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Neural network approach for modification and fitting of digitized data in reverse engineering*

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Abstract: Reverse engineering in the manufacturing field is a process in which the digitized data are obtained from an existing object model or a part of it, and then the CAD model is reconstructed. This paper presents an RBF neural network approach to modify and fit the digitized data. The centers for the RBF are selected by using the orthogonal least squares learning algorithm. A mathematically known surface is used for generating a number of samples for training the networks. The trained networks then generated a number of new points which were compared with the calculating points from the equations. Moreover, a series of practice digitizing curves are used to test the approach. The results showed that this approach is effective in modifying and fitting digitized data and generating data points to reconstruct the surface model.

Key words: Reverse engineering, Digitized data, Neural network modification and fitting
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INTRODUCTION

Growing global competition requires manufacturers to deliver more competitive products with better quality and lower prices. Reducing the product development period of the product is one of the most important and challenging tasks faced by the manufacturing industry. The traditional production pattern that products are produced from the drawing can not satisfy the requirement of modern manufacturing industry. The design of products containing complex sculptured surfaces sometimes starts with a clay model or other existing parts. The process of developing a CAD model for an existing part is called reverse engineering. Reverse engineering is playing a more and more important role. To modify or reproduce such parts in Computer Integrated Manufacturing (CIM) environment, CAD models must be created. Examples include small toys for children to large parts used in industry such as computer casings, motorbike casings, partial casings of airplanes and so forth. The CAD models for these parts can be created based on digitized data captured from part prototypes (Abdalla *et al*., 2000; Bopaya and Yasser, 1994; Lin, 2001; Robert *et al*., 1994). Fig.1 provides a schematic of some of the applications of reverse engineering to an industrial environment (Bremer and Drewing, 2001; Tamas *et al*., 1997). It can be seen from Fig.1 that two of the main issues in reverse engineering are 3D digitizing and generating models or design representations based on the existing products. Subsequently, these models and design representation are used to manufacture the products.

Two methods are generally used for digitizing surfaces based on laser scanners and coordinate measuring machines respectively (Seiler *et al*., 1996). The digitized points captured with either of these methods are used to reconstruct the models and manufacture the parts. In reverse engineering, the reconstruction of the surface and the NC path generation directly from the digitized data points may meet with difficulty because of the lack of data information due to the worn or damaged parts or some unreliable digitizing method. In this case, the digitized data must be modified and interpolated during the preprocessing. Gu and Yan (1995) first proposed a

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neural network approach to reconstruction of existing freeform surfaces, where the BP (Back Propagation) algorithm is used to realize the reconstruction. The back propagation algorithm has the characters of nonlinear approximation and restraining the sampling noise. In spite of the above advantages, back propagation suffers from several problems such as a local minimum can always be generated and the convergence process is extremely slow, which may render the algorithm impractical for many applications, especially for large sets of training samples. Multilayered feedforward network is the typical example of global approximation network, which has the disadvantage of extremely slow learning and training speed. In this paper, the local network was adopted to learn and train digitized points and generate new points for interpolation and modification in reverse engineering. CMAC (Cerebellar Model Arculation Controller), B-spline and RBF (radial basic function)(Deng *et al*., 2000) are the typical examples of the local neural network, which has fast learning speed and good approximation function(Sun, 1997). It has been successfully applied to some simulation experiment and practical experiment.

