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Neural Network based Adaptive Control and Optimisation in the Milling Process

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In this paper, an adaptive controller with optimisation for the milling process is designed based on two kinds of neural network. A modified BP neural network is proposed adjusting its learning rate and adding a dynamic factor in the learning process, and is used for the on-line modelling of the milling system. A modified ALM neural network is proposed adjusting its iteration step, and is used for the real-time optimal control of the milling process. The simulation and experimental results show that not only does the milling system with the designed controller have high robustness and global stability, but also the machining efficiency of the milling system with the adaptive controller is much higher than for the traditional CNC milling system.

Keywords: Adaptive control with optimisation; Milling process; Neural network; System identification

1. Introduction

In traditional CNC systems, machining parameters are usually selected prior to machining according to machining handbooks or the user's experience, and so the selected machining parameters are usually conservative to avoid machining failure. Even if the machining parameters are optimised off-line by an optimisation algorithm, they cannot be adjusted during the machining process [1]. The machining process is variable owing to tool wear, temperature change and other disturbances. To ensure the quality of machining products, to reduce the machining costs and increase the machining efficiency, it is necessary to optimise the machining process at the time that the machine tools etc. are selected for CNC machining. The machining parameters must then be adjusted in real-time so as to satisfy the optimal machining criteria.

Adaptive control of the machining process is the traditional method to solve the above problems [2]. Because the machining process is nonlinear and varies with time, it is difficult for the traditional identification method to provide an accurate model [2]. The optimisation of machining parameters is nonlinear with constraints, so it is difficult for the traditional optimisation algorithms to solve this problem [1].

Neural networks (NN), based on the principles of human brain operation, have received considerable and increasing interest over the past decade. Compared to the traditional computing methods, an NN is robust and global. It can be used to learn any nonlinear function and can be used for any nonlinear optimisation problem. So NN are widely used for system modelling, machine learning, function optimising, image processing and intelligent control [3–5].

In this paper, a BP NN is used for modelling the milling system and an ALM NN is used for the optimal control of the milling process. To realise the on-line modelling of the milling system, a modified BP NN is proposed based on the traditional BP algorithm. The learning rate is adjusted by the Golden divided method and a dynamic factor is used during the learning process so as to develop the convergence speed of the BP NN. To realise real-time optimal control of the machining process, a modified ALM NN is proposed by adjusting its iteration step size in the optimisation process, so that the convergence speed of the ALM NN is improved. Combining the modified BP NN with the ALM NN, an adaptive controller with optimisation for the milling process is designed. The simulation and experimental results show that the milling system with the designed controller has a high robustness and global stability, and also the machining efficiency of the milling system with the adaptive controller is much higher than for the traditional CNC milling system.

2. Modelling of Milling System Based on the Modified BP NN

The milling process can usually be optimised by adjusting the feedrate or spindle speed. In this paper the feedrate is selected as the optimised variable, and the milling state is estimated by the measured cutting force. Figure 1 is the diagram of the modelling of the milling system based on the modified BP NN.

The modified BP NN consists of three layers, i.e. the input layer having only one neuron, the hidden layer having 10

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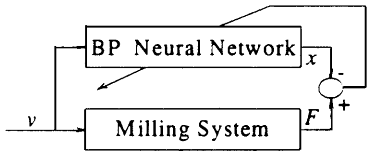

Fig. 1. A BP neural network based identification of the milling system.

neurons and the output layer having only one neuron. The input of the modified BP NN is the milling feedrate and the output is the milling force. To develop the convergence speed of the BP learning algorithm, a modified BP learning algorithm is proposed adjusting the learning rate and adding a dynamic factor. The milling system $Fc = Fc(v)$ is modelled by the modified BP learning algorithm as follows:

1. Calculate the output of each hidden neuron for each sample n:

$$(x_j^h)_n = f(x_n^i * w_j^h)\ (j = 1, \ldots, 10) \tag{1}$$

where $f(x) = 1/[1 + e^{-x}]$ is a sigmoid function, x_n^i is the input of the sample n, $n = 1, \ldots, N$, N is the number of samples, w_j^h is the weight value between the input neuron and jth hidden neuron.

2. Calculate the output of the output neuron for each sample n:

$$x_n^o = f\left(\sum_{j=1}^{10}((x_j^h)_n * w_j^o)\right) \tag{2}$$

where w_j^o is the weight value between the jth hidden neuron and the output neuron.

3. Calculate the average square root of the output error:

$$e(k) = \sqrt{\left(\frac{1}{2}\sum_{n=1}^{N}(x_n^T - x_n^o)^2\right)} \tag{3}$$

where x_n^T is the output of the sample n.

