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Study of Intelligent Prediction Control of Surface Roughness in Grinding

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Abstract. A surface roughness intelligent prediction control system during grinding is built. The system is composed of fuzzy neural network prediction subsystem and fuzzy neural network controller. In the fuzzy neural network prediction subsystem, the vibration data are added to the inputs besides the grinding condition, such as feed and speed, so as to improve the dynamic performance of the prediction subsystem. The fuzzy neural network controller is able to adapt grinding parameters in process to improve the surface roughness of machined parts when the roughness is not meeting requirements. Experiment verifies that the developed prediction control system is feasible and has high prediction and control accuracy.

Introduction

It is well known that the quality of the surface part plays a very important role in the performance of machined parts by grinding. The common way of control surface roughness is to add the spark-out grinding number of times, and the roughness value is obtained by off-line measurement. The way can't satisfy the need of the modern manufacture. Many experts have been studying the grinding surface roughness, and have got achievements [1,2,3]. But by now, the on-line measurement and control roughness is still a difficult problem because the grinding process is non-linear, random and indeterminate，and it's difficult to build exact surface roughness model.

In this paper, we build a roughness intelligent prediction control system. It can dynamically predict the workpiece surface roughness in process with fuzzy neural network. When the desired roughness is not met, it can propose the new grinding parameters for the grinding process with fuzzy neural network, further control the workpiece surface roughness.

Roughness Intelligent Prediction Control System

Structure and Principle. The proposed roughness intelligent prediction control system is shown as Fig.1. It is composed of fuzzy neural network(FNN) roughness prediction subsystem and fuzzy neural network(FNN) controller. In Fig.1, a_p is grinding depth; Va is the vibrate amplitude; fa is table feed; n_w is the workpiece rotation velocity; n_s is the grinding wheel rotation velocity; R is the roughness measured by roughness measurer; R_p is the prediction roughness by the roughness prediction subsystem; R_d is the desired roughness; dR is the roughness deviation.

The roughness intelligent prediction control system works as followings.

In the first stage, the switch 1 is connected, and the switch 2 is disconnected. The surface roughness of machined parts is measured by the roughness measurer, and compared with the desired roughness. If the desired roughness is not met, the roughness deviation dR, the workpiece rotation velocity n_w, the grinding wheel rotation velocity n_s, the vibrate amplitude Va and the grinding depth a_p are entered into the fuzzy neural network(FNN) controller. Then the controller proposes the change value of the table feed dfa for the grinding process to control roughness. At the same time, the surface roughness R obtained by roughness measurer, the workpiece rotation velocity n_w, the grinding wheel rotation velocity n_s, the table feed fa , the vibrate amplitude Va and the grinding

depth a_p are entered into the roughness prediction subsystem as the training data. In this stage, the roughness prediction subsystem doesn't work and only accepts the data to train the fuzzy neural network. With the number of train data increasing, the prediction accuracy of the roughness prediction subsystem is higher and higher. When the prediction accuracy meets the requirement, the second stage begins. In this stage, the switch 2 is connected, and the switch 1 is disconnected. The roughness measurer doesn't work. The roughness prediction subsystem predicts the surface roughness, which is then compared to the desired roughness. If the desired roughness is not met, then, the roughness controller proposes a new table feed for the grinding process, further control the workpiece surface roughness.

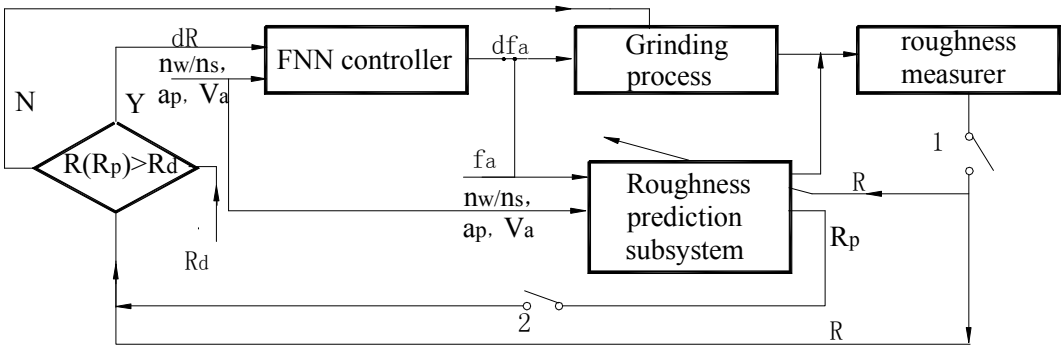

Fig.1 Roughness prediction control system

Roughness Prediction Subsystem. Extensive studies have been carried out in the workpiece surface roughness for the grinding process. The theory equations and the empirical equations were developed [4,5,6]. From the equations, we get that roughness is in direct proportion to the workpiece rotation velocity n_w, table feed fa and grinding depth a_p, and in inverse proportion to the grinding wheel rotation velocity n_s. Since the wear of the grinding wheel has a direct effect on the workpiece vibration and both have effect on the workpiece surface roughness, the roughness is in direct proportion to the vibrate signal amplitude Va.

