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Assembly Quality Prediction Based on Back-propagation Artificial Neural Network

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Abstract

Because of the severe geometrical distortion induced by the optical system and the limited kinetic accuracy of mechanical system in the vision-based mobile-phone lens's assembly system, the nonlinear, perspective distortion errors and the kinematics errors generally exist in the assembly process of the mobile-phone lens. It is necessary to predict the assembly quality of the vision-based mobile-phone lens's pick-and-place system so as to eliminate the immediate effect on the assembling process before extracting quantitative assembling. Comparison with current research methods, the back-propagation artificial neural network is applied to predict the assembly quality of the vision-based mobile-phone lens's pick-and-place system. Firstly, the mobile-phone lens's assembly quality characteristics are defined and sampled; Secondly, a back-propagation artificial neural network of the mobile-phone lens's assembly quality prediction is presented; Finally apply some training samples obtained from the experiments to train and test this back-propagation artificial neural network. The results show that the proposed method is effective to predict the assembly quality of the vision-based mobile-phone lens's pick-and-place system with high accuracy and high reliability.

Keywords: *assembly quality; computer vision; BP; artificial neural network*

1. Introduction

Study shows that the manipulation in the LENS's assembly process is mainly aimed to finish picking and placing actions [1]. Figure 1 displays an automatic mobile-phone LENS and BARREL's assembly system which consists of two actions, picking and placing.its working process includes four sections: 1) the equipment is initialized and take a photo of LENS's or BARREL's, while the image acquisition is triggered and the object is illuminated; 2) convert the analog image signals into digital image signals, transmit and save the digital image signals in an industrial computer; 3) denoise and enhance the digital image, match and identify the object LENS or BARREL, calculate the coordinate of the object; 4) control a mechanical system to finish X-Y-Z-R motion through a serial communication interface,drive the sucker work (pick up or place down) and complete the Lens's assembly operation [2, 3].

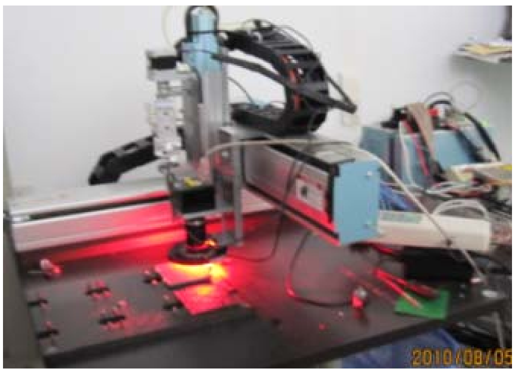

Figure 1. A mobile-phone LENS and BARREL's pick-and-place robot

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In a few company, some engineers begin to develop an assembly quality detection system by means of measuring the fitting press force. Although this method is intuitive and simple in principle. In that system, only one single factor (fitting press force) is used to predict the result of the assembly quality prediction; what's more, it can not be applied on some fit-force-variable occasions.

In recent years; artificial neural network (ANN) has been trained to perform complex functions in various fields, including identification, classification, and other practical applications. ANN is characterized by the advantages [4]: (1) that the need for extensive experimentation is avoided as limited numbers of experiments are sufficient to predict the degree of nonlinearity; (2) they require less time for development than the traditional mathematical models with a higher speed; (3) their ability to learn complex relationships without requiring the knowledge of the model structure. Since neural network is excellent in approaching nearly all nonlinear functions; we prefer it to predict the assembly quality in the vision-based mobile-phone lens's pick-and-place system. It is preferable to use a non-parametric technique such as back-propagation (BP) artificial neural network to represent the non-linear relationship in the vision-based mobile-phone lens's pick-and-place system.

