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Abstract

Production automation has been the focus of the research to improve product quality and to increase productivity. Implementation of computer-based untended machining has attracted great attention in the manufacturing community. In this paper, a framework for sensor-based intelligent decision-making systems to perform on-line monitoring is proposed. Such a monitoring system interprets the detected signals from the sensors, extracts the relevant information, and decide on the appropriate control action. Emphasis is given to applying neural networks to perform information processing, and to recognize the process abnormalities in a machining operation. A prototype monitoring system is implemented. For signal detection, an instrumented force transducer is designed and used in a real time turning operation. A neural network monitor based on a feedforward back-propagation algorithm is developed. The monitor is trained by the detected cutting force signal and measured surface finish. The superior learning and noise suppression abilities of the developed monitor enable high success rates for monitoring the cutting force and the quality of surface finish under the machining of advanced ceramic materials.

1 Introduction

Computer Integrated Manufacturing (CIM) systems have emerged in response to the requirements for greater flexibility, productivity, high precision and quality of the product. The manufacturing industry is now considering untended machining as a viable alternative to achieve these requirements. Although an untended machining process needs almost no attendence of an operator, tasks, such as sensing the effect of process variables and adjusting the conditions accordingly, have to be done by appropriate sensors and associated monitors. Consequently, development of an effective on-line monitoring system is the key to a successful implementation of an untended machining process.

A substantial research work has been done in this area [1-5]. Recognizing the need to allow the intelligent human operator out of the manufacturing loop, powerful sensors, either built-in or attached to machine tools are designed and fabricated with great success. Examples of typical sensors are force dynamometers and vibration detectors. When they are used in the machining system, information related to the machining process can be abstracted from the measured signals and interpreted through signal processing. Based on the interpretation, an inference is usually made whether the machining process should continue on, or a control action should be taken to make correction. It has been well accepted that a general on-line monitoring system consists of, at least, sensing elements, signal processing devices, signal processing algorithms, information interpretors, and a decision-making mechanism. A literature survey of the developed on-line monitoring systems dictates that the major concern of an automated machining system is identificaiton of the tool wear status as the machining process is going on [1-6]. This concern would be more evident in precision machining since the tool wear has direct influence on part dimensions and the quality of surface finish. Furthermore, prompt identification of a severe tool wear assures a safe cutting operation. Consequently, on-line tool wear information is indispensable in order to achieve a fully automated machining operation.

The main objective of this paper is to develop an intelligent on-line monitoring system through a neural network approach. The monitoring system detects the cutting force produced during machining, estimates the tool wear status and finish quality from dynamic variation of the detected cutting force signals, and makes the decision for taking corrective action when it is needed. The paper presents the design of a force transducer and its application of signal detection in a real-time machining process. It also presents the development of a neural network monitor. The monitor is built on feedforward back-propagation algorithm. It is first trained for information processing, and later applied for the cutting force and surface finish monitoring during the machining of advanced ceramic materials.

2 On-line Monitoring Methodology

Figure 1 presents a general picture of an on-line monitoring system. It consists of three major parts, i.e., a force transducer, a neural network monitor, and a decision-making advisor. The basic working principle of this monitoring system is in-process verification through indirect measurement. This means that the detected cutting force signal may not directly reflect the tool wear status or surface finish quality. However, a mathematical model is built to establish the inherent relationships between the detected cutting force signal and the monitoring targets, such as tool wear and finish quality. Interpretation of the detected signal retraces the tool wear progress and finish quality during machining. Neural network techniques are unique in this regard.

2.1 Force Transducer

The transducer shown in Fig. 1 basically consists of a tool holder, four strain gages, two bridge amplifiers, and a data acquisition device. The strain gages are attached to the tool holder. During machining, the generated cutting force produces strains on the tool holder. The strain gages convert the strains to measurable voltage signals through the bridge amplifiers. The data acquisition device digitized and stored the voltage signals. A quantitative relation between the cutting force and the measured voltages, established from a calibration process, recovers the magnitude of the cutting force from the measured voltage signals. It is evident that the higher the measured voltage, the larger the cutting force produced during machining. Detection of the dynamic variation of the cutting force produced during machining may provide useful information on the tool wear status and finish quality of the surface being machined.

