APPLICATION OF RBF FOR STRIP SHAPE RECOGNITION

Yanling Lu, Zhe Xu, Junfei Qiao, Jianmin Duan

College of Electronics & Information Engineering, Beijing University of Technology, Beijing, 100022, P. R. C.,
xu2002@bjut.edu.cn
xiaolunihao@emails.bjut.edu.cn

Abstract: Based on radial basis function neural network (RBF NN)，the paper proposed a new algorithm for strip shape recognition. Compared with back propagation (BP) algorithm and improved least squares method (LSM), RBF NN shows excellent overall performance, such as learning speed, recognition precision and anti-interference capability.

Keyword: Strip Shape, Pattern Recognition, RBF，BP，Improved LSM

1. INTRODUCTION

In strip shape control, to obtain the expected shape, shape recognition is carried out according to the error between real shape and target shape, and then control amount of the actuators can be determined. Conventionally shape patterns are classified by LSM (Zhang et al., 1996; Ander and Keijser, 1991), but the precision is not enough for high-precision shape control. Then, BP (Zhang 2002) and hereditary algorithms (Ren, 2002) were used to recognize shape and can satisfy the recognition of many strip shapes, but they still have too long training time and poor recognition precision to no-learned sample. This paper proposed a new strip shape recognition method-RBF algorithm. Compared with BP NN algorithm and improved LSM, the RBF algorithm is not merely suitable for six kinds of typical strip shape defects, but also for complex shapes. In addition, it has excellent overall performance.
The rest of the paper is organized as follows. The strip shape data processing is detailed in section 2. Section 3 deals with the basic function networks structure of RBF, and then improved LSM is detailed in section 4. Finally the experimental result of RBF is discussed in section 5 and conclusion in section 6.

2. STRIP SHAPE DATA PROCESSING

2.1 Normalized Processing of Strip Shape Data

Firstly, real strip shape defect and normal shape defect should be processed unitarily. The system supposes that the shape measuring mechanism (tension meter) have 26 sections in strip width direction. According to real measured shape δ_{mi} and the selected target shape δ_{ti}, the strip shape adjustive error $\Delta\delta_i$ can be calculated**:**

$$\Delta\delta_i = \delta_{mi} - \delta_{ti} \qquad (1)$$

The shape error $\Delta\delta_i^{'}$ is processed unitarily：

$$\Delta\delta_i^{'} = \frac{\Delta\delta_i}{\Delta\delta_j} \qquad \Delta\delta_i^{'} = [-1,+1] \qquad (2)$$

Where $\Delta\delta_j = \max_{i=1}^{n} |\Delta\delta_i|$

2.2 Selection of Basic Shape Mode (defect)

The strip shape curving after rolled is defined as the remained stress error distribution along the lateral direction. In fact, Legendre polynomials can be used to denote the basis shape mode (Peng, 2000). This polynomial is more close to real shape, and it is good for improving the stability and accuracy of NN.

The standard normalized equation of left edge wave is shown in Fig.1 (a):

$$Y_1 = p_1(y) = y \tag{3}$$

The standard normalized equation of right edge wave is shown in Fig.1 (b):

$$Y_2 = -p_1(y) = -y \tag{4}$$

The standard normalized equation of center wave is shown in Fig.1(c):

$$Y_3 = p_2(y) = \frac{3}{2}y^2 - \frac{1}{2} \tag{5}$$

The standard normalized equation of bilateral wave is shown in Fig.1 (d):

$$Y_4 = -p_2(y) = -(\frac{3}{2}y^2 - \frac{1}{2}) \tag{6}$$

The standard normalized equation of quarter wave is shown in Fig.1 (e):

$$Y_5 = p_3(y) = \frac{1}{8}(35y^4 - 30y^2 + 3) \tag{7}$$

The standard normalized equation of edge center wave is shown in Fig.1 (f):

$$Y_6 = -p_3(y) = -\frac{1}{8}(35y^4 - 30y^2 + 3) \tag{8}$$

Where p_i (y) (i=1, 2... 6) is Legendre orthogonal polynomial. The defect shape is denoted in reference coordinate, whose origin is at the middle of strip, that is to say, y=0 is at the middle of the strip, both end points of the strip is denoted respectively as y=-1, y=1.For points along strip width direction, it should be y $\in$[-1, +1].

