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Rough Diamond Machining Process Based on Neural Network

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Abstract: *In recent years, mechanical engineers have improved the machining accuracy and machining efficiency by different techniques. This paper studied the rough diamond machining process based on neural network. By using the RBF neural network algorithm, in the process of machining, automatic selection of the appropriate machining parameters without human intervention effectively has improved the machining precision and speed which has demonstrable effect.*

Keywords: *Neural network, Rough diamond machining, Processing technology, RBF neural network*

1. Introduction

In the increasingly complex modern machinery manufacturing, with mechanical parts having developed to be high - tech sophisticated, mechanical manufacturing technology is becoming increasingly complex. The traditional mechanical manufacturing technology has been unable to meet the requirements of sophisticated machining precision parts (Mali et al., 2009). In traditional machining, the main processing parameter is a fixed value set by mechanical engineer's experience which is constant in the whole process. The maximum cutting allowance, the feeding rate is generally set as conservative numerical value according to the experience, so that the machining efficiency is greatly reduced, machining accuracy cannot meet the accuracy index of sophisticated mechanical parts. (Kanthababu et al., 2012). How to machining mechanical parts to meet the requirements of high precision is the chief consideration of mechanical manufacturing engineers. In recent years, with the rapid development of artificial intelligence technology, neural network algorithm is widely used in many application fields of intelligence (Kanthababu et al., 2008). The neural network is a parallel processing unit where the population processes parallel formed by countless neurons through some internal organization and structure. Different neurons have different weight values. The data is input from the input layer of neural network and output as the neural network training consequence to the output layer through the multilayer network structure. (Jain et al., 2009).The neural network has massive neurons. Different ways of distrubution represents different data information, so the network has high robustness and adaptability. The network structurecan ensure the accuracy of the output results even damaged, which greatly enhances the fault tolerance ability of the network. And it can be widely used in complex applications of artificial intelligence.

2. Material and Methods

2.1. Neural Network Feature Recognition Based on Genetic Algorithm Optimization

(1) The genetic algorithm: The genetic algorithm follows the rule of survival of the fittest in nature. Its basic principle is designing to encode parameters of the problem to form chromosom. By using iterative method, we can get random constant in the range of [-0.5, 0.5]. The initialization parameters have great influence on training neural network, but normally it is difficult to get accurately (Lawrence et al., 2016). In this regard, I introduce genetic algorithm in neural network, hoping to get the optimal initial weights and thresholds.

(2) The input of neural network. When recognizing characters utilizing neural networks, corresponding input must meet two different requirements. One is the different characteristics adopt different input, the expression of the same characteristics of different instances can be different, but must be similar; two is input need to contain all kinds of information identification characteristics need. From

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this analysis, the surface of the minimum subgraph of attributed adjacency graph has edge and ring simultaneously which can be given some weight to gain the input of the neural network. Among them, the score formula is:

$$F = \sum_{j=1}^{m} e_j + \sum_{k=1}^{m} l_k \tag{1}$$

When calculating the serial number of parts, identify the first element as the feature base. According to the score, rank the bases from large to small. If the number of features is less than 9, the value of remaining elements is 0. If more than 9, it can be neglected because being too away from the feature base to play the corresponding role in the recognition process. With the above analysis, the input nodes of the NN is determined as 9.

(3) Neural network structure: NC machining feature recognition is one kind of pattern recognition. 3 layers network structure of BP neural network can solve the above problem well. In BP network, there is an affinity between the number of implicit layer neural network N2 and input layer number N1 which is n2=2n1+1. When the input parameter is 9, the output parameter is 5. Bearing the formula, the number of implicit layer neural network is 19, and the network structure is 9-19-5. Train the network using the Levenberg-Marquardt algorithm. Training times is 1000, the training target is 0.01 and the learning rate is 0.1.

