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NEURAL NETWORK BASED CONTROL ALGORITHM IN ROBOTISED UNMANNED FLEXIBLE MANUFACTURING SYSTEM

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Abstract: *The aim of this paper is to present the control algorithm of tool monitoring system (TCM) that can detect tool breakage on-line by using a neural decision system. In proposed system, the sensors are used to collect the signals during milling through a data acquisition module. The signal processing module analyses the machining signals for extracting features sensitive to tool wear. The monitoring module uses a strategy to analyse the signals from the sensors and to provide reliable detection of tool and process failures. A neural network is used in TCM as a decision making system to predict the condition of the tool. In this study, the cutting forces are used as the indicator of the tool flank wear variation.*
Key words: *control, robots, monitoring, tool breakage, neural network*

1. INTRODUCTION

Detection of cutting tool condition is essential for faultless machining in flexible manufacturing systems (FMS). Unmanned Flexible Manufacturing System (UFMS) is the most developed type of FMS. Such system replaces human operator with robots, thus reducing labour costs and prevents human errors. Because there is no human operator present, the decision making system must monitor and control the whole process. Some decision making system are commercially available, other are still in the exploratory stages. Systems developed in laboratories, are often multisensor systems embodying complex artificial intelligence strategies. In commercially available systems, the one sensor approach dominates. The main task of decision-making system is to analyze data from sensors and to make appropriate control actions. The tool must be in good condition during whole metal cutting process, therefore, automatic detection of tool breakage is essential. Several different approaches have been proposed to automate the cutting tool monitoring process. These include classical statistical approaches (Bhattacharyya et al., 2007) as well as fuzzy systems (Kuo, 2003) and neural networks (Mulc et al., 2004). (Cus & zuperl, 2007) have used fuzzy expert systems (Iqbal et al., 2007), fuzzy pattern recognition (Haber & Alique, 2003), and fuzzy set theory for detecting tool wear and tool breakage (Fu & Hope, 2006). The computer numerical control (CNC) machine tools are not capable of tool breakage detection. They cannot stop the process if the tool becomes damaged; therefore a monitoring algorithm for unexpected tool breakage is developed. Neural networks have been used often to monitor the progress of tool wear during milling (Chien &Tsai, 2003) to predict the breakage of brittle tools, to select the optimum cutting conditions and tool exchange cycle, to estimate tool life by using flank wear measurements (Achiche et. al., 2004). This paper presents a new monitoring system using neural networks to monitor tool failure in real time. The neural decision making system is used with cutting force and machining parameters as input factors. The simulation and experimental results showed that this system is accurate enough for monitoring abnormal tool states in real time.

2. MONITORING AND CONTROL STRUCTURE

The proposed monitoring system consists of sensor, signal processing module, data acquisition module, monitoring module and decision making systems to interpret the sensory information and to decide on the essential corrective action.

A 3 component piezoelectric dynamometer (Kistler 9255) is selected to monitor the cutting forces in the X and Y directions. An analogue signal from the force sensor is converted to a digital form. Signal generated by the sensor and conditioned by amplifier is send through data acquisition module to the signal processing module and monitoring module, which is directly

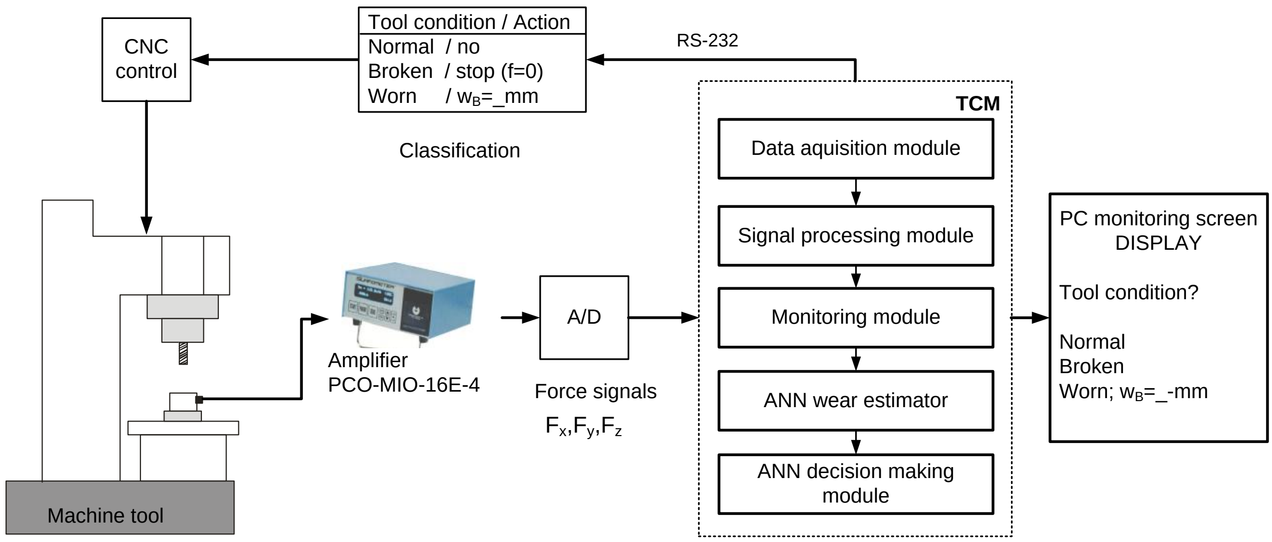

Fig. 1. Flow chart of real time TCM

connected to the machine control (CNC).