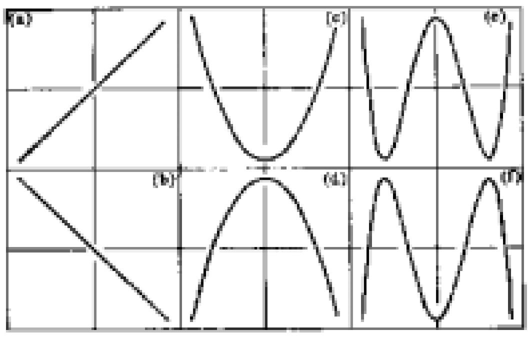

Fig.1 six kinds of stress distribution of standard shape mode

3. RBF STRIP SHAPE RECOGNITION

As now well-known, artificial NN is very good at the problem of nonlinear estimate. Strip shape recognition based on RBF network uses real measured shape as a especial sample and the similarity or subject degree μ_k can be calculated by N kinds of standard sample y^k, k=1,2…N.

3.1 RBF Networks Architecture

As shown in Fig.2, RBF NN consists of input layer, hidden layer, output layer, among which input layer and output layer correspond respectively to input vector space and classified mode, Hidden layer is composed of a number of nodes with radial activation functions, called radial basis functions, usually the Radial functions in the hidden layer adopt Gaussian kernel function:

$$\varphi_j(x) = \exp\left[-\frac{\|x - c_j E\|}{2\sigma_j^2}\right], (j\text{=1, 2…h}) \tag{9}$$

Where φ_j is the output of the jth unit in hidden layer, x is input vector, c_j is the jth Gaussian kernel unit center, E is unit vectors with $n \times 1$ dimension, σ_j is the radius of the radial function, ||g|| denotes the Euclidean norms, usually

$$\|x - c_j E\| = (x - c_j E)^T (x - c_j E) \tag{10}$$

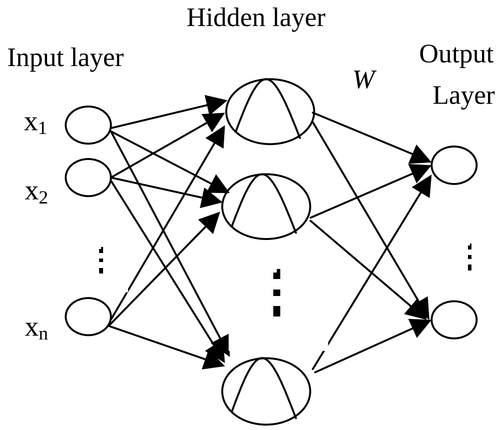

Fig.2 Radial basis function networks architecture

Each of the input components feeds forward to the radial function; the outputs of these functions are linearly combined with weights into the network output, the kth output.

$$y_k = \sum_{j=1}^{h} w_{kj}\varphi_j(x), \text{(k=1, 2… m)} \tag{11}$$

Where h is the number of hidden layer node, w^{kj} is the weight value from the jth hidden layer nodes to the kth output layer nodes.

3.2 RBF Learning Algorithm

RBF learning algorithm includes learning of hidden layer and learning of output layer. The learning of the hidden layer adopts the K-mean clustering method to determine radial function center c_j and radius σ_j, and the learning of output layer adopts gradient descent method to determine weight value *W* between the hidden layer and the output layer.

The clustering method of K-mean uses usually iterative training method; it is to make the square sum of the distance (from each sample to the clustering center) least.

