FIRST INTERNATIONAL CONFERENCE ON MANUFACTURING TECHNOLOGY

27-29 December 1991

Hong Kong
Convention & Exhibition Centre

PROCEEDINGS

Hosted by

蔣氏工業慈善基金有限公司
CHIANGS' INDUSTRIAL CHARITY FOUNDATION LTD.

A neural network-based machining adaptive control system

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Summary

This paper presents a neural network-based approach to incorporate an adaptive control system into machining process control. Chip forming patterns, surface finish, power consumption are predicted based on the established database and knowledge base. Neural network techniques are introduced to integrate the dynamic machining performance with tool wear progression. The adaptive control strategy is determined based on the results derived from neural network modelling to optimise the machining operation.

Introduction

On-line assessment of machining performance becomes more important with the advent of automated machining systems. It is known that present machining theories and machinability databases are all established based on ideal machining conditions, i.e. machining with unworn cutting tools. In actual machining processes, however, machining performance may vary significantly with tool wear progression, thus resulting in unpredictabilities. Therefore, in-process assessment of machining performance, including chip control, surface finish, power consumption and tool wear states, is a prerequisite to an adaptive control system, which is in turn essential to the optimisation of machining process and the quality assurance of a finished product.

Establishment of machining database and knowledge base

A machining database for unworn cutting tools is set up off-line from extensive machining experiments concerning chip forming patterns, surface finish and power consumption based on the previous work [1-2]. Knowledge base is developed to describe the effects of work materials, tool geometries, chip breaker configurations and cutting conditions on the machining process performance, aiming at providing a reliable prediction of the machining performance under arbitrary machining conditions.

Strategy of comprehensive tool wear estimation

A machining operation is a complicated process, even worsened by tool wear taking place. Reliable estimation of comprehensive tool wear [3] is a prerequisite to any on-line assessment of dynamic machining performance. Multivariate time series models of 3-D dynamic cutting force signals are developed to provide an effective way to estimate comprehensive tool wear, i.e. more than one type of wear, such as major flank wear, crater wear and minor flank wear. A multivariate time series model with autoregressive order n and moving average order m, i.e. ARMAV(n, m) [4], can be expressed as

$$X_t = \sum_{k=1}^{n} \Phi_k X_{t-k} + a_t - \sum_{k=1}^{m} \theta_k a_{t-k} \tag{1}$$

where the p-dimensional vector of process variables is given by the observation vectors $X_t = [X_{1t}, X_{2t},...,$

$X_{pt}]T$, and the white noise $a_t = [a_{1t}, a_{2t}, ..., a_{pt}]T$. The parameter matrices Φ_k's and θ_k's are estimated based on the observation vectors and therefore describe the instantaneous dynamics of the machining process. The orders of an adequate model can be determined by the F-test [4].

Neural network-based adaptive control system

The advantage of using neural network techniques lies in that neural networks are capable of modelling a complicated process only based on experimental input-output data [5]. In addition, once a neural network is trained off-line, its algorithm can be implemented on-line. Therefore, it is feasible to integrate the neural network algorithm into an adaptive control system.

Back-propagation (BP) algorithm [5] is selected to learn the patterns mapping from the input-output training data. A BP neural network employs one or more hidden layers of neurons fully connected through weights to the input and output layers. A neuron acts as a non-linear transfer function $f(Z^j)$ which allows the non-linear mappings between input and output patterns, i.e.,

$$Y_j = f(Z_j) = f(\sum_{i=1}^{n} W_{ji} \cdot X_i + B_j) \quad (2)$$

where Z_j is the weighted linear summation of all the inputs to the jth neuron, Yj the output value activated by the jth neuron, and Bj the bias of the jth neuron.

The effectiveness of a neural network depends heavily on the appropriate selection of the input features to the neural networks. In this work, since major flank wear, crater wear and minor flank wear influence the tool configuration/geometry, surface quality and power consumption altogether, the features sensitive to them are extracted from the established multivariate time series model to train the neural network. Fig. 1 shows the features selected for developing neural networks.

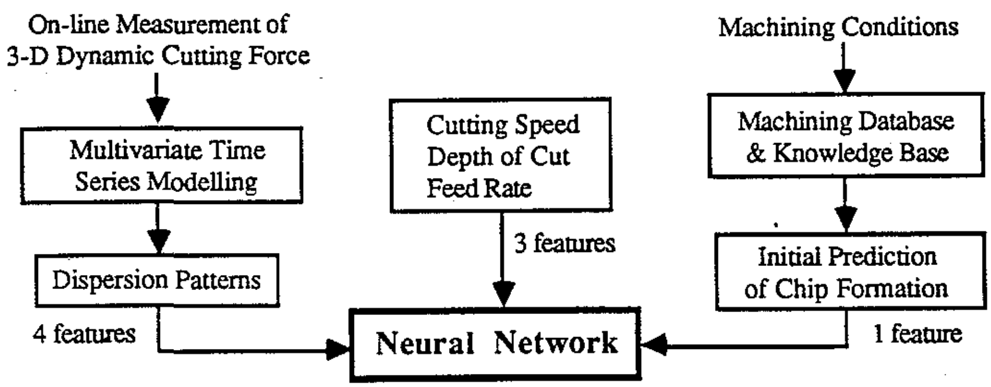

Fig 1. Feature selection of Neural networks.

Based on the developed neural network algorithm, the information about dynamic machining performance is updated during machining operations. According to the on-line assessing results of machining performance, a set of decision-making rules is produced to take the corresponding control actions through the CNC machine, such as adjusting cutting conditions, replacing cutting tools and compensating dimensional deviations. Fig. 2 shows the schematic diagram of this adaptive control system.

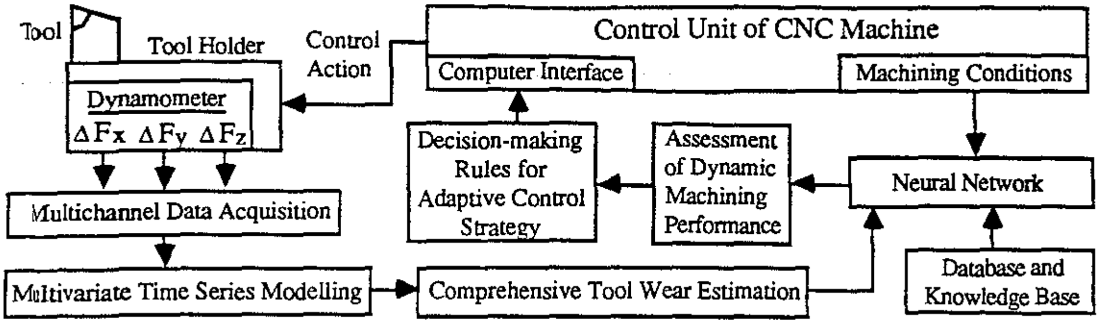

Fig 2. Schematic diagram of the machining adaptive control system.

Conclusion

The method presented in this paper would form a basis for in-process control of the chips produced, tool change action and dimensional compensation due to tool wear in automated machining systems.

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