It provides reliable detection of tool and process failures. A signal processing module has the following properties: very accurate discrimination of state condition, easy application to pattern classifier, and high speed of signal processing.

AR model and band energy using digital filters were selected as signal processing technologies. Features extracted from signal processing are used as inputs to a pattern classifier, which decides the state conditions. The signals were monitored using a fast data acquisition card (National Instruments PC-MIO-16E-4) and software written with The National Instruments CVI programming package.

The system development course consists of two main steps: First, a neural network tool wear model is developed from a set of data obtained during actual machining tests performed on a Heller milling machine using a Kistler force sensor. The relationship between the machining parameters/sensor signals and flank wear is captured via this network. A well known neural network having a back-propagation learning algorithm is then used as a decision making system to monitor tool failure. Before the use of neural network it was necessary to teach the network the tool states.

Figure 1 shows the basic architecture of the proposed system. A neural decision making module was developed in Matlab software.

Network has two hidden layers and uses a set of 5 normalized inputs for tool condition prediction: (1) cutting speed, (2) feed rate, (3) depths of cut, (4) forces, (5) tool wear. Output layer consist of only two neurons: (1) normal and (2) broken/worn. It has tool-breakage detection capability and is based on pattern recognition. The neural network stores a number of reference force patterns that are characteristic of tool breakage. When a tool tooth breaks, pattern is identified and a break is declared within 10 ms of the breakage. The goal of developing the control algorithm of TCM is not only to produce a reliable, but also as cheap as possible monitoring system.

3. EXPERIMENTS, RESULTS AND DISCUSSION

The monitoring experiments involve an end milling process of steel parts using two end mill cutters: normal and on tooth broken. The vertical machining center Heller BEA 02 used has a maximum spindle speed of 15.000 rpm, a minimum feed resolution of 5 μm and feed rate of 35 m/min.

The force sensor is filtered by the band-pass filter from 0.5 to 1.5kHz.The experiment was conducted using a four edge milling cutter with 12 mm diameter. The workpiece material used in the machining test was Ck 45 and Ck 45 (XM) with improved machining properties. The workpiece material used in the machining test was Ck 45 and Ck 45 (XM) with improved machining properties. The neural network was capable of detecting tool conditions accurately in real time.

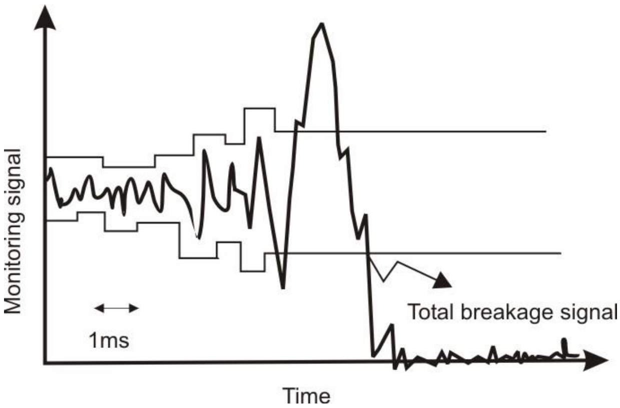

Fig. 2. Dynamic limit strategy with indicative tool breakage pattern

The accuracy of training data was 97.8%, and the accuracy of testing data was 91.2%.

The output node value of a back-propagation neural network was mapped as 0.01 for the normal cutting state, and 0.99 for the tool breakage.

When the neural network outputs are over 0.9 (tool breakage), it sends the signal “Tool broken” to the display. When both the neural network outputs are below 0.9, it sends the signal “Tool condition Normal”.

Developed decision system incorporates dynamics limits for tool breakage detection. The two dynamic limits above and below the monitor signal follow the monitor signal continuously (Figure 2).

Slow but large load changes due to variations in cutting depth (hardness, oversize) are tolerated at a ratio up to 1:4.

4. CONCLUSION

In robotised flexible manufacturing system a monitoring system is developed that can detect/control tool breakage and chipping in real time by using a combination of artificial neural networks.

An intelligent monitoring module is used to extract the features of tool states from cutting force signals.

The proposed control algorithm of TCM is easy to install in existing or new machines, and do not influence machine integrity and stiffness. The simulation and experimental results showed that this system is accurate enough for monitoring abnormal tool states in real time.

Future research should consider applying different intelligent decision making techniques, such as fuzzy logic, genetic algorithms, genetic programming and ANFIS to see which technique is the most accurate and reliable.

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