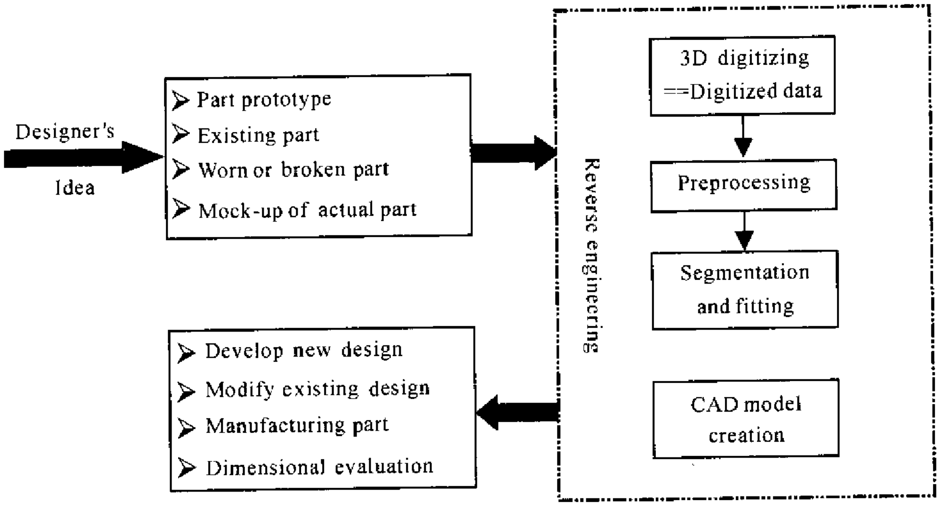

Fig.1 Process methodology and application

DESCRIPTION OF LOCAL NEURAL NETWORK

The geometry modeling, especially the modeling of the complex surface in reverse engineering, commonly adopted the fitting of the spline function. This kind of method has the disadvantages of complex boundary conditions and difficult modification as well as large computing amount. The problem becomes even more severe when a surface is partially damaged or worn. Applying the nonlinear mapping ability of the artificial neural network to the geometry model is a new try. The method is especially suitable for the modeling of the measured surface. Since local neural network has fast learning speed and good function approximation, a kind of local neural network structure was designed for use in the construction of computer models for existing freeform surfaces.

Because the shape of the basic function used in CMAC neural network is very simple, it has the advantages of being easy to realize and fast learning speed. But at the same time, its approximation precision is not high because of its disadvantages in that only the step function is available to approximate. Based on these disadvantages, B-spline neural network, namely BMAC is designed for approximation. B-spline basic function network can be regarded as a kind of radial basis function (RBF) network; just the different basic function makes the difference. Hence, we studied the effectiveness of RBF networks in fitting curves and surface.

In order to evaluate the method, we used a series of points from a mathematically known surface to train the network. Then, using the practical measured points as the sample points, the relationship between the parametric u and v and the coordinates values of x, y, z can be obtained from the trained neural networks.

DESIGN AND TRAINING OF THE NEURAL NETWORK MODEL

An RBF network can be regarded as a special two-layer network which is linear in the parameters by fixing all RBF centers and nonlinearities in the hidden layer. The nonlinearity within an RBF network can be chosen from a few typical nonlinear functions. The selection of the nonlinearity is not crucial for performance. However the performance of an RBF network critically depends upon the chosen centers. The orthogonal least squares (OLS) method can be used as a forward regression procedure to select a suitable set of centers from a large set of candidates (Chen *et al.*, 1991). The simulation and practice experiments demonstrate the effectiveness of the OLS learning algorithm.

According to the characteristic of the parametric surface, the RBF network with two inputs and a scalar output is designed. The schematic is shown in Fig.2. The mapping from the inputs to the outputs is implemented according to:

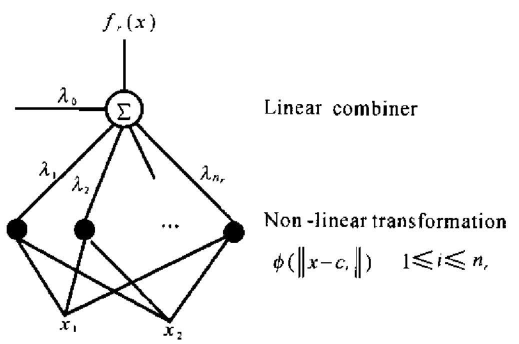

Fig.2 Schematic of radial basis function network

$$f_r(x) = \lambda_0 + \sum_{i=1}^{n_r} \lambda_i \phi(\| x - c_i \|) \quad (1)$$

Where, x is the input vector, $\phi(\| x - c_i \|)$ is the radial basic function, λ_i are the weights, $0 \leqslant i \leqslant n_r$ is the number of the centers. Generally, the Gaussian function is adopted as the RBF. Two steps can implement the design of the RBF networks. At the first step, the OLS algorithm is used to select centers $c_i (0 \leqslant i \leqslant n_r)$. At the second step, the weights $\lambda_i (0 \leqslant i \leqslant n_r)$ are defined.

