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INTELLIGENT CONTROL OF MILLING OPERATIONS

Y. S. Tarng and S. T. Hwang

Department of Mechanical Engineering, National Taiwan Institute of Technology
Taipei, Taiwan, 10672, R. O. C.

ABSTRACT

In order to improve productivity, an intelligent control system is presented in the paper. In this intelligent control system, a feedforward neural network and a fuzzy feedback mechanism are adopted to achieve a constant milling force with an adjustable feedrate under a variety of cutting conditions in milling operations.

INTRODUCTION

Milling is one of the most popular but complex machining processes, Due to the variations in cutting conditions, part programmers usually use conservative cutting parameters to operate milling machines for protecting the tool and workpiece from an overload of milling force so as to reduce the productivity of milling machines. In recent years, the need for increasing productivity has greatly accelerated the development of adaptive control in milling operations. Basically, the use of an adaptive control system to increase productivity is achieved by an automatic control of feedrate to maintain a constant milling force [1].

Although various forms of modern adaptive control algorithms to design the adaptive control system in milling has been proposed [2], the use of these adaptive control algorithms to design an adaptive controller needs to analyze and model the controlled plant including the servo–loops and the milling process dynamics first. In order to achieve fully adaptive control in milling operation, an intelligent control of milling processes which is not required to analyze and model the controlled plant is developed in this paper. This is because the intelligent control system can adaptively acquire the knowledge of the controlled plant through on–line learning.

The proposed intelligent control system is based on a feedforward neural network to acquire the inverse–dynamics model of the controlled plant. In addition to this, a fuzzy feedback mechanism is used to perform the adaptive modification of connection weights for the feedforward neural network. As a result, the inverse–dynamics model of the controlled plant can be adaptively modified in response to the variations in cutting conditions so as to obtain an adjustable feedrate with a constant milling force automatically. Finally, experimental cutting tests are also performed to verify the feasibility of this adaptive learning control system.

DESIGN OF AN INTELLIGENT CONTROL SYSTEM

Fig.1 shows the basic structure of an intelligent control system. Assuming that the neural network with a transfer function of G^{-1} is identical to the inverse–dynamics model of a controller plant and the output of the fuzzy feedback mechanism U_f is equal to zero, the output of the controlled plant Y can be expressed as:

$$Y = G\,U_{com} = G\,U_n = G\,(G^{-1}\,Y_d)$$
$$= (G\,G^{-1})\,Y_d = Y_d \qquad (1)$$

where U_{com} is the command of the controlled plant and U_n is the output of the inverse–dynamics model.

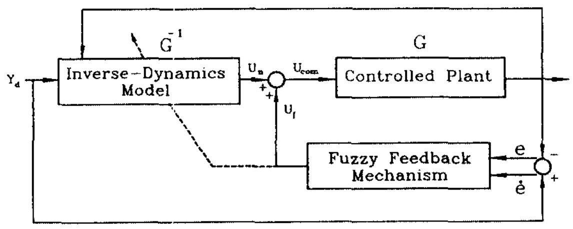

Fig.1

As shown in equation (1), the output Y is equal to a constant desired value Y_d. In reality, parameters of the controlled plant may vary so as to change the dynamics of controlled plant. Therefore, on–line identification of the inverse–dynamics model of the controlled plant is required. In order to accomplish this, a fuzzy feedback mechanism is adopted here. The fuzzy feedback mechanism is used to fuzzify the parameter variations of the controlled plant or disturbances acting on the controlled plant. Then, the output of the fuzzy feedback mechanism U_f is generated to modify connection weights of the neural network for obtaining the inverse–dynamics model of the controlled plant adaptively. Once the output of the fuzzy feedback mechanism U_f is minimized, U_{com} is almost exactly equal to U_n and no connection weights need to be adjusted. Thereby, the inverse–dynamics model of controller plant is obtained and the output Y is equal to the desired input Y_d again.

In the following, a feedforward neural network with the back–propagation learning algorithm [3] and the fuzzy feedback mechanism [4] to form an adaptive learning control system is explained and applied to milling operations for the on–line adjustment of feedrate.

FEEDFORWARD NEURAL NETWORKS

Basically, feedforward neural networks are composed of a large number of simple, highly interconnected artificial neurons and organized into several layers, i.e., input layer, hidden layer, and output layer. The principal component of a neural network is an artificial neuron which evaluates the inputs and determines the strength of each one through its weighting factor. In other words, the larger the weight between two neurons, the stronger is the influence of the connection.