In this research field,a wide variety of approaches of ANN have been taken towards this task in the machining and assembly quality prediction such as support vector machine (SVM), principal component analysis (PCA), principal component regression (PCR), differential evolution algorithm (DEA), mahalanobis-distance discriminant analysis (MD-DA), probabilistic neural network (PNN), GA-BP ANN. In recent years; there is a greater interest in using ANN as problem solving algorithms which can perform mapping; modeling; classification; regression; clustering and multivariate data analysis. The flexibility of neural network predestines them to deal with difficult non-linear problems and any kind of data. Joseph; Babu [5] used ANN to generate models of batch processes relating product quality to process input variables and processing conditions; presented an architecture for a shrinking horizon model predictive control of batch processes. Woll; Suzanne L.B. [6] presented an alternative online technique for part quality monitoring that focuses on the analysis of complete data patterns. ANNs were successful in predicting part quality based on data patterns when an entire sensor profile was analyzed.Edwards; P.J. [7] applied an ANN in the prediction of paper curl. Mohd Zain; Azlan [8] indicated that ANN technique gave a better prediction of surface roughness compared to the result of regression technique. Li; Zhiguo [9] presented a numerical study to illustrate the proposed method and its application in quality control of autobody assembly processes. Leo Chau-Kuang Liau [10] presented an optimization approach with the built ANN model,which was used to estimate the optimal RH-controlled conditions to minimize the fabrication time of required PBG films. Kunpeng Wang [11] established an ANN meta-model for the impact of choice complexity on production rate.

This paper addresses the problem of developing a BP ANN to predict the lens's assembly quality with on-line adaptation to changing processing conditions.

2. BP ANN Modeling Approach

2.1. BP ANN

BP ANN is a generalization of the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. A typical multilayer perceptron (shown in Figure 2) consists of an input layer; one or more hidden layers, and one output layer. What's more; the neurons of the same layer should not be linked together; and each output will only affect the input of the next layer. BP ANN can be regarded as excellent nonlinear function mapping from input to the output. The network's learning consists of two procedures: positive spread and converse spread. In the positive spread process; the neuron input is disposed orderly from the input layer to the hidden layers; then transmits to the output layer. If the output is not expected, their discrepancy will return back and the weight matrixes are modified; which in turn make the output more close to the expected.

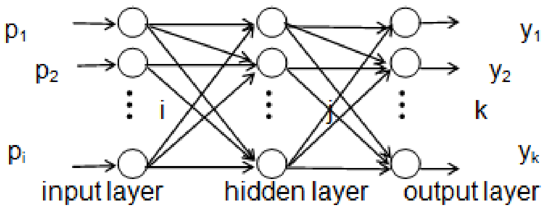


Figure 2. Structure of BP ANN

The input variable i of the input layer is p_i.

The input variable j of the hidden layer x_j is:

$$x_j = \sum_{j=0}^{m-1} w_{ji} p_i - b_j \tag{1}$$

Where w is the weight factors, b_j is the threshold of the hidden layer.

The output variable j of the hidden layer O_j is:

$$O_j = f(x_j) = \frac{1}{1+e^{-x_j}} \tag{2}$$

Where f is an activation function neuron between the hidden layer and the output layer; which may be a linear or nonlinear function of x_j.

The input variable k of the output layer u_k is:

$$u_k = \sum_{j=0}^{m-1} v_{kj} o_j - c_k \tag{3}$$

Where c_k is the threshold of the output layer.

The output variable k of the output layer y_k is:

$$y_k = f(u_k) = \frac{1}{1+e^{-u_k}} \tag{4}$$

The BP algorithm for multiplayer networks is a gradient descent optimization procedure where an error function E performance index is minimized, which can be calculated from function:

$$E = \tfrac{1}{2} \sum_k (t_k - y_k)^2 \tag{5}$$

Where k is the number of the training or testing samples, t_k is the corresponding expected output value of the prediction categories, y_k denotes the actual output of a neural network.

The network learns to infer the relationship between the layers by adjusting the network's weights and thresholds so as to minimize the error in its predictions on the training set. The adjustment of the weight w is in converse direction;in other words; it is in the direction from the output layer to the hidden layer; and the offset Δw_{kj} is calculated by Eq.(6):

$$\Delta w_{kj} = -\eta \frac{\partial E_p}{\partial w_{kj}} \tag{6}$$

Where η is a learning rate, $\eta \in [0,1]$.
As to the output layer neurons,

$$\Delta v_{kj} = -\eta \delta_k a_j \tag{7}$$

Where

$$\delta_k = y_k(1 - y_k)(t_k - y_k) \tag{8}$$

As to the hidden layer neurons,

$$\Delta w_{ji} = \eta \delta_j O_i \tag{9}$$

Where

$$\delta_j = a_j(1 - a_j)\sum_k \delta_k v_{kj} \tag{10}$$

2.2. Key Characteristic Assembly Parameters

The characteristic assembly parameters mainly include:

1) the LENS's similarity and the BARREL's similarity (S1,S2): are important parameters calculated by the similarity function that calculates a scalar value between the gray values in the template and the gray values at the current position in the acquired image within the respective ROI. As for mobile-phone lens's pick-and-place system, the similarity includes LENS's similarity S1 or BARREL's similarity S2 at the two different positions.

