APPLICATION OF NEURAL NETWORK TECHNOLOGY IN MACHINING ERROR RECOVERY

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ABSTRACT: In order to improve the machining error problem, the application of neural network technology in machining error recovery is designed. In the process of parts processing, due to the error caused by the change of the size and position of the blank, the technicians usually repeat the processing to reduce the corresponding error according to their own experience. The BP neural network is used to simulate the error recovery problem. The BP algorithm is improved by using the integrated momentum method, the adaptive learning rate and the bipolar S compression function method. A neural network model is established to optimize the machining parameters. The influence of processing times, process stiffness and feed rate on the error of machined parts is analyzed by the data obtained by experiments. The network structure of 5-15-12-2 hidden layer neurons is used to verify the feasibility of BP machining error resolution. The results show that the above process is correct and the experimental results are good. Furthermore, the development and application of neural network technology in machining are further promoted. Based on the above finding, it is concluded that the application of neural network technology in machining error recovery will be able to solve the whole problem of mechanical processing error of neural network.

KEY WORDS: Neural network; machining; error reconstruction; BP algorithm.

1 INTRODUCTION

In the context of international competition, the mechanical manufacturing industry relying on traditional technology and technology has become the past, and they have long been unable to meet the high demand for product accuracy and quality. The quality of a mechanical product cannot be separated from the manufacturing quality of the parts. It is determined by the quality of the manufacture and assembly of the parts. The most important index to measure the quality of parts is their machining accuracy. However, in the actual processing, parts processing is simply impossible to ensure that the ideal results are exactly the same, there will be some processing error exists [1]. Usually, depending on the worker's processing experience, repeated work may reduce the error appropriately, but the effect is limited. Neural networks can be used to perform complex logical and nonlinear operations, [2], which is applied to machining error recovery problems, and the feasibility needs further study.

2 LITERATURE REVIEW

The primary goal of machining is to ensure that the product meets the requirements of geometry, that is, the required size, surface shape and solid structure of the machined product can meet the desired effect. However, the reality is that the production error has a serious impact on the machining accuracy and product quality, and even directly limits the production efficiency of the machining enterprises. Repetitive machining is usually used to reduce the complex error and improve the machining accuracy [3]. But it is worth noting that repeated work leads to lower productivity, and the number of repeats depends on the experience of the technician. This virtually increases the difficulty and uncertainty of the actual operation, so the method is not feasible.

In the field of modern manufacturing technology, the wider application of computer has greatly promoted the informationization and automation of the development of machinery manufacturing. At the same time, it is toward the network and intelligent direction of rapid development. The study of error mapping based on neural network technology is also increasing. In order to solve the problem better, the scholars do the following research. Ma Jianwei reduces machining errors by optimizing feed rates and analyzing variations in the error. Based on artificial neural network, taking 17-4 PH steel as experimental material, Chandramouli established the machining model and optimized the process parameters. Devarasiddappa applied the neural network to the surface quality control of aeronautical alloy materials [4]. In this paper, the back propagation (BP) of neural networks is used to

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simulate the complex process of error resolution, and a network model is established, which provides a theoretical and practical reference for the application of neural networks in machining

3 METHODS

3.1. Basic structure of neural network

Neural network is an artificial mathematical model that mimics the structure and function of the brain. It is a digitized and theoretical application of the human brain neural network. It has the advantages of biological neural network, that is, good fault tolerance and associative memory functions, strong adaptability and learning ability, and the integrity and parallelism of information processing. These are usually made up of a certain number of neurons [5]. The neuron is the basic processing unit of the neural network [6]. It is a single input or multi input nonlinear component. The simplified model is shown in figure 1. Each input of the artificial neuron is subjected to a related weight to influence the stimulus of the input, which is similar to the variable intensity of the synapses in the biological neurons. It determines the strength of the input signal, which is generally considered as a connection strength test. The initial weighting of the artificial neural network can be adjusted according to a certain rule, which also affects the synaptic strength in biological neurons.