SIMULATION EXPERIMENT

In order to test the method, we used a series of points from a mathematical known surface to train the network. After the networks were trained, they generated a series of points to be compared with the points generated by the mathematical equations of the known surface. The error between the two sets of points is an indication of the performance of the method. Using the same sampling data points, the BP network was also trained for comparison with the RBF network.

1. RBF network simulation experiment

The parametric equation of the surface can be expressed as follows:

$$y = (\sin x_1 / x_1) * (\sin x_2 / x_2) \quad (2)$$

The intervals of x_1 and x_2 are selected from the range $[-2\pi, -2\pi]$ respectively during simulation experiment. The step is 0.12π. The parametric variables x_1 and x_2 are input layer nodes and y the output nodes respectively. The coordinate values of y generated from the theory surface are the target values of the neural networks designed as the networks corresponding to the functions $y(x_1, x_2)$. The results are shown in Fig.3. The error between the original coordinate values of y and the generated coordinate values of y are compared. And Fig.4 shows the error surface. Obviously, the RBF networks fitting surface is feasible and the learning speed is fast.

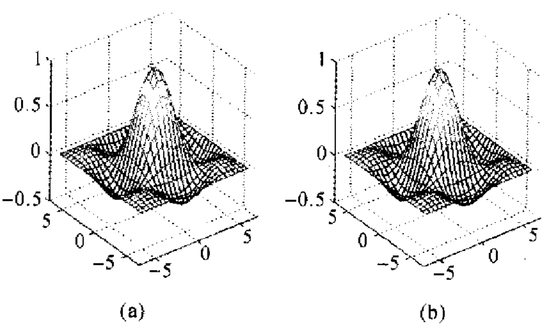

Fig.3 Comparison between (a) the original coordinate and (b) the fitting result

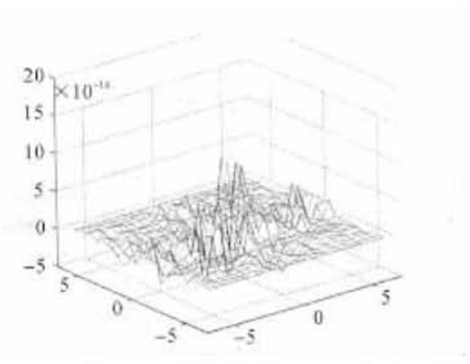

Fig.4 The error surface between the original and the fitting

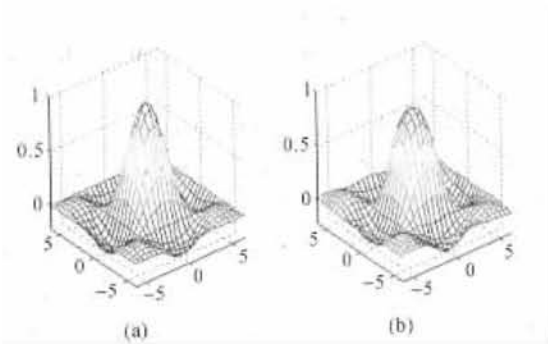

Fig.5 Comparison between (a) the original coordinate and (b) the fitting result

APPLYING EXPERIMENT

In reverse engineering, most existing parts have complex free-form shape which can be represented by parametric surfaces. Commonly used parametric surfaces are Bezier, B-splines and non-uniform rational B-spline (NURBS) surfaces. NURBS are the most popular method in CAD/CAM systems, which have global and local flexibility and can represent complex surfaces. The practical sampling points were captured from the non-contact 3-D digitizing system developed by the authors. The laser-scanning probe scans line by line from the selected coordinate origin to the boundary which is set first. We are interested in the relationships between the parametric variables and the coordinate values. The application experiment results are shown in Fig. 7, Fig. 8, Fig. 9 and Fig. 10. The fitting results demonstrate that the approach is feasible and practical for the fitting of existing freeform surfaces.