4. Calculate the BP error of the output layer for each sample n:

$$d_n^o = x_n^o(1 - x_n^o)(x_n^T - x_n^o) \tag{4}$$

5. Calculate the BP error of the hidden layer for each sample n:

$$(d_j^h)_n = (x_j^h)_n(1 - (x_j^h)_n)d_n^o w_j^o \tag{5}$$

6. Adjust the weights between the hidden layer and the output layer:

$$w_j^o(k + 1) = w_j^o(k) + \eta(k + 1)\sum_{n=1}^{N} d_n^o(x_j^h)_n + \alpha(k + 1)\Delta w_j^o(k) \tag{6}$$

where $\eta(k+1)$ is the learning rate, $\alpha(k+1)$ iss the dynamic factor, $\Delta w_j^o(k) = w_j^o(k) - w_j^o(k - 1)$. If

$\Delta e(k) = e(k) - e(k - 1)$, then $\eta(k + 1) = \eta(k)*0.618$
$\alpha(k + 1) = \alpha(k) * 0.618$, otherwise $\eta(k + 1) = \eta(k)/0.618$
$\alpha(k + 1) = \alpha(k)/0.618$

7. Adjust the weights between the input layer and the hidden layer:

$$w_j^h(k + 1) = w_j^h(k) + \eta(k + 1)\sum_{n=1}^{N}(d_j^h)_n x_n^i + \alpha(k + 1)\Delta w_j^h(k) \tag{7}$$

where $\Delta w_j^h(k) = w_j^h(k) - w_j^h(k - 1)$.

9. Repeat steps 1 to 7 until $e(k) \leq e_d$, where e_d is the desired error.

3. Optimal Control of the Milling Process Based on the Modified ALM NN

Considering a general nonlinear optimisation problem as follows:

$$\text{Objective Min:}\quad F(X) = F(x_1, \ldots, x_n) \tag{8}$$

$$\text{Constraints S.T.:}\quad G_j(X) \leq 0 \quad (j = 1, \ldots, m) \tag{9}$$

ALM NN is essentially a method attached to a punishing function, i.e.

$$A(X, \lambda, r_p) = F(X) + \sum(\lambda_j\phi_j + r_p\phi_j^2) \tag{10}$$

where $\phi_j = \mathrm{Max}\left[G_j(X), \frac{-\lambda_j}{2r_p}\right]$

$$\lambda_j(k + 1) = \lambda_j(k) + 2r_p\phi_j \quad (j = 1, \ldots, m)$$
$$r_p(k + 1) = r_p\gamma \quad (\gamma > 1)$$

Then the iteration formula of the optimised variable can be expressed as follows:

$$X(k + 1) = X(k) - \mu(k)\nabla A(X, \lambda, r_p) \tag{11}$$

where $\mu(k)$ is the iteration step;

$$\nabla A(X, \lambda, r_p) = \left[\frac{\partial A}{\partial x_1}, \ldots, \frac{\partial A}{\partial x_n}\right]^T$$

$$\frac{\partial A}{\partial x_i} = \frac{\partial F(X)}{\partial x_i} + \sum_{j=1}^{m} S_j(\lambda_j + 2r_p\phi_j)\frac{\partial G_j}{\partial x_i}$$

$$S_j = \begin{cases} 1 & G_j(X) \geq -\lambda_j/2r_p \\ 0 & G_j(X) < -\lambda_j/2r_p \end{cases}$$

There are many optimising objectives used in machining, such as the highest productivity and lowest costs, and the rate of metal cutting which represents the milling efficiency is selected as the optimising objective in this paper. The milling depth d and milling width w are variable in the milling process, and so are considered in the modelling of the milling system, so the optimised variables are selected as the milling speed v in this paper, i.e.

$$F(v) = v \tag{12}$$

Moreover, there are many constraints in the optimisation of milling parameters. The key constraints are selected as follows:

$$\begin{cases} G_1(v) = v - v_{\max} \leq 0 \\ G_2(v) = v_{min} - v \leq 0 \\ G_3(v) = Fc(v) - [F] \leq 0 \end{cases} \tag{13}$$

where v_{max} and v_{min} are, respectively, the maximum and minimum cutting speed, $Fc(v)$ is the output of the BP NN, and $[F]$ is maximum cutting force.