2.2. Algorithm Design

Trains the RBF is trained and studies repeatedly by using massive machining sample data in this paper until the error of the output value and the target value of the neural network is reduced to the specified error range. To training and learn by RBF neural network, the biggest advantage is there’s no need to establish the complicated mathematical model at first, because the majority of machinery manufacturing is nonlinear. The establish of mathematical model is very difficult; sometimes it can even be impossible to find a appropriate and accurate mathematical model. Using the nonlinear approachable ability of the neural network, it can train and learn network without prior knowledge. The selection of neural network scale should be moderate, otherwise, it will waste the computational resources and lead to the lack of neural network approachable ability, or the computing resources may fall into the dead cycle. The neural network structure design mainly includes the the output layer, the input layer, the determination of node number of latent layer and the number of hidden layer. The design standard of the initial weights: The initial weight is very essential for the neural network self-learning which directly affects the speed of neural network training and studying. Initial weights of the neural network directly determine the whole learning process starts from that part of the error surface.

In the network structure designed in this paper, input layer has 4 neurons according to the empirical value, node number of latent layer is 12, and the output layer has 2 neurons due to the experience. Generally, the methods of the datanormalization methods are the maximum minimum method and the mean variance method. The input and output of the neural network selection criteria: network input must choose those that have a great influence on output, and can be easily detected or extracted variables. Different input variables must be independent from each other and can not influence each other. Usually, the input variables of the neural network can't directly access unless after extracting some parameters that can express the characteristic from the original data by signal processing or feature extraction technology as the input of the neural network. The fitting training process of RBF neural network are as follows: Firstly, progress system modeling of neural network and then construct the suitable RBF neural network. After the initialization, train the RBF neural network until it meets the studying requirement. Next, begin the prediction of the neural network. Input the test data in the RBF neural network for the network prediction and end with output the result.

2.3. Diamond Processing Technology

From the mining of diamond mine to classification, and then to the whole process of diamond processing, each process is permeated with the essence of high-tech. The key process of diamond processing is shown in Table 1.

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Table 1: Key processes of diamond processing

Craftwork	Content	Difficult point	Development
Diamond cut design marking	First essential process in diamond processing process. The basic principle of diamond design is to maximize the commodity value of diamonds. In the design, not only consider the shape of bit shank, neatness and the complexity and multiplicity of the etching, but also compare the yield of bit shank and value of end product so as to determine the marking position and Processing flow.	Because of the shape of bit shank, neatness and the complexity and multiplicity of the etching, it requires not only the great spatial imaginative ability but also the rich experience of diamond processing and commerce. Therefore, the diamond designer responsible for the work is always very experienced.	In recent years, the computer 3D simulation technique and digital camera technology have made the design of drill blank marking very simple. The basic process is that using cameras to produce the drill blanks in different directions. And the 3D image information of the drill billet is input into the computer which can give the diamond cut and parameters according to the Designer.
Cleavages	It's an old process in diamond processing. In modern diamond processing, splitting drills are mainly used in the following situations: (1) diamond crystals and crystal fragments with larger notches; (2) drill blanks with obvious cleavage fracture surfaces or contact twin planes; (3) drilled blanks with more "skins".	The application range of splitting drill is not as wider as trephine, and the technology is more difficult. There are two steps in the splitting process, one is grooving, and two is cutting the drill blank with a blunt thin blade.	Modern grooving adopts a variety of high and new technology, such as laser grooving, electric etching tank and ultrasonic groove whose efficiency is greatly improved.
Trephine	The function of sawing progressing is to remove the outer skin and defect of drill stock reasonably and economically, and separate big drill into several meaningful drill blanks.	The traditional sawing method is to drill the billet with a mechanical circular saw. This method is still widely used all over the world, but the traditional mechanical saw drilling technology has a fatal disadvantage, that is, it can not control the feed speed and pressure of saw drilling precisely.	The pressure of saw blade on drill blank is controlled by microcomputer automatically according to certain program. In addition to the numerical control machine saw drilling, in recent years, foreign countries also use high-tech to develop some new saw drilling equipment, such as ultrasonic saw drilling machine, laser saw drilling machine, high-energy electron beam saw drilling rig and electric corrosion saw drilling machine, etc.
Wheel drilling	Diamond drilling is one of the most important processes for diamond design. The wheel drilling is used to finish the waist. Once the waist completed, the size of the diamond is basically determined. Take the round diamonds for example, a slight change in the finished diamond diameter D can influence the change of weight greatly, so as to change the price of diamonds.It can be seen that the size of diamond waist is directly related to the yield and value of finished diamond.	The key is to determine the center line of the best design cut type of the drilled billet, and to ensure the centerline of the drill billet, the stick axis and the rig axis to coincide. It's hard to do this by manual car drilling in the past.	Now, the semi-automatic or automatic drilling rig integrated by camera, microcomputer control system and car drilling has solved this problem well. It can not only display the maximum diameter of the waist shaped drill blank may make a through the camera and computer image processing software, and can automatically adjust the car rig shaft, to ensure symmetry and high precision car drill waist shape, to get the largest yield.
Abrasive drilling	Grinding drill is the largest amount of labor input (50% - 60%) in diamond processing, and the drilling loss rate is also the largest (40%~60%). The color, sparkle and surface of finish diamond depends on this process.	The technical difficulty of abrasive drilling is accurate control of angle ratio and the direction of wire grinding face (best grinding direction). The former determines not only the quality and brightness of the finished diamond, but also the weight. The latter mainly affects the surface machining quality and machining efficiency of diamond.	The modern new semi automatic and automatic abrasive drill not only can drill very accurately according to the previously given surface and angle ratio requirements drill under the control of CNC which reduce loss rate to a minimum in the process of and improve the yield of drill blanks.