Considering all of the above relationships, we proposed the relation of roughness and machining parameters as follows

$$Ra=R(n_w/n_s)^x(a_p)^y(fa)^z(Va)^m. \quad (1)$$

Where, R, x, y, z and m are the experimental constant. This relationship is the theory basis of our proposed roughness prediction model in this paper.

In Eq.1, R, x, y, z and m are on the case-by-case basis. The values of R, x, y, z and m established under one grinding condition generally cannot be used for roughness prediction of other conditions. To settle the problem, the fuzzy neural network is introduced, because the fuzzy neural network has self-learning and self-adapted ability. In this fuzzy neural network, the neural network is used to implement fuzzy inference. The parameters in fuzzy inference are expressed with neural network connection weights.

Eq.1 is calculated logarithm in the both side. Supposing lgR=R1, we can get the following

$$\lg R_a = R_1 + x\lg\left(\frac{n_w}{n_s}\right) + y\lg a_p + z\lg f_a + m\lg Va\,. \quad (2)$$

We use the logarithm of velocity ratio n_w/n_s, the logarithm of grinding depth a_p, the logarithm of traverse feed velocity f_a and the logarithm of vibration amplitude Va as inputs of fuzzy neural network, and the logarithm of the roughness is as the output, shown in Fig.2.

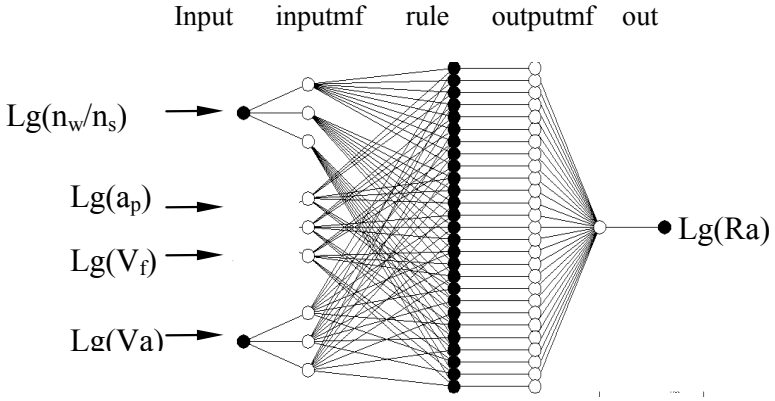

Fig.2 Architecture of the fuzzy neural network

From Eq.2, we know that there exists lineary relation between the roughness logarithm and the logarithm of n_w/n_s, a_p, f_a and Va. So, we adopt T-S type fuzzy inference to obtain R1, x, y, z and m. The rule form is as followings: If $x_1=A_1$, $x_2=A_2$, $x_3=A_3$, $x_4=A_4$, then $f_j = p_j x_1 + q_j x_2 + r_j x_3 + s_j x_4 + t_j$

The fuzzy neural network is of feed forward multi-layer construction, which has five layers. The first layer is to enter the variable. The second layer is fuzzified layer. The membership function is as follows

$$y_i^{(2)} = \exp[-(x - m_{ij})^2/\sigma_{ij}^2]. \tag{3}$$

Here, $y_i^{(2)}$ is the second layer output of the i-th input variable. m_{ij} and σ_{ij} is gauss function midpoint and width of the j-th term of the i-th input variable x_i respectively.

The third layer is the rule node. It represents fuzzy rule. The output is as follows

$$y_j^{(3)} = \prod_{i=1}^{n} y_i^{(3)}. \tag{4}$$

Here, $y_j^{(3)}$ is the third layer output of the j-th input variable.

In the forth layer, the conclusions of rule node are defined. The output is as follows

$$y_k^{(4)} = \omega_{kj}^4 (p_j x_1 + q_j x_2 + r_j x_3 + s_j). \tag{5}$$

Here, $y_k^{(4)}$ is the forth layer output of the k-th input variable. ω_{kj}^4 is weight.

The fifth layer is output variable layer, in which the defuzzication is accomplished. The following formula is used

$$y_l^{(5)} = \lg R = \sum y_k^{(4)} m_{ijlk}\sigma_{ij\,lk} / \sum y_k^{(4)} \sigma_{ij\,k}. \tag{6}$$

Here, $y_l^{(5)}$ is the fifth layer output of the l-th input variable.