After completing sample clustering, the radius σ_j of the clustering center can be calculated; this parameter measures the range of input data from each node.

$$\sigma_j = \frac{1}{N_j}(X^p - c_j E)^T (X^p - c_j E) \tag{12}$$

Define the target function of the network:

$$J = \frac{1}{2}(U - Y)^T (U - Y) \tag{13}$$

Where *U* is expected output, *Y* is real output of the network, weight value *W* is adjusted by error gradient descent method. In order to minimize *J*, iterative formula is:

$$W(t+1) = W(t) + \eta (U - Y)^T \tag{14}$$

Where *t* is the iterative times

4. IMPROVED LEAST SQUARE METHOD

The basic thought of the improved LSM is to fit measured shape into Legendre polynomials (Zhang, 2002):

$$\sigma(y) = a_1 p_1(y) + a_2 p_2(y) + a_3 p_3(y) \tag{15}$$

There are n dots spread over strip width direction [-1, +1], namely $y_1, y_2 \ldots y_n$, so

$$\sigma_1 = a_1 p_{11} + a_2 p_{21} + a_3 p_{31} \tag{16}$$

$$\sigma_2 = a_1 p_{12} + a_2 p_{22} + a_3 p_{32} \tag{17}$$

$$\vdots$$

$$\sigma_n = a_1 p_{1n} + a_2 p_{2n} + a_3 p_{3n} \tag{18}$$

The key problem here is to determine strip shape characteristic parameter a_1, a^2, a^3, and to ensure that the fitting error square sum is least. In MATLAB, this can be solved by left deviation directly.

5. SIMULATION RESULTS

With RBF NN, step of strip shape recognition is as follows. The training sample is based on 6 standard samples corresponding to 6 standard shape modes and their 14 groups of linear combination, among which 10 samples are used to train the network, other 10 are used to test the network. The simulation experiment is executed on MATLAB, firstly, set up a network, and then input sample to train the network. There are 26 input nodes in network, 6 outputs corresponding to 6 standard sample modes; the node number of the hidden layer is optimized through training. The network is trained to determine the architecture parameter by the learning samples. If target output error is 1e-20, it is satisfied after 9 times of learning (adopting 9 nerve cell). Being trained, the RBF NN algorithm is tested by test sample, for learned test sample

$$Y = 0.7 * Y_4 + 0.3 * Y_5 \tag{19}$$

The recognition result is expressed with curve form shown in Fig.3, whose mse (Mean Square Error) =5.8549e-032

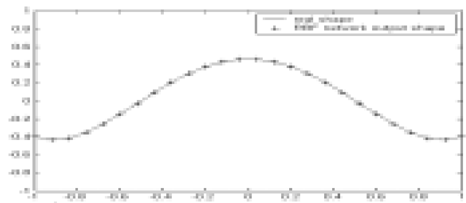

Fig.3 RBF NN flatness pattern recognition

The test result with BP NN algorithm is shown in Fig.4, in which the architecture of the BP is 26-12-6, and the target error is 1e-20, then mse = 4.7417e-006

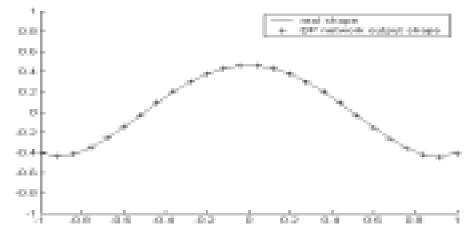

Fig.4 BP NN flatness pattern recognition

As shown in Fig.5, the fitting curve is the output results of improved LSM, where mse =5.5259e-033

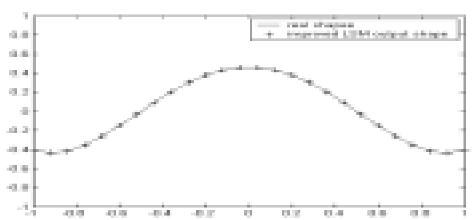

Fig.5 improved LSM pattern recognition

For no-learned test sample:

$$Y = 0.4*Y_1 + 0.1*Y_3 + 0.5*Y_6 \qquad (20)$$

The recognition curve of RBF NN is shown Fig.6, in which mse = 6.4111e-004

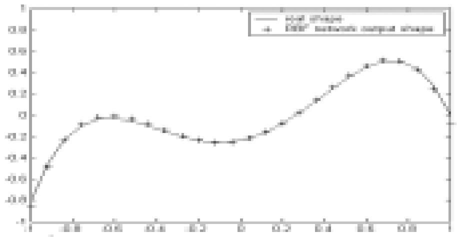

Fig.6 RBF NN flatness pattern recognition

The test result with BP NN algorithm is shown in Fig.7, in which mse = 0.0370.