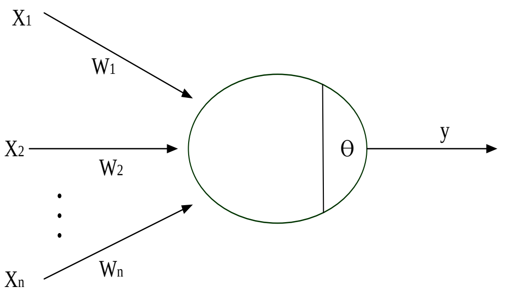

Figure 1 Simplified neuron model

The neurons in figure 1 have n input components, and Wi (i＝1,2,…,n) represents the weights (the strength of neurons and synaptic connections) of the input component Xi (i＝1,2,…,n). Xi is connected with its multiplier Wi, and the output is passed through the transfer function after the deviation theta. It can be expressed as:

$$Y(t) = f\left(\sum_{i=1}^{n} W_i X_i(t) - \theta\right) \quad (1)$$

The above neural network has a high degree of parallelism. It is a neural network that is formed by a combination of many of the same simple processing units in parallel. Although its individual function is simple, a great deal of parallel activity strengthens its ability to process information. Depending on the high degree of non-linear global action, each neuron in the neural network can accept a large number of other neurons input. After the parallel network is output, the other neurons are affected. The relation between them is controlled and the nonlinear mapping from input to output is realized. It forms good fault tolerance and associative memory function, as well as strong adaptive and self-learning ability.

3.2. Analysis of error resolution

In the process of mechanical processing, the size of blank and the error of shape and position, the eccentricity of the clamping card can cause the change of the machining allowance. However, uneven work-piece material can cause change in cutting force and deform the process system. Thus, the machining error is produced, that is, the error re representation in machining. Due to the error in processing, the coefficient of re image is always less than 1 and processed several times. Proper processing allowance can reduce the machining error caused by error re processing. For the error re processing problem in machining, the coefficient of resolution is less than 1. It is assumed that the original part has oval error and the cutting depth of cutting tool is ap1 and ap2 on the long axis and short axis of the ellipse. In the machining process, the cutters are y1 and y2, and the finished parts still have oval error. The re mapping coefficient can be calculated from the error resolution theory:

$$\varepsilon = \frac{y_1 - y_2}{a_{p1} - a_{p2}} = \frac{F_{y1} - F_{y2}}{k_{系}(a_{p1} - a_{p2})} \quad (2)$$

In the formula, k系 is the process rigidity. Fy1 and Fy2 is the radial component of the long and short axis of the ellipse. However, in the formula $F_y = C_y f^y a_p^x HBS^n$, Cy represents the coefficients relating to tool cutting conditions. f is the feed, and HBS refers to the material hardness of the part. x, y and n are related index indexes.

Assuming that x≈1, then the simplified form of formula 1 is:

$$\varepsilon = \frac{C_y f^y HBS^n}{k_{系}} \quad (3)$$

The initial error of the component is set to EB, and the final error after multiple machining is EE.

The error after processing is complicated nonlinear function relation with blank error, process system rigidity, feed, work-piece hardness and processing times. In theory, the machining error is independent of the machining depth AP, that, is, the depth of cut is independent of each time. It is assumed that the ratio of three cutting depth to total cutting depth is P1, P2 and P3, and there is P1 + P2 + P3 = 1. Therefore, P1 and P2 are replaced by the first and second cutting depth to the total cutting depth for processing times Z. Under normal circumstances, there are at most three times about the number of repeat processing Z. The cutting depth rate of the first (P1) and second (P2) is used as output for network training.

3.3. Design and implementation of BP network

The essence of BP network is a kind of error back propagation learning [7]. It not only has input and output layers, but also has different numbers of hidden layers. Its structure is shown in figure 2. It is a multi layer network with generalization of W-H learning rules and weight training for nonlinear differentiable functions.