The mixed algorithm of two stages is adopted. In the first stage, a self-organization learning algorithm determines the initial input and output membership functions and the existence of fuzzy logic ruler. First, find the midpoint and width of the membership function; then determine the

connection weight through competing learning algorithm.

In the second stage, a supervisor-learning algorithm adjusts the input and output membership functions, so as to obtain the expected output. The following error function is adopted

$$E=1/2\ (y_d - y_1^{(5)})^2. \tag{7}$$

Here, y_d is the expected output. According the descent gradient algorithm

$$\omega_{kj}(t+1)= \omega_{kj}(t) - \eta(\partial E/\partial \omega_{kj}). \tag{8}$$

$$\partial E/\partial \omega_{kj} =\partial E /\partial\ y_k^{(4)}\cdot\partial\ y_k^{(4)}/\partial\omega_{kj}=\partial E / \partial y_1^{(5)}\cdot\partial y_1^{(5)}/\partial\ y_k^{(4)}\cdot\partial\ y_k^{(4)}/\partial\omega_{kj}. \tag{9}$$

As the same reason,

$$m_{ijlk}(t+1)= m_{ijlk}(t)+\beta(y_d- y_1^{(5)})\cdot\sigma_{ij\ lk}\ y_k^{(4)}/\Sigma\sigma_{ij\ lk}\ y_k^{(4)}. \tag{10}$$

$$\sigma_{ij\ lk}(t+1)= \sigma_{ij\ lk}(t)+\beta(y_d- y_1^{(5)})\cdot y_k(m_{ijlk}(\Sigma y_k^{(4)}\sigma_{ij\ lk}) - (\Sigma y_k^{(4)}\sigma_{ij\ lk}\ m_{ijlk}))/(\Sigma y_k^{(4)}\sigma_{ij\ lk})^2. \tag{11}$$

where, η and β are learning factor.

FNN Controller. In generally speaking, the surface roughness is got from the fine grinding and spark-out grinding stage, in which the grinding depth a_p is very small and it's difficult to be controlled by motor. Moreover, statistical analysis shows that the table feed fa has a significant effect on the surface roughness[7]. So, we adjust the table feed fa to control the workpiece surface roughness in this FNN controller. The controller is a five layer fuzzy neural network. The inputs are the roughness deviation dR, the ratio of the workpiece rotation velocity n_w and the grinding wheel rotation velocity n_s, the vibrate amplitude Va and the grinding depth a_p, and the output is the change value of the table feed dfa. The algorithm of this FNN is similar to that of the prediction subsystem FNN.

Experiment.

Fig.3 shows the experimental control system for cylindrical traverse grinding process. Fig.4 shows the photograph of experimental control system. The experiments had been finished on the MMB1320 semiautomatic external grinder. The grinding liquid is emulsion, and the grinding wheel is GB70RAP400×32×203. The grinding wheel rotation velocity n_s is 1790r/m. The wheel's dressing depth and lead are 0.01mm and 0.08mm respectively. The workpiece is divided into two parts: the first part for original table feed, the other part for adapted table feed. The material of the workpiece is bearing steel.

The experiment procedures are as followings:

1. Set up the workpiece.
2. Perform the first part of workpiece cut in grinding operation.
3. Generate the prediction surface roughness R_p from FNN roughness prediction subsystem.
4. Compare R_p with R_d to obtain the dR value, and then trigger the FNN controller to generate the adaptive change value of the table feed dfa.
5. Perform the second part of workpiece cut in grinding operation using the new table feed.
6. Measure the adaptive surface roughness R_{FNNC} after the adaptive table feed is applied.
7. Compare R_{FNNC} and Rd. If R_{FNNC} is less than R_d, the experiment is considered successful.