2. BP network simulation experiment

The back propagation (BP) algorithm is a gradient descent method within which the weights are adapted in proportion to the partial derivative of an error function with respect to the weights. The BP network suffers from several problems, such as the convergence process is extremely slow and only a local minimum can be achieved. Fig. 5 shows the comparison results of original surface and learned surface. Fig. 6 demonstrates the learning error during iteration. From the results, we can know that the convergence can be prone to local minimum.

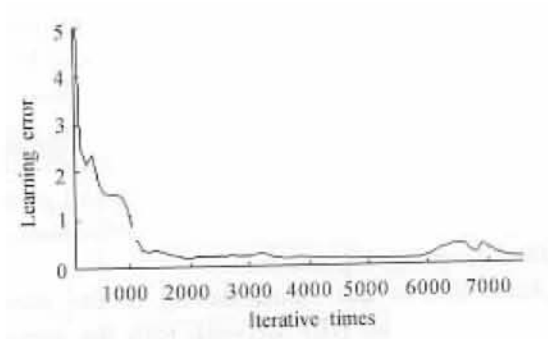

Fig.6 The learning error during iterations

DISCUSSION AND CONCLUSIONS

The parameters that affect the performance of the RBF networks are the centers and the spread of the Gaussian function. The OLS algorithm provides a systematic approach to the selection of RBF centers, one which is far superior to a random selection of centers. As we shall see, spread should be large enough that neurons respond strongly to overlapping regions of the input space. We suppose the spread is 0.7 in this paper.

As long as the limited number of points can be measured from the existing surfaces, the neural networks approach can be carried out to fit the existing surfaces. It is particularly useful when the existing surfaces are complex or incomplete or partially worn or damaged. After being preprocessed, the digitized data can be sent to CAD/CAM software such as UG II to create a model of that physical part. The points generated by the trained network can also be directly used to generate tool paths for machining the surface.

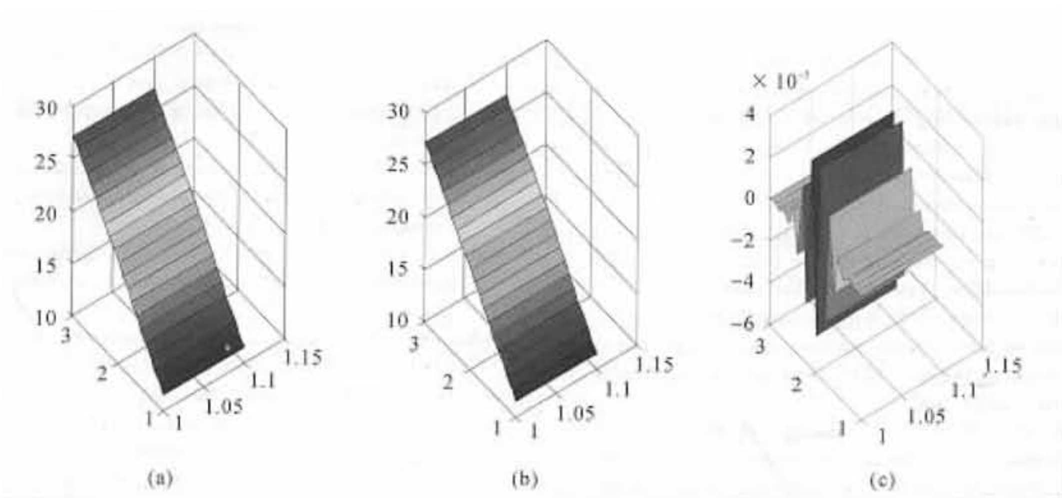

Fig.7 Comparison between original coordinate and the fitting
(a) original coordinate x; (b) the fitting x; (c) fitting error