2.2 Neural Network Monitor

It has been known that the cutting force is related to the cutting parameters such as the feed, depth of cut, and spindle speed selected during machining. For the purpose of monitoring a machining process through the cutting force and surface finish detection, a mapping function betweent the two detected signals and the three cutting parameters should be established. In order to perform this information processing from the detected cutting force and surface finish signals, a feedforward back-propagation is implemented as an on-line monitor in this research [7-8]. The main characteristics of the on-line monitor are 1) layered architectures; 2) strictly feedforward connections between the neurons; and 3) no lateral, self, or back-connections.

Figure 2 presents the basic structure of the implemented on-line monitor in this work. The monitor has two independent models, namely the cutting force model and the surface roughness model. Each of the two models consists of an input layer, a hidden layer, and an output layer. In the cutting force model, the three nodes in the input layer represent feed, depth of cut, and cutting speed. In the hidden layer, two nodes are chosen for maximizing the effect to generalize the input information into the correlation of the activity among the three input nodes, rather than to simply memorize the input patterns [8].

Based on the principle of back-propagation network (BPN), all the information flow is feed forward. Using the hidden layer extracted from the input patterns, the network forms a mapping from the three input nodes to a single output node, either the predicted cutting force or the predicted surface finish. These networks undergo supervised learning, i.e., they are taught to classify input into one of the several *a priori* categories. In this work, variable thresholds on the hidden nodes and the output nodes, and variable weight connections between individual nodes are used. For each node, a sigmoid shape (S-shape) transfer function is used. Therefore, each node represents a non-linear function in the form of,

$$Y_j = \frac{1}{[1 + exp(-(X_j + \theta_j))]}$$

where $X_j = \sum Y_i W_{ij}$, Y_j = output of node in layer j, Y_i = output of node in preceeding layer i

The three main stages in training the monitor, or finding useful values for the weights and threshold values, are listed as follows.

1. The forward pass: where the outputs of each node is calculated.
2. The backward pass: where weight and threshold changes of each node take place.
   Weights are adjusted by:

   $$w_{ij}(t+1) = w_{ij}(t) + \eta\delta_j Y_i^{'} + \alpha(W_{ij}(t) - W_{ij}(t-1))$$

   In this equation $w_{ij}(t)$ is the weight from hidden node i or from an input node j at time t, $Y_i^{'}$ is either the output of node i or is an input, η is gain term, α is momentum term, and δ_j is an error from node j. If node j is an output node, then

   $$\delta_i = Y_i(1 - Y_i)(d_j - Y_j)$$

   where d_j is the desired output of node j and Y_j is the actual output.
   If node j is an internal hidden node then

   $$\delta_j = Y_i^{'}(1 - Y_i^{'}) \sum_{0}^{k} \delta_k W_{jk}$$

   where k is over all nodes in the layers above node j.
3. Termination: where the network stops training when the network's output is close to the desired output. The error for the network is calculated by:

   $$E = \frac{1}{2} \sum_{i=1}^{k} (d_j - Y_j)^2$$

2.3 Training the Network Using Machining Data

Experimental tests of machining a specific ceramic material were conducted to provide training examples for adjusting the weights connecting the nodes distributed in the input, hidden and output layers. Each training example was a set of the selected values of the three cutting parameters and the value of the detected cutting force during machining, or the measured surface finish. To ensure that the train examples are information rich, a method called *factorial design at two levels* was used to set the values of the three cutting parameters. Specifically, 0.2 mm/rev and 0.40 mm/rev for feed, 0.1 mm and 0.2 mm for depth of cut, and 400 rpm and 600 rpm for spindle speed were used. For a combination of these cutting parameter settings, 8 machining tests were carried out for obtaining the measurements of the cutting force and surface finish. Figures 3a and 3b present the recorded cutting force and surface finish measurements. Note that the mean value of the cutting force data and the mean value of the surface profile heights serve as their representatives in the training process. Figures 4a and 4b give the graphical representations of the mean values of the measured cutting force and surface finish. As a result, 16 training examples were available for training the two networks. The quality of these training examples, regarding the information carried with, can be evidenced by examining four pair measurements, for example, under two-level feed settings. The average of these four pair measurements is a good estimate of the main effect of feed on the cutting force, or the surface finish.