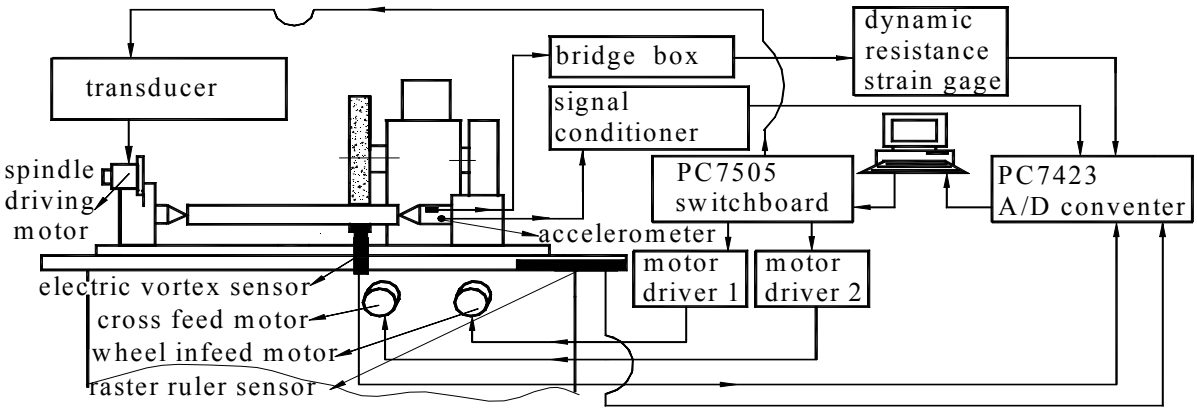

Fig. 3 Experimental control system for cylindrical grinding process

Results and Discussion.

Fig. 5 shows the roughness results of the fuzzy neural network prediction subsystem with vibration amplitude, neural network prediction without vibration amplitude and actual measurement. It can be seen from Fig.5 that the prediction roughness results of the proposed fuzzy neural network predictive model with vibration amplitude is very close to the measured one, and is better than that of the neural network prediction without vibration amplitude. The reason is that the vibration signals reflect the changing conditions of the grinding wheel wear and workpiece surface roughness in different time and in different place. Besides, the fuzzy neural network algorithm is also introduced. The prediction accuracy of fuzzy neural network roughness predictive subsystem is 98.8%.

The correctness and cover rage of the training data effect the model accuracy directly Since the accuracy of proposed prediction model depands on training data.

Fig.4 Photograph of experimental control system for cylindrical grinding process

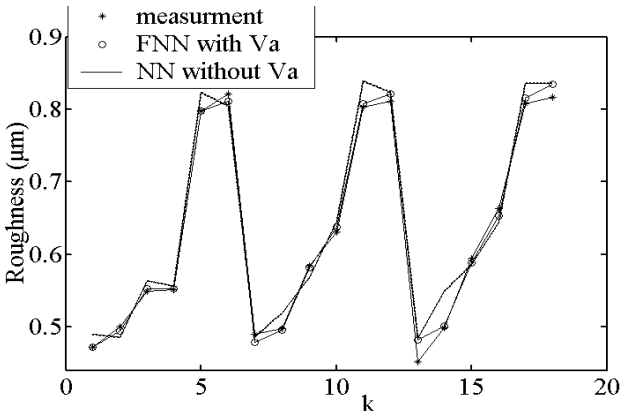

Fig.5 Prediction results of FNN roughness predictive subsystem

The experiment results of roughness intelligent prediction control are listed in the table1. Table 1 shows that the proposed roughness intelligent prediction control system performed 16 successes out of 18 tests.

Table 1 Testing experimental data for the roughness intelligent prediction control system

	n_w [r/m]	f_a [mm/r]	a_p [mm]	Va [v]	R_p [μm]	R_d [μm]	dR [μm]	df_a [mm/r]	R_{FNNC} [μm]
1	125	8	0.015	0.093	0.47	0.35	0.12	7.70	0.25
2	125	8	0.025	0.096	0.49	0.35	0.14	7.67	0.3
3	125	15.2	0.015	0.087	0.55	0.35	0.20	14.95	0.32
4	125	15.2	0.025	0.092	0.55	0.35	0.20	15.04	0.24
5	125	24.8	0.015	0.091	0.80	0.35	0.45	24.61	0.35
6	125	24.8	0.025	0.093	0.81	0.35	0.46	24.66	0.26
7	170	8	0.015	0.091	0.48	0.35	0.13	7.64	0.23
8	170	8	0.025	0.094	0.50	0.35	0.15	7.75	0.34
9	170	15.2	0.015	0.100	0.58	0.35	0.23	15.02	0.25
10	170	15.2	0.025	0.102	0.64	0.35	0.29	14.90	0.24
11	170	24.8	0.015	0.101	0.81	0.35	0.46	24.49	0.41
12	170	24.8	0.025	0.102	0.82	0.35	0.47	24.48	0.34
13	200	8	0.015	0.110	0.48	0.35	0.13	7.65	0.38
14	200	8	0.025	0.108	0.50	0.35	0.15	7.71	0.23
15	200	15.2	0.015	0.107	0.59	0.35	0.24	14.89	0.29
16	200	15.2	0.025	0.109	0.65	0.35	0.30	14.88	0.34
17	200	24.8	0.015	0.108	0.82	0.35	0.47	24.51	0.26
18	200	24.8	0.025	0.110	0.83	0.35	0.48	24.55	0.3

Conclusions

The surface roughness intelligent prediction control system during grinding is developed. Desired workpiece roughness can be obtained in process. The experimental results indicate the proposed prediction control system has high accuracy. It provided a positive opportunity for developing modern grinding technology.

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