LEARNING IN THE NEURAL NETWORK

The objective of learning in neural networks is to acquire a function that maps inputs to desired outputs. It is realized through the modification of the connection weights according to an appropriate learning algorithm. In the present paper, an error–correcting technique which is often called the back–propagation learning algorithm [3] is employed to modify the connection weights. If the response of neural networks is correct, no weights need to be changed. However, if there is an error in the output response of neural networks, the difference between the desired and the actual outputs is used to guide the modification of connection weights appropriately.

FUZZY FEEDBACK MECHANISM

The use of the fuzzy feedback mechanism is to fuzzify the parameter variations of the controlled plant or disturbances acting on the controlled plant and then to generate the proper output error U_f of the neural network. The fuzzy feedback mechanism (Fig.2) consists of a fuzzifier, a knowledge base, a fuzzy inference engine and a defuzzifier. The functions of these components are that: the fuzzifier fuzzifies the inputs; the knowledge base provides the shapes of membership functions and linguistic control rules; a fuzzy inference engine performs a fuzzy reasoning based on the linguistic control rules; and the defuzzifier generates a crisp output value when the fuzzy operations is completed.

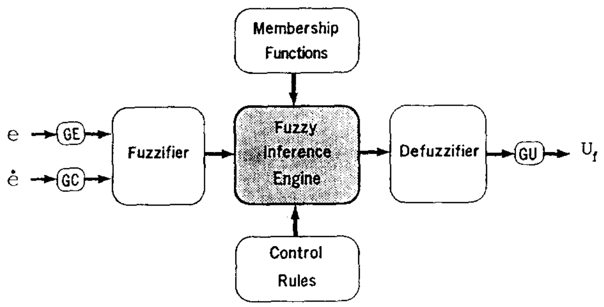

Fig.2

It is shown that the fuzzy feedback mechanism used here (Fig.2) is a two–input–one–output system. The measured force F_{act} is compared with the reference force F_{ref} and converted into two inputs: the error force e and the change of the error force ė. That is:

$$e(i) = F_{ref} - F_{act}(i) \qquad (2)$$

$$\dot{e}(i) = F_{act}(i-1) - F_{act}(i) \qquad (3)$$

where i is the index of time increment for sampling force.

After the two inputs are multiplied by the input scaling factors, GC and GE, the two inputs are mapped into suitable linguistic values by using the membership function of fuzzy sets. In the paper, the following linguistic sets are assigned: NB (negative big), NS (negative small), ZR (zero), PB (positive big), PS (positive small).

Once the two inputs are fuzzified into fuzzy sets, a number of linguistic rules which define individual control situation are applied (Table 1). Basically, these linguistic rules are designed to generate a large output when the error force e and the change of the error force ė become big. As a result, the weights of the feedforward neural network are quickly adjusted. On the other hand, a small output is produced to modify the weights of the feedforward neural network as these errors become small.

Table 1

E \ CE	NB	NS	ZE	PS	PB
NB			NB	NS	
NS			NS	ZE	PS
ZE	NB	NS	ZE	PS	PB
PS	NS	ZE	PS		
PB		PS	PB		

INTELLIGENT CONTROL SYSTEM IN MILLING

Based on the above discussion, an intelligent control system to maintain a constant milling force under varying cutting conditions with adjustable feedrates is developed. Fig.3 shows the block diagram of the intelligent control system in milling. To avoid a large transient milling force, the peak milling force F_{act} in a tooth period is the criteria to be controlled in the adaptive learning control system. It is shown that the measured milling force F_{act} passes through a tapped delay line (TDL) filter whose output vector contains the delayed values of the measured milling force. Then, the delayed values of the milling force are fed into the feedforward neural network. It is found that good control performances can be achieved by using a multi–layer feedforward neural network with a 5–10–1 type. A limiter constraining the command signal of the controlled plant U_{com} with an upper bound is added in the control loop to avoid any damage due to the rapid feedrate.

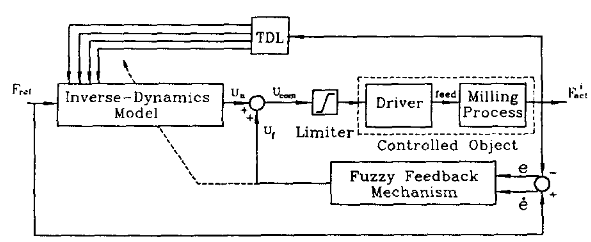

Fig.3

CONCLUSION

To increase productivity, a new adaptive learning control system in milling processes is developed. The main advantage of this approach is that the use of an adaptive learning control of milling processes is not required a priori knowledge about the servo–loops and the milling process dynamics. Furthermore, the proposed control scheme has many promising features, such as the capability of parallel processing, the utilization of a large amount of sensory information, on–line learning, and so on. Further research will need to find the stability conditions of the developed control system in order to select the appropriate structures of the feedforward neural network and the fuzzy feedback mechanism.

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