The LENS's or BARREL's similarity S is computed as follow [12] :

$$s = \frac{1}{n}\sum_{i=1}^{n} \frac{d_i^{'T} e_{q+p'}}{\left\| d_i^{'} \right\| \left\| e_{q+p'} \right\|} \tag{11}$$

Where n is the number of points in the ROI.

2) the gray value of the workpiece's area (G1,G2):

Although the goal of illumination in this machine vision system is to make the important features of the LENS or BARREL visible, the local gray value of the LENS or BARREL's image area can not be kept constant and affected by the failure of the LED light source; the stability of the power and the different ambient light. And so, the local gray value of the LENS or BARREL's area is measured and selected as one of the input parameters.

3) the force situation (A1, A2): At a different location of the mechanical movement,the mechanical parts have a different acceleration with different load force maximum. And so; the axial maximum force situation (A1, A2) is taken into consideration and selected as one input parameter. Because the appropriate experimental way has not been found yet, the force situation parameter isn't measured and analyzed in the following experiment.

4) the matching time (T1, T2): The parameters (T1, T2) are defined to describe the time for matching the LENS or BARREL in an image which influences the stability of the assembly system in some degree.

2.3. Levenberg Marquardt Algorithm

For many years, some scholars have done a lot of researches on how to accelerate the convergence speed of BP ANN. In 1994; Hagan et al firstly applied the numerical optimization Levenberg Marquardt algorithm (LMA) into the BP ANN [13, 14]. Levenberg Marquardt algorithm, an iterative procedure; provides a numerical solution to the problem of minimizing a nonlinear function. These minimization problems arise especially in least squares curve fitting and nonlinear programming.

The modification of the BP ANN weight is aimed to search and make the error function $E(w)$ the smallest, and if the current weight is $w(t)$, the next weight will be: $w(t+1) = w(t) + \Delta w(t)$, which can be obtained by the following equation:

$$\hat{H}(w(k)) = \hat{H}(w(k)) + \beta_k \hat{Q}) \quad (12)$$

Where $\hat{Q}$ is a given positive definite matrix.

Select the search direction as:

$$d(k) = -\hat{H}^{-1}(w(k))^{-1} g(w(k)) \quad (13)$$

Where $g(t)$ is the gradient vector of $E(w)$, $\hat{H}$ is the positive definite matrix Hessian.

$$w(k+1) = w(k) + \eta_k d(k) \quad (14)$$

It is a typical problem that the speed of the BP ANN's training convergence is very slow, and the training easily fall into a local minimum. Experiments show that LMA can help to overcome this problem:with the global convergence of the gradient method, training a BP ANN with LMA can greatly improve the convergence speed; which is faster than with other methods.

3. Experiments and Simulation Results

3.1. Structure Parameters of BP ANN

The BP ANN to predict the assembly quality is divided into three layers:one input layer; one hidden layer and one output layer. Based on experience and the effect of simulations, the architecture of the BP ANN is designed with 6-18-3, which signifies 6 neurons in the input layer; 18 neurons in the hidden layer; 3 neurons in the output layer.

The 6 nodes of the input layer are the main characteristic assembly parameters: $p_i = [\mathrm{S1, S2, G1, G2, T1, T2}]$. The output layer is set to be 3 nodes. The assembly quality in the vision-based mobile-phone lens's pick-and-place system is predicted to three categories (perfect, pass, and no good). The output parameter is a matrix defined as:

$$\begin{bmatrix} \text{perfect} \\ \text{pass} \\ \text{no good} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (15)$$

The input sampling data are normalized; and limit their distribution between 0 and 1 with the following formula:

$$y = \frac{x - \mathrm{MinValue}}{\mathrm{MaxValue - MinValue}} \quad (16)$$

Where x and y are the values before and after normalization, Max Value and Min Value are the minimum and maximum values for each row accordingly.