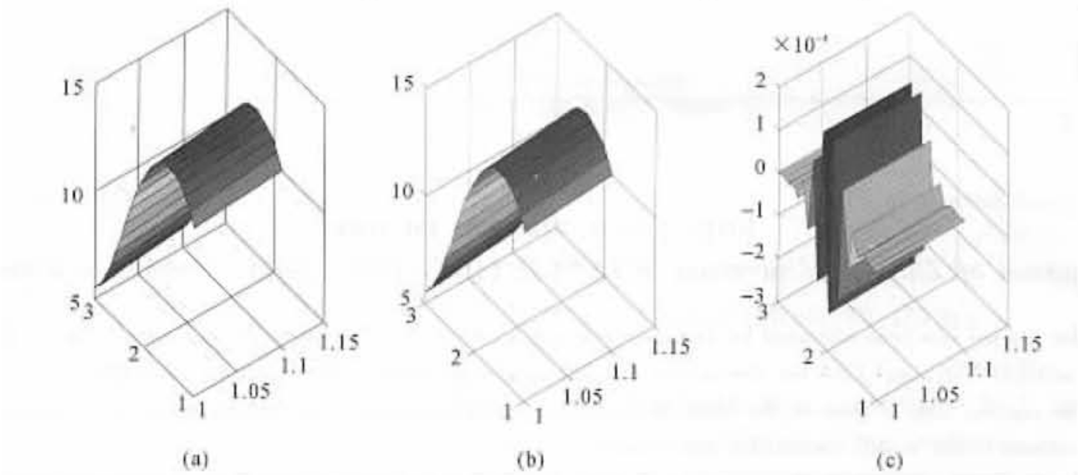

Fig.8 Comparison between original coordinate and the fitting
(a) original coordinate y; (b) the fitting result y; (c) fitting error

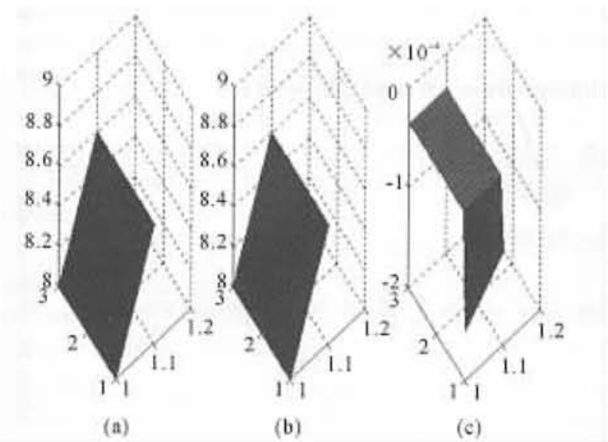

Fig.9 Comparison between original coordinate and the fitting
(a) original coordinate z; (b) the fitting result z; (c) fitting error

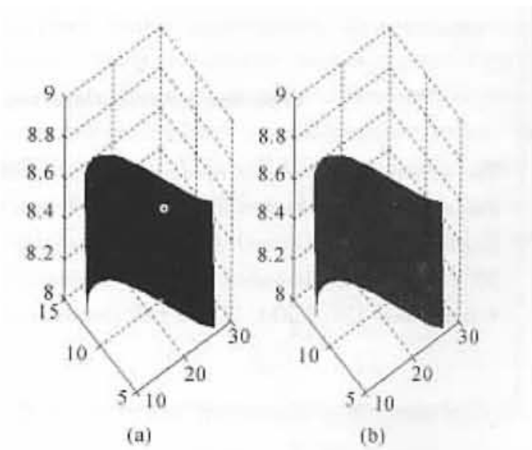

Fig.10 (a) The theory surface and (b) the trained surface

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