3. Results

3.1. Design of Neural Network Model

I use ANN model to predict the cutting performance of the diamond. In the MATLAB the multilevel perceptual neural network structure brings out the ANN model. The structure of the ANN model is as the table2 shows. Through the model, it establishes nonlinear relations of the parameter relation of the cutting performance of the diamond including the shear strength parameter (c), the linear velocity (n) and

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the thrust (t). This is shown in the following formula.

Ph=f(c,n,t).

Vm=f(c,n,t).

In the formula, c stands for the strengthen stands for the linear velocity and t stands for the thrust. Ph stands for the cutting speed and Vm stands for the rate of bead wear. The conclusion of the neural network model is given in the table2. Through the ANN model, the estimated performance of the cutting speed and the wear rate are 0.001329 and 1.08e-06.

Table 2: Neural network parameters

Network type	Multi-layer feed forward background
Adaption learning function	Gradient descent method
Training algorithm	Levenberg-marquard
Transport function	Sigmoid
The amount of input neuron	0.
The amount of output neuron	02
Hidden layers	01
The amount of hidden neurons	06
Number of training periods	500
Data set number	36

3.2. The Training of Neural Network

(1) Improve the generalization ability of neural network. In this paper, the generalization ability of BP neural network model is improved by normalizing the sample data. The normalization method used in this paper is to deal with the data of each column, so that the sample data on each column is evenly distributed. The sample data is shown in Table 3. The input and output parameter data normalization methods the sample data of thare counted as shown in Table 4:

Table 3: Sample data sheet

Tool Type	10	10		10	10
Extended length	34	34		39	48
Tool Diameter	10.3	10.3		15	12
Aperture Ratio	2.91	2.91		2.6	4
Basic Dimensions	12	12		17.5	13.5
Radial Width	0.5	0.5	……	3	0.5
Depth of Cut	2	2		0.5	1
Dimensional Precision	10	10		12	13
Roughness	1.6	1.6		0.8	1.6
Spindle Speed	2000	2000		350	4000
Feed Speed	800	800		60	550
Process Time	4.8	4.8		64.2	31.8

Table 4: The sample data is normalized to the statistical table

Data of input sample	Tool extended length	Linear independence of information normalization
	Tool Diameter	Logarithmic compound function normalization
	Tool aperture ratio	Linear independence of information normalization
	Basic dimensions	Inverse tangent normalization
	Width of cut	Logarithmic compound function normalization
	Depth of cut	Linear independence of information normalization
	Dimensional accuracy	Logarithmic compound function normalization
	Surface roughness	Logarithmic compound function normalization
Data of output sample	Spindle speed	Logarithmic compound function normalization
	Feed speed	Logarithmic compound function normalization
	Process time	Logarithmic compound function normalization

(2) Neural network training error curve. BP neural network is trained until the error sum of the training network is less than the error target. Finally, the training error curve of the BP neural network is

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shown in Figure 1:

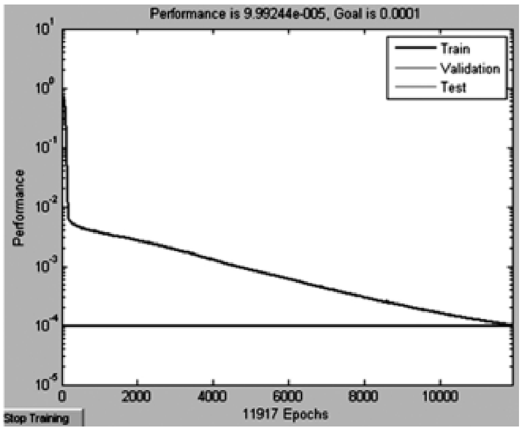

Figure 1: Error curve

(3) Neural network performance test curve. Completing BP neural network training, use the SIM function to test the network performance; analyses training results using the postreg function. The test procedure is as follows: a=sim (net, P); m, B, R, = postreg (a, t). 3 figures neural network performance test shown in Figure 2, the postreg function returns the value of m=0.9999 b=, 1.4957e 005, r=1.0000. The "O" in the graph represents the output data, the red line represents the ideal regression line, and the dotted line represents the optimal regression line. It can be seen from the graph 2 that the trained neural network has good performance.

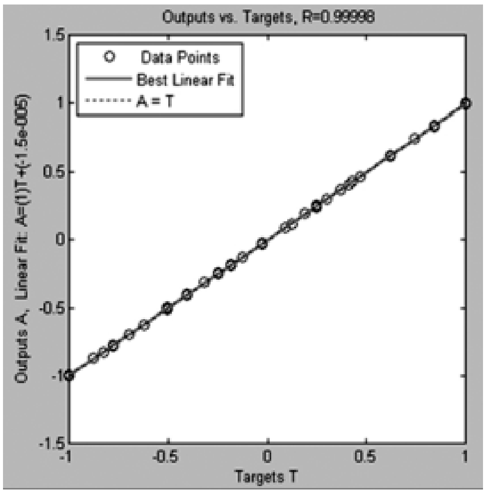

Figure 2: Performance test chart

(4) Compare BP divine network prediction and validation data. The validation data is input into the trained BP neural network for output verification, and the prediction accuracy of the BP neural network is expressed by absolute error. The comparison of test error and prediction is shown in Table 5.

Table 5: Prediction and trial error comparison table

Spindle Speed	Prediction	816.18	644.82		1893.76
	Test	800	600		2000
	Absolute error	0.0202	0.0747		0.0531
	Mean absolute error		0.0551		
Feed speed	Prediction	887.61	190.69	……	1559.47
	Test	800	200		1500
	Absolute error	0.0987	0.0487		0.038
	Mean absolute error		0.0364		
Process time	Prediction	4.70	31.15	……	5.27
	Test	4.8	32.4		6.6
	Absolute error	0.0197	0.0382		0.2010
	Mean absolute error		0.0389		

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4. Discussions

According to the characteristics of mechanical system CNC machining, the selection of the network input in this paper are tool type, tool diameter, cutting width, cutting depth, network output for the tool feed speed and cutting force size. The RBF neural network is trained by the sample data collected on the mechanical processing. Learning continuously through the network make it approach to the error range. At the end of the learning, it uses the network self-learning system in accordance with requirements and outputs the error of network learning results. The output parameters are applied to the actual parameters of machine tool set. According to the actual verified by the proposed algorithm, the accuracy of the rough diamond processed by NC was 7% higher than the traditional processing methods. And the machining efficiency is improved by 11%. It proves that this method has high application value and has good practicability.

Because the high demand of precision and efficiency of NC machining in modern large-scale machinery manufacturing, the traditional method of setting NC machining parameters with engineer's experience cannot meet. Aiming at the problem existing the rough diamond processing, with a strong self-learning ability, input massive learning samples, constantly optimize neural network by learning, until it reaches the requirement of error range. Then end the training, output the network training result. Then the results will be applied into the set parameters of machine tools used of mechanical NC machining. Using the optimized NC machining parameters, the diamond with higher precision can be machined. And it can also provide machinery manufacturing enterprises with high-tech CNC machining ability in society with the increasingly fierce competition.

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