Combining (12), (13), (11) and (2), the iteration formula of the optimised variable v can be obtained as follows:

$$v(k+1) = v(k) - \mu(k)\frac{\mathrm{d}A}{\mathrm{d}v} \tag{14}$$

where

$$\frac{\mathrm{d}A}{\mathrm{d}v} = -1 + S_1(\lambda_1 + 2r_p\phi_1) - S_2(\lambda_2 + 2r_p\phi_2) + S_3(\lambda_3 + 2r_p\phi_3)\frac{\mathrm{d}Fc(v)}{\mathrm{d}v}$$

$$\frac{\mathrm{d}Fc}{\mathrm{d}v} = Fc(1 - Fc)\sum w_j^o w_j^h x_j^h (1 - x_j^h)$$

To increase the convergence speed of v, the $\mu(k)$ in (14) is adjusted as follows:

$$\begin{cases} \mu(k) = \mu(k-1)\alpha & (A(k) < A(k-1)) \\ \mu(k) = \eta(k-1)\beta & (A(k) \geq A(k-1)) \end{cases} \tag{15}$$

where $\alpha > 1$, $\beta < 1$.

4. NN Based Adaptive Control with Optimisation in Milling Process

The milling system with the adaptive controller can be constructed based on NNs as in Fig. 2. The milling system $Fc = Fc(v)$ is modelled on-line by the modified BP learning algorithm. The milling feedrate is adjusted and the milling process is optimised in real-time by the modified ALM NN.

5. Simulation and Experiments

The simulation and experiments have been carried out with a CNC end milling system, in which the diameter of the cutting tool is 10 mm, the number of teeth in the cutting tool is 3, the workpiece is T20 grey cast iron. The cutting force is measured by a KISTLER 9257A, amplified by a YE5850, and converted and processed by a 8098 single board computer. The adaptive controller is operated by a PC and the adjusted feedrates are sent to the CNC.

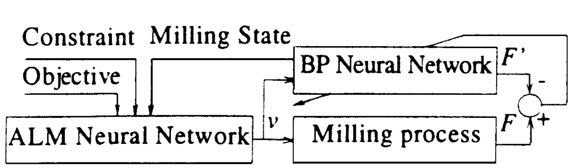

Fig. 2. A neural network based adaptive milling system.

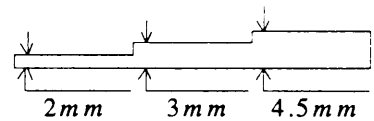

Fig. 3. Variation of milling depth.

5.1 Variation of the Cutting Depth

To prove the high robustness and stability of the adaptive control milling system, the simulation and experiment for variable milling depth shown in Fig. 3 have been carried out, where the spindle speed is 300 r/min^{-1}, the initial command feedrate is 90 mm/min^{-1} and its allowable adjusting rate is [0%, 200%].

To model the milling system, the small initial weights of the modified BP NN are produced randomly, the initial learning rate and the dynamic factor is 0.5. To optimise the milling feedrate, the constraints are $[F]$=360 N, 7.5 mm min^{-1} $\leq$ 180 mm min^{-1}. The initial iteration step is 0.5.

5.1.1 Simulation

Figure 4 gives the simulation result where the milling speed is adjusted on-line to maintain the cutting force at the maximum constrained value, i.e. the milling system achieves maximum efficiency.

5.1.2 Experiment

Figure 5 shows the experimental result which is similar to the simulation. As the modified ALM does not need an accurate milling model, the number of NN learning iterations is selected as 4 so as to achieve the modelling on-line. To increase the convergence of NN learning, the initial weights of the modified BP NN are selected as the stable values learned in the simulation. The sampling cycle of the cutting force is 1 ms, the control cycle of the feedrate is 0.4 s, and the other conditions are the same as for the simulation.

5.2 Variation of the Cutting Width

To prove the higher machining efficiency can be achieved by the adaptive control milling system, milling experiments of the cam, shown in Fig. 6, have been done by both the traditional CNC milling system and the adaptive control milling system.

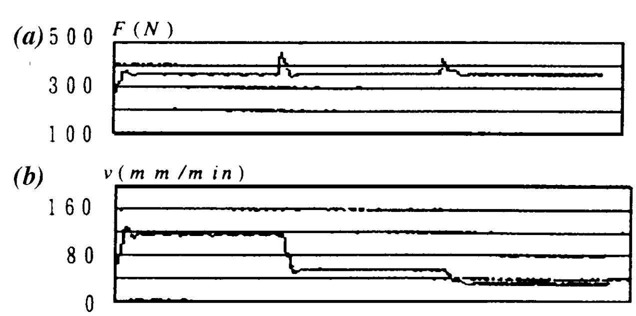

Fig. 4. Simulation of ACO milling. (*a*) Response of cutting force. (*b*) Response of feedrate.