The weights derived from the training of these two networks using the 16 training examples are illustrated in Figs. 2a and 2b. It is evident that the cutting force for a given combination of the three cutting parameter settings can be predicted by

$$Force = 2.94 * (-4.31 * \text{feed} - 2.86 * \text{depth of cut} - 2.97 * \text{spindle speed}) - 4.42 * (-5.64 * \text{feed} - 3.88 * \text{depth of cut} - 7.93 * \text{spindle speed})$$

Comparisons between the predicted and measured cutting forces, and between the predicted and measured surface finish can be made to show the closeness between them, indicating the superior learning and noise suppression abilities of the developed neural network monitor in the information processing.

3 Application: On-Line Monitoring of a Turning Process

It should be pointed out that the implementation of the developed monitor in a real time machining operation requires an additional piece of information, i.e., the estimate of the dynamic variation of the monitoring target(s), such as the cutting force or/and surface finish. This additional information enables the monitor to distinguish the external noise related to the machining process abnormalities from the natural, or inherent process variation, evidences of which are shown in Figs. 3a and 3b. In this work, estimates of the dynamic variations of the two monitoring targets were obtained by two steps. The first step was to obtain the two estimates at each of the 8 machining tests. These estimates are presented in Figs. 4a and 4b. In the second step, two pooled estmiates, representing the natural variation of the cutting force and surface finish during machining, were calculated from the 16 estimates. These two pooled estimates were the standard deviation of the cutting force variation (2.12 Newtons) and the standard deviation of the surface finish (0.52 μ m), respectively.

To demonstrate applicability of the proposed on-line monitoring system, a prototype monitoring system using the developed neural network monitor is implemented on a CNC machnining center to monitor the machining of advanced ceramic materials. The objective of such a monitoring system is to control the appearance of micro-cracks on the machined surface, the dimensional accuracy, and the finish quality of the machined surface. An assumption is made that a large cutting force leads to a severe surface damage. Therefore, the two monitoring targets are the cutting force and the surface finish generated during machining. Figures 5a and 5b are the two monitoring charts obtained during the machining process. The center lines of these two charts represent the predicted cutting force and surface finish through training. The upper and lower limits on the two charts are the warning lines of the monitoring system. They are constructed based on the 3-σ principle, which indicates that the machining process is in its normal status as long as the detected cutting force signal, or the measured surface finish, is within the upper and lower limits. Whenever a detected signal is out of the two limits, the machining process goes on to an abnormal status. It is evident that the two monitoring charts shown in Figs. 5a and 5b illustrate the machining process under monitoring is in a normal status because all the detected and measured signals are within the limits.

The prototype system has been used with satisfaction regarding the assurance of good machining performances. Under many circumstances, the detected cutting force signal hit the upper warning line. The machining operation stopped immediately and severe surface damage was observed. The worn tool was replaced by a new tool and the machining process resumed its normal status. When the detected cutting force signal hit the lower warning line, a severe tool breakage was observed. The breakage caused the depth of cut during machining dropped to an almost non-touching between the workpiece and the tool. However, false alarmings sometimes happen, especially during the cutting force monitoring due to the complexity of cutting mechanism, such as effects of built-up edges and nonhomogeneous distributions of workpiece material properties. As a result, the decision-making advisor built in the monitoring system will call on a human intervention only under circumstances when the two monitoring targets are hitting their warning lines. There is, however, an associated side-effect, i.e., the decrease of the sensitivity of the monitoring system for an effective detection of the process abnormalities. Further improvements are being made to balance the need between the false alarm elimination and the sensitivity of detection.

