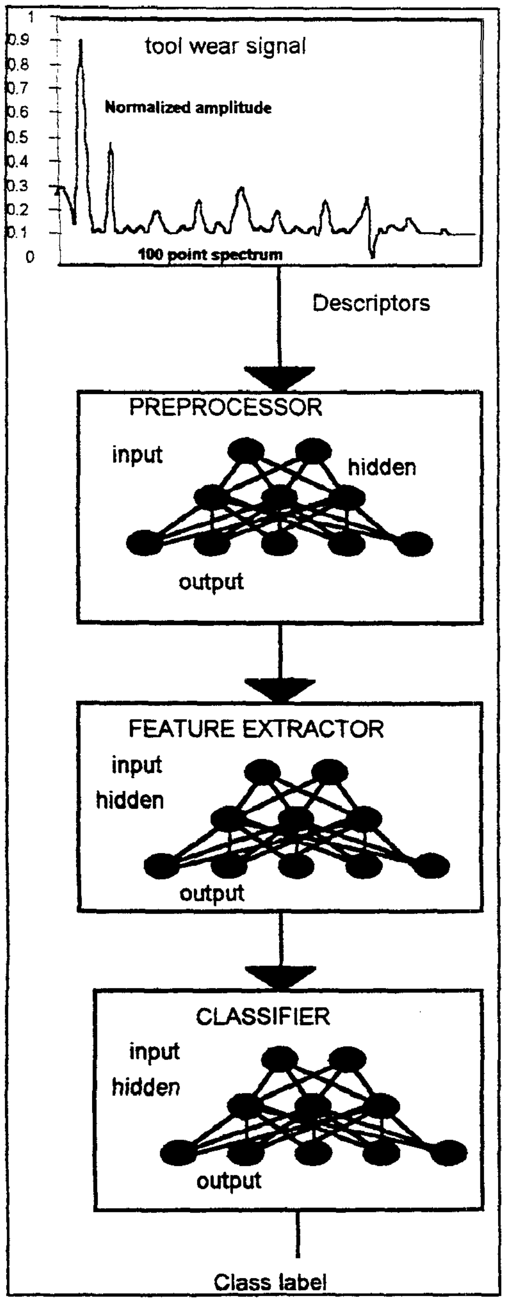

FIGURE 1: BLOCK SCHEMATIC OF THE SYSTEM

The robustness of tool wear recognition system depends on the type of the neural network chosen, number of input and output layers, number of hidden layers, number of training samples used, initial weights and algorithms used for updating the weights, and the activation function used in the output layer. We have used simple to implement but robust back-propagation neural network for all the three modules in order to test the validity of the scheme. The basic algorithm for backpropagation is presented by Rumelhart and McClelland [15].

5. RESULTS

The preprocessor module is the first module, used to preprocess the data, and is based on the information provided by the descriptors. The preprocessor network uses the backpropagation network, trained to discriminate between the tool wear signals considered normal and those of possibly faulty components. The input to the network are the high frequency descriptor, low frequency descriptor and additional inputs corresponding to difference between the consecutive readings of the same descriptor. Two nodes were used in the hidden layer and one output layer. This network was trained with 15 of the available 50 patterns for 3000 iterations with an error of 0.05.

Two identical back propagation networks were used for feature extraction, one for the high frequency section and other for the low frequency section. This layer also has to compress the data. Hence 80 input nodes (40 for each section), 7 hidden nodes and was trained with 12 different signatures representing faulty data set with an error of 0.05.

The output layer has 4 output nodes with linear threshold function centred at 0.5. Any output higher than 0.5 is reported as a fault and outputa lower than 0.5 are considered as absence of faults. The network was trained with 12 different patterns out of a total of 25. Training was achieved with 2500 iterations with an error of 0.05. The complete system (preprocessing, feature extraction and classifier modules together were able to classify 48 out of 50 signatures (which includes noisy tool wear signals with various levels of wear) correctly (96 %). The classification accuracy was compared with conventional statistical classifiers including linear discrimant classifiers [13], Bayesian type [14], and Hidden Markov Model type [14]. The relative classification accuracy achieved is shown in Table I. Figure 2 and Figure 3 shows a typical tool wear signal representing healthy tool and signal with noise.

6. CONCLUSIONS

A tool wear signal processing scheme based on multiple neural networks has been reported here. Preliminary results for neural network based modular system has been reported . The proposed scheme has resulted in robust classification compared to coneventional statistical classifiers. Further work in improving the tool wear detection accuracy with robustness using dynamic neural net architectures and hybrid HMM-neural net type classifers is under investigation.

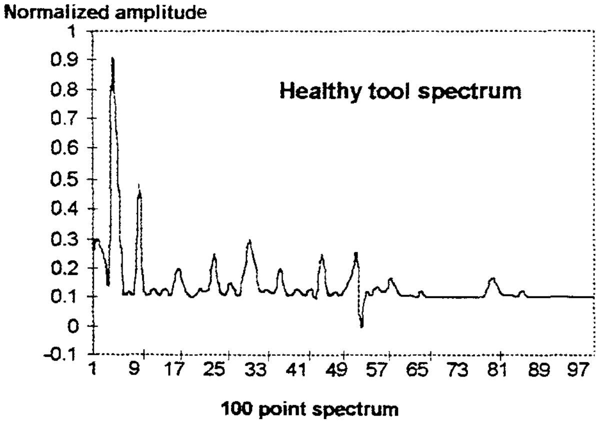

Figure 2: Healthy tool spectrum

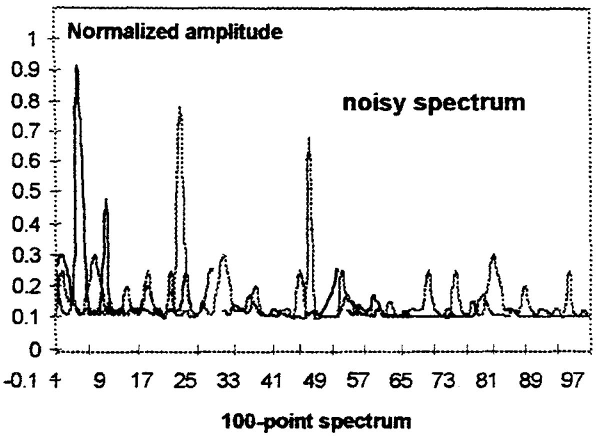

Figure 3: Noisy Spectrum

TABLE I

Classifier type	Classification accuracy
LDF	78 %
Bayesian	86 %
HMM	88 %
Neural Net	96 %

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