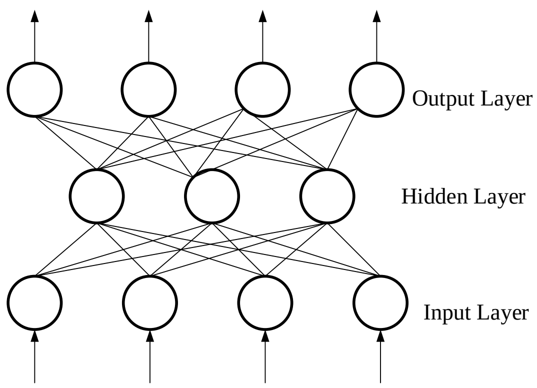

Figure 2 Basic structure of BP network

The activation function of the BP network is usually a differentiable s-type logarithmic or tangent function [8]. BP networks are mainly used for function approximation, pattern recognition, classification and data compression. In the practical application of artificial neural networks, the 80%~90% artificial neural network adopts BP network or its deformation form. It is also the core part of the forward network, which embodies the best part of the artificial neural network. For relatively complex neural networks, the activation function is no longer linear, but a nonlinear planar region. Its interface is extended arbitrarily, and the fault tolerance is better. Its structure is not completely limited by the problem or object. The number of input neurons and the number of output neurons in the network are determined by the requirements of the problem. However, the number of hidden layers between input and output, and the number of neurons per layer, are determined by the designer. The BP network or its deformation form is used to solve the case of the problem, which can account for 90% of the actual application of the neural network.

BP algorithm, that is, the error back propagation method, calculates the network weights by continuously decreasing the slope of the error function, analyzes the variation of the deviation, outputs and modifies the weights until the desired value is reached [9]. It is a supervised learning algorithm, and the main idea is: for q input learning samples: P1, P2, ... Pq, the corresponding output samples are: T1, T2, ... Tq. The purpose of learning is to use the actual output of the network: That is, the error between the A1, A2, ... Aq and the target vector T1, T2, ...Tq is used to modify its weight so that the Al(l＝1,2...q) is as close as possible to the desired Tl. The sum of squared error of the network output layer is minimized. It is the process of top-down propagation of information from the input layer through the hidden layer to the output layer. If the output layer does not get the expected value, the error value is calculated, and then the bottom-up error propagation is reversed, and the weights of each neuron are modified until the expected value is satisfied Based on the BP algorithm, an additional momentum method, adaptive learning rate and bipolar S compression function method are used to improve the function.

It is a complex nonlinear function to solve the machining error complex problem using neural networks. However, any nonlinear mapping capability of BP networks can be used to model this function relationship. Therefore, it is reasonable to choose BP neural network model [10]. Based on the experimental data of hundreds of sets, the law of machining error re mapping is analyzed and the network model is designed and implemented.

4 RESULTS AND DISCUSSION

4.1. Data processing analysis

The Brinell hardness (HBS) of the material is measured at first, then the tool parameters are adjusted. The dial gauge is used to measure the initial error of EB and fixe the value of f, P1, P2 and P3. The rigidity of the system is measured by the system rigidity instrument, and the error after processing is EE. In the process of practical application, in order to reduce the man-made system error, the experimental results are objectively reflected and the experimental data are standardized. The original data of x were used to subtract the average value of v and then divided by the standard deviation σ, z values were obtained as follows:

$$Z = \frac{x - v}{\sigma}$$

The following is the data measured with the cast iron of Φ50.

Table 1 Influence of processing times and margin on component error

-	EB (mm)	-	P_1	-	P_2	-	P_3	-	EE (mm)
-	0.253	-	50	-	50	-	0	-	0.028
-	0.253	-	100	-	0	-	0	-	0.032
-	0.253	-	75	-	25	-	0	-	0.084
-	0.702	-	33.3	-	66.7	-	0	-	0.034
-	0.698	-	66.7	-	33.3	-	0	-	0.032