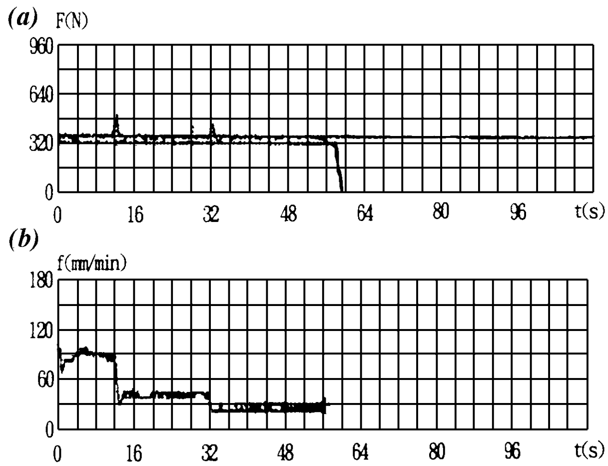

Fig. 5. The experimental result of the ACO milling process. (*a*) Response of cutting force. (*b*) Response of feedrate.

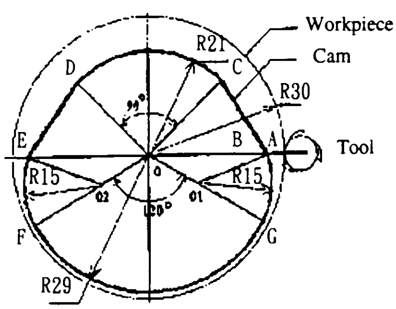

Fig. 6. Milling of a cam.

5.2.1 Traditional CNC Milling Experiment

The milling parameters can be selected from the handbook as follows [6]:

Spindle speed: $n = 400$ r.p.m.
Feedrate: $f_1 = 30\ \mathrm{mm\ min^{-1}}$ (A to E)
$f_2 = 40\ \mathrm{mm\ min^{-1}}$ (E to F, G to A)
$f_3 = 50\ \mathrm{mm\ min^{-1}}$ (F to G)
Cutting depth: $d = 2$ mm.

Figure 7 is the response of cutting force and feedrate by the traditional CNC milling system using the above milling parameters. In Fig. 7, the maximum cutting force is maintained at about 320 N from point A to point D. While the cutting force is decreased owing to the cutting width being decreased from point D to point B, the cutting parameters cannot be adjusted. So the milling system cannot achieve the maximum milling efficiency.

5.2.2 Adaptive Control Milling Experiment

The initial milling parameters for the adaptive control system are the same as for the traditional CNC milling system. To compare the machining efficiency to that of the traditional CNC milling system, the maximum cutting force is selected to be the same as for the traditional CNC milling system, and the constraints of the adaptive milling system are selected as:

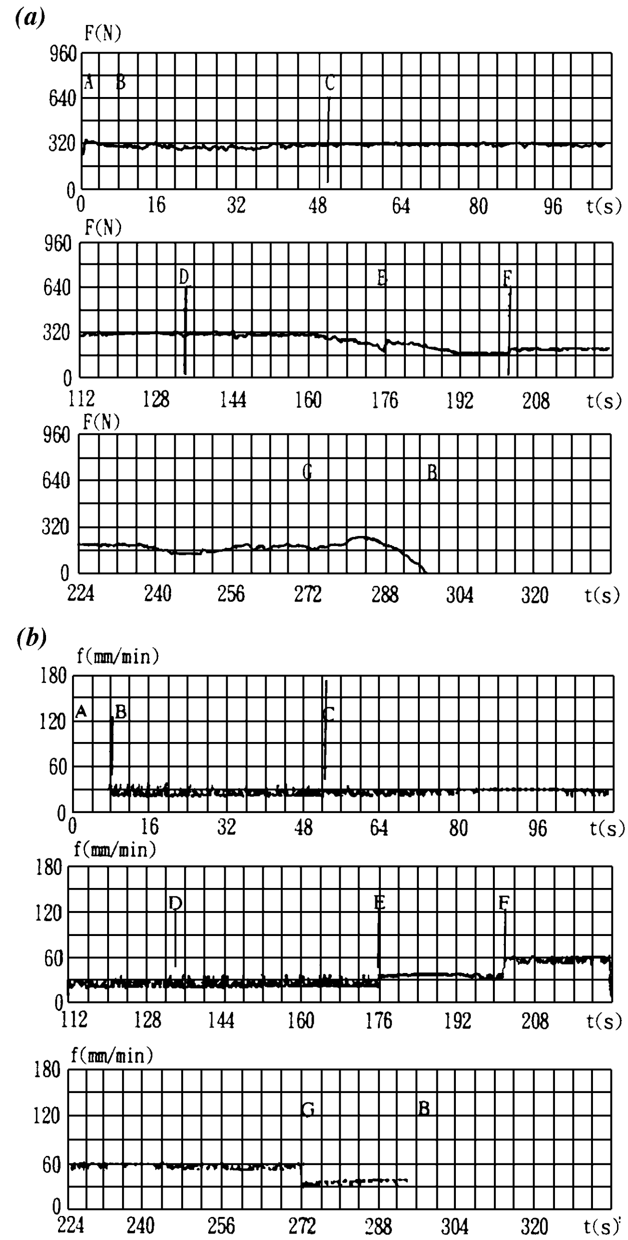

Fig. 7. Milling of a cam without adaptive control. (*a*) Response of cutting force. (*b*) Response of feedrate.

$[P]$=4.5 kW, $[F]$=320 N, $7.5\ \mathrm{mm\ min^{-1}} \le v \le 180\ \mathrm{mm\ min^{-1}}$. The other parameters of the adaptive controller are the same as for the adaptive milling experiment with the variation of cutting depth.

Figure 8 is the response of cutting force and feedrate using the adaptive controlled milling system. Comparing the Fig. 8 to Fig. 7, the cutting force for the adaptive control milling system is maintained at about 320 N, and the feedrate of the adaptive milling system is close to that of the traditional CNC milling system from point A to point E, but the feedrate of the adaptive milling system is much higher than for the traditional CNC milling system from point E to point B, so the milling efficiency of the adaptive milling system is improved

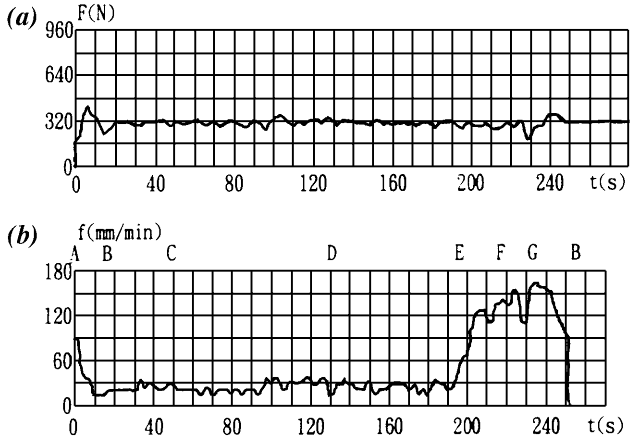

Fig. 8. Milling of a cam without adaptive control. (*a*) Response of cutting force. (*b*) Response of feedrate.

by about 15% compared with that of the traditional CNC milling system.

6. Conclusion

The object of this paper is to design an adaptive controller with optimisation based on the modified BP NN and ALM NN. The learning rate of the BP NN is adjusted in the learning process and a dynamic factor is added to increase the convergence speed of the BP learning process. The milling system can be modelled on-line, based on this modified BP NN. The iteration step size of ALM NN is adjusted in the iteration process to increase the convergence speed. The milling process can be optimised in real-time by the modified ALM NN. The simulation and experiments show that the adaptive milling system with the modified BP NN and ALM NN has a high robustness and global stability, and that the adaptive milling force achieves the maximum constrained value, i.e. the milling system achieves maximum efficiency.

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References

1. Y. Liu, T. Chen, L. Zuo and S. Yang, “K-L optimization of cutting parameters in machining”, Journal of Huazhong University of Science and Technology, 24(5), pp. 50–52, 1996.
2. Y. Liu, L. Zuo, T. Cheng and S. Yang, “On adaptive sliding-mode following control”, Journal of Huazhong University of Science and Technology, 24(5), pp. 44–46, 1996.
3. L. M. Zhang, Model of Artificial Neural Network and its Application, Fudan University Publishing House, 1992.
4. M. P. Kennedy and L. O. Chua, “Neural networks for nonlinear programming”, IEEE Transactions Circuits System, 35, pp. 554–564, 1988.
5. Y. Liu and S. Yang, “Perceptron-based nonlinear Sliding model control”, Information and Control, 25(4), pp. 193–198, 1996.
6. Z. H. Zhou, Metal Cutting Principle, Shanghai Science and Technology, 1992.