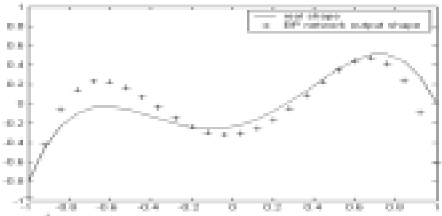

Fig.7 BP NN flatness pattern recognition

As shown in fig.8, the fitting curve is the output results of improved LSM, in which mse = 2.3083e-032

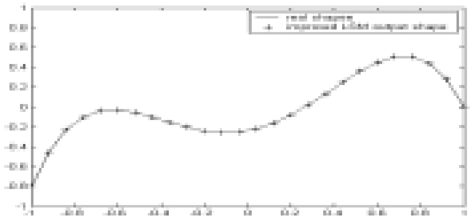

Fig.8 improved LSM pattern recognition

The system of strip shape control is a complicated system, and there are many nonlinear factors and outside interference, so the anti-interference capability need be considered in the recognition methods. In the next experiment, each sample is disturbed at random, for example:

$$Y = 0.4*Y_2 + 0.6*Y_6 \qquad (21)$$

It is disturbed by the random interference whose mean is 0.1288, the test result of RBF NN algorithm is shown in Fig.9, in which mse = 6.0987e-004

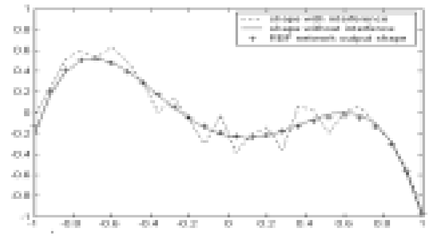

Fig.9 RBF NN flatness pattern recognition

The test result with BP NN algorithm is shown in Fig.10, the squares error: mse = 0.0075

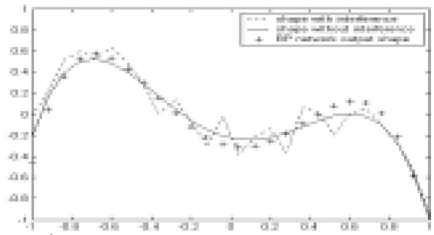

Fig.10 BP NN flatness pattern recognition

With the improved LSM, experiment result to the sample is shown in Fig.11, in which: mse = 0.0019.

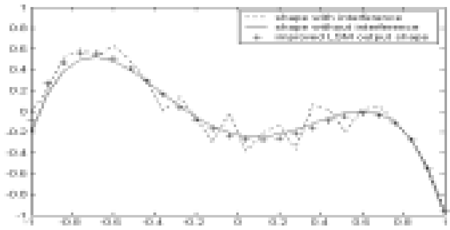

Fig.11 improved LSM pattern recognition

Observed by the testing results, RBF NN algorithms merely need ten times to complete the iterative operation, but BP NN algorithm usually need thousands of times. The RBF NN needs 10 to 12 seconds to train the NN and recognize the sample; BP NN needs 40 to 44 seconds. Moreover, for learned samples, RBF NN shows very high recognition precision; and for no-learned samples, it also shows higher precision than BP NN algorithms. So, RBF NN has faster learning speed and wider application, and better stability. On the other hand, the improved LSM needs only 6 to 7 seconds to recognize the samples, and is superior to the NN methods in speed and recognition precision. But there is much interference in the actual strip workshop, and the RBF NN algorithm just can improve the precision by adding the node number of the hidden layer and training time, so RBF NN algorithms are worth to be researched continually.

7. CONCLUSIONS

RBF NN algorithm proposed is good at strip shape recognition, it has faster training speed and higher recognition precision than BP NN algorithm, the improved LSM is superior to the NN method in speed and recognition precision, but its anti-interference ability is inferior to RBF NN algorithm's.

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Acknowledge

This work is supported by NSFC (National Natural Science Foundation of China, 50274003) & Project on Beijing New-star of Science & Technology (2003A05)