4 Conclusions

A prototype system to perform an untended machining operation has been developed. Through an on-line detection of the cutting force and the control of surface finish measurements, the monitoring system has been successfully used to assure satisfactory performance during the machining of advanced ceramic materials. Serving as the brain of the untended machining system, the neural network monitor processes the machining-related information from the detected signals, compares the extracted information with the pre-determined warning limits, and passes the results to the built-in decision-making advisor. The advantages of artificial neural networks are explored in this work. It has been shown that through appropriate selection of architecture of the network, noise can be minimized and the process variables can be predicted accurately, indicating that neural networks will become an attractive modeling tool for use in on-line monitoring of machining processes.

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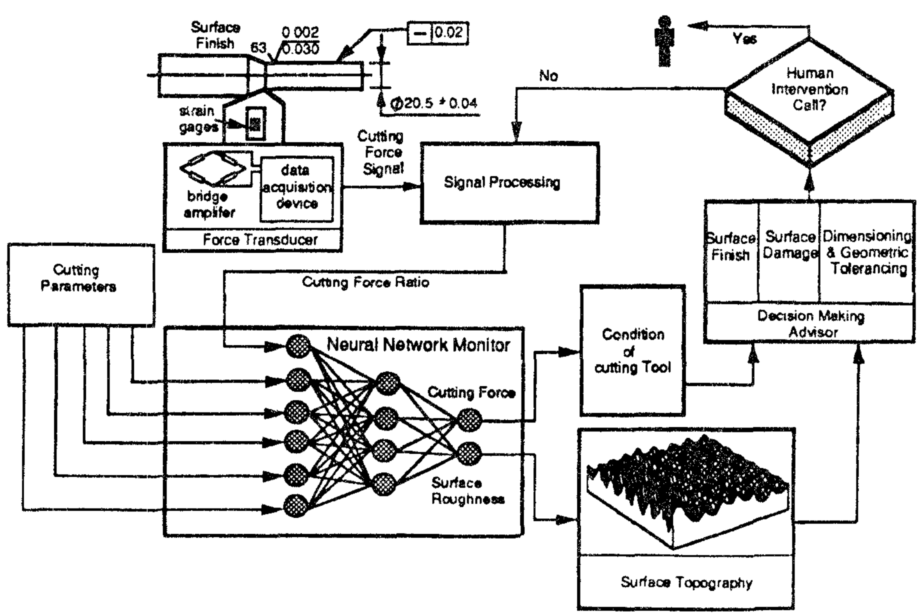