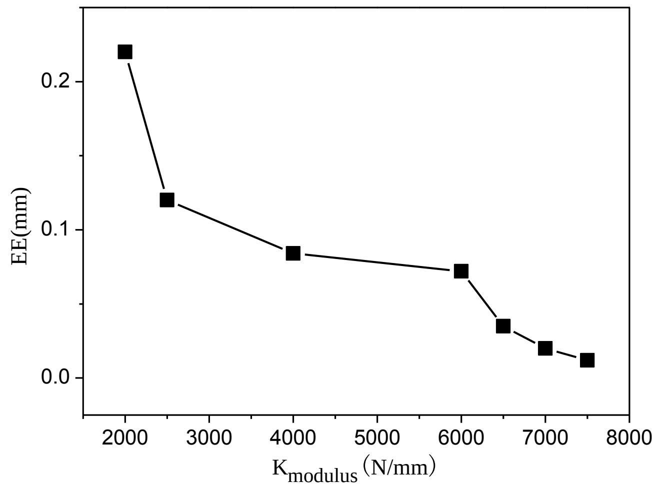

Figure 3 The influence of technological rigidity on error

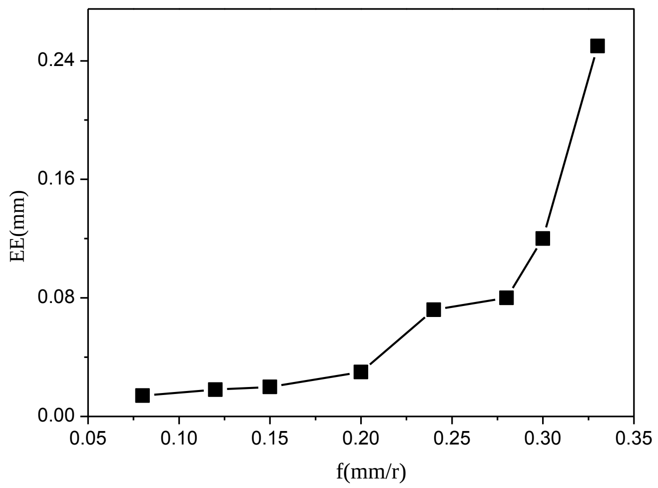

Figure 4 Influence of feed rate on error

Table 1 data show that the experimental data is consistent with the law of machining error re mapping, that is, with the increase of processing times, the final error of parts is smaller. In the case of multiple machining, the smaller the machining allowance is, then the smaller the error of the parts is, and then the greater the error is. As shown in figure 3 and 4, it is shown that Under the same process rigidity and processing times, the smaller the feed rate, the smaller the final error of the component. Generally speaking, the number of machining, the process rigidity and the feed rate have great influence on the error of the machined part.

4.2. BP network program training and testing

BP network structures usually do not use multiple hidden layers. The increase in the number of hidden layers increases the uncertainty of the error surface gradient, and increases the probability that the network will fall into local minimum points. Therefore, there are two optimal hidden layers in the network. Different network structures are used for training. The maximum training times are 20000, SEE is the sum of squares between the two outputs of the target and the network, and the training results are shown in table 2.

Table 2 Training results of number of neurons in different hidden layers

Network structure	5-8-4-2	5-10-5-2	5-12-10-2	5-14-10-2	5-15-12-2	5-18-9-2	5-18-15-2
SEE	8.8250	6.7853	0.8274	0.1041	0.1000	0.2629	0.0999
Training time	20000	20000	20000	20000	12894	20000	15436

Through analysis and comparison, it is shown that the number of hidden layer neurons is too large, and the accuracy of data results is increased. Long time training can be time-consuming and can lead to over matching, so the most reasonable network structure is 5-15-12-2.

The training process: Two hidden layer neurons are set, and the weights of first, second hidden layers are initialized respectively by using nwtan and Rands functions. The initial learning rate, momentum coefficient and target SEE are input, and then trained by BP algorithm, the error curve is obtained, and the weights of the network and the sum of squares of errors are obtained.

The testing process: The weights of the output of the training network are imported, and the normalized test data and weights are calculated to obtain the original data of the network output. After the inverse Z value transformation, the correct first and second processing ratios are output.

The training network and test set are used to test the mature network. The results show that the training set is used to test the BP network, and its convergence is good, but the test set test will show some errors. If the input of the test set is close to the nodes used in training, the error will decrease correspondingly, which means that the machining parameters optimization based on BP network can be realized on the basis of a large number of comprehensive experimental data.

5 CONCLUSION

In the machining process, the error of parts is inevitable. The arbitrary mapping capability of BP neural networks is used to simulate the complex function problem of error resolution. The nonlinear relationship between the coefficient of reflection and the material, process stiffness and feed is analyzed. By improving the BP algorithm, the number of neurons in the first and second hidden layers of neural networks is determined to be 15 and 12. The 5-15-12-2 structure of the BP network is most reasonable. It has higher convergence and less error, and there is no over matching phenomenon. The training set and test set are used to test the generalization ability of network, and the validity and feasibility of BP network for machining re machining are verified.

In the field of machinery, there are many similar error mapping phenomenon. For these complex function problems, people usually cannot directly solve the model to solve it, and neural networks can be used to solve such problems. In this paper, the BP network is discussed, there are many places to be further studied and improved. It is hoped that the completion of this study will be able to solve the whole problem of mechanical processing error of neural network.

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