Figure 1 Basic Structure of the Implemented On-Line Monitoring System

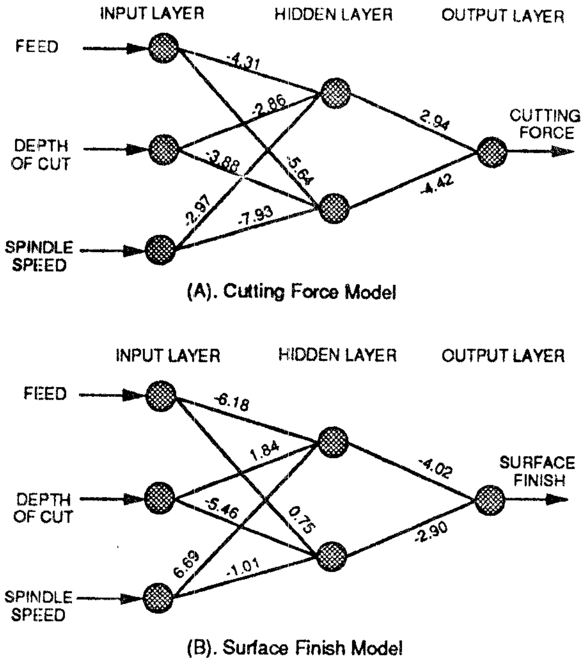

Figure 2 Basic Structure of the On-Line Monitor

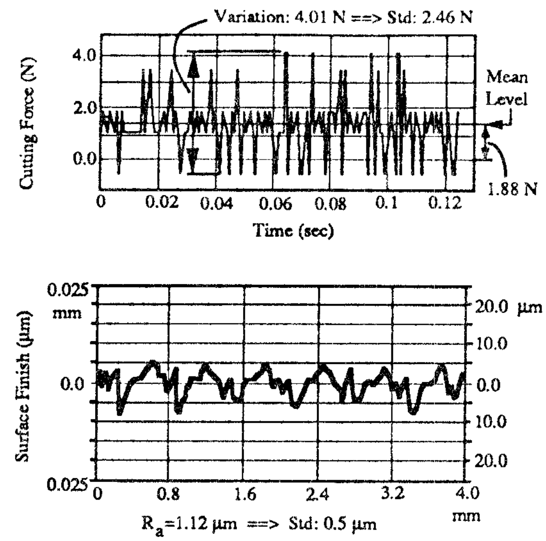

Figure 3 Recorded Cutting Force and Surface Finish Measurements

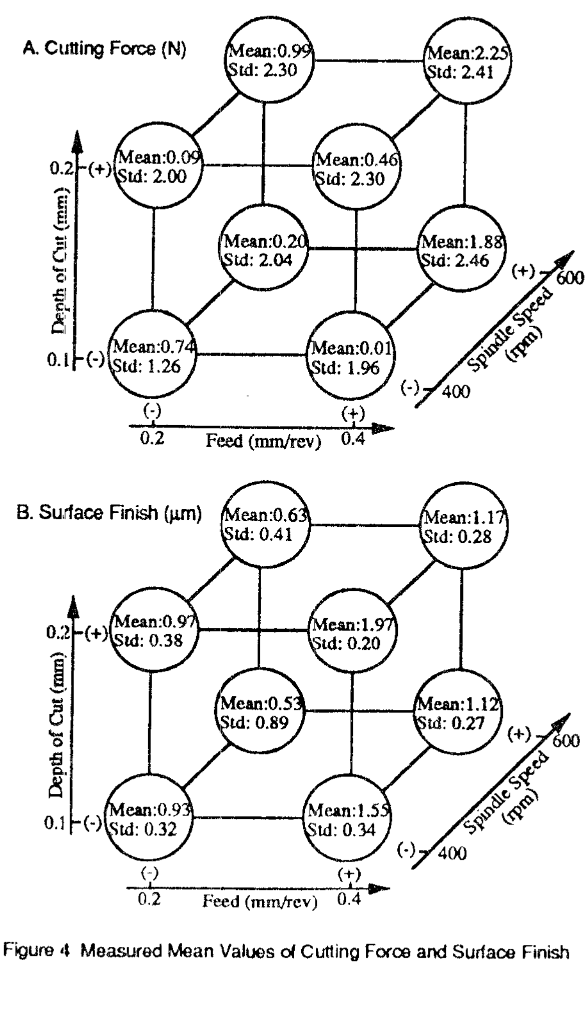

Figure 4 Measured Mean Values of Cutting Force and Surface Finish

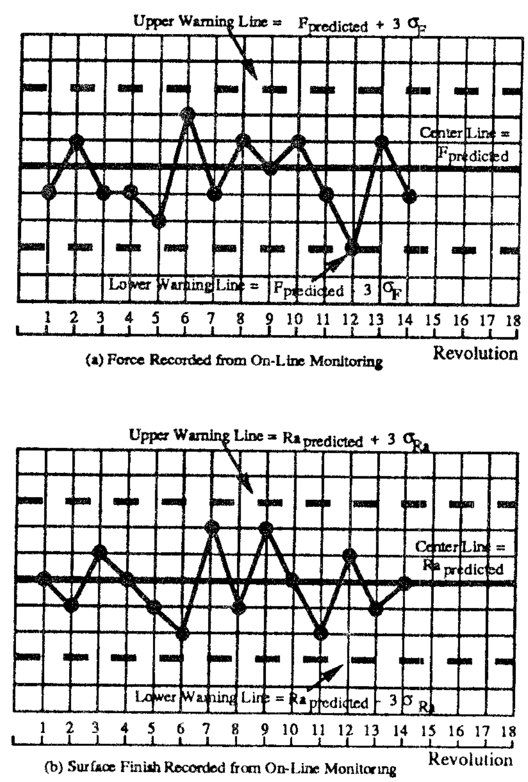

Figure 5 On-line Monitoring Charts Recorded during Machining