The BP ANN is trained with Levenberg Marquardt algorithm. The activation function between the input layer and the hidden layer is a sigmoid function. The transfer function between the hidden layer and the output layer is a pure line function.

The neural network is trained so that the net weight changes to adapt the relationship between the input and the output. The increase of the training samples inevitably results into the accuracy of the relationship reflecting the inherent laws will be better; but the training samples are often limited by the real experimental conditions.

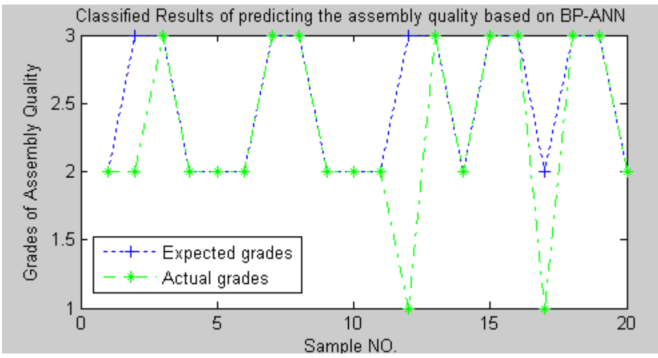
The main assembly parameters obtained in the experiments are shown in Table 1:

Table 1. The Main Assembly Parameters

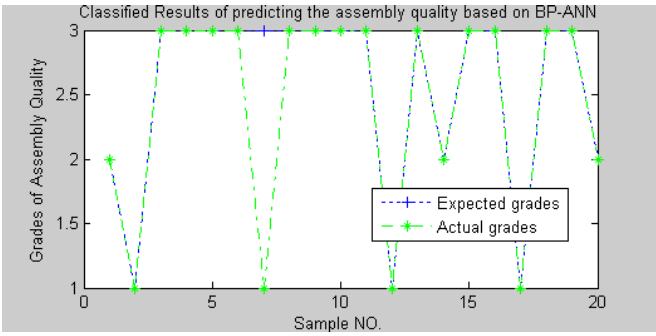
S1 (Score)	S2 (Score)	G1	G2	T1 (ms)	T2 (ms)	Categories
75.11079785	73.27226518	55.95	55.57	12.26	11.38	perfect
72.9311141	72.54509014	55.51	55.66	11.19	12.98	pass
59.86476039	59.48502851	54.18	54.87	11.84	13. 24	NG
73.26689022	72.9626632	55.07	55.32	11.82	12.80	NG
	⋮	⋮	⋮	⋮		⋮
74.06012427	74.62856153	54.61	55.54	11.85	12.54	perfect

3.2. Assembly Quality Prediction

Drive the above-described experiment setup to work for 60 times, the 40 training samples and the 20 testing samples are obtained. The results of the assembly quality prediction based on BP ANN are shown in Figure 3(a). Drive the experiment setup to work for 100 times; the 80 training samples and the 20 testing samples are obtained. The results of the assembly quality prediction based on BP ANN are shown in Figure 3(b).



(a) 40 training samples, 20 testing samples



(b) 80 training samples, 20 testing samples

Figure 3. Simulation results with different number of training samples

In Figure 3(b); it can be found the prediction accuracy (%) in training samples reached 95.From Figure 3(a) to Figure 3(b), it also can be found that the assembly quality prediction accuracy (%)of network increases from 85 to 95 with the number of training samples increases from 40 to 80. The resulting assembly quality prediction shows that the assembly quality prediction technique modelled with a BP ANN is effective to predict the assembly quality in the vision-based mobile-phone lens's pick-and-place system. Continued works will be made to choose the enhanced input parameters of the neural networks that affect the assembly quality more directly by changing the assembly parameters and calculating some new characteristic parameters of the lens's image, so as to improve the accuracy of the assembly quality prediction process for a higher degree.

4. Conclusion

A novel method based on BP ANN has been proposed to predict the assembly quality of the vision-based mobile-phone lens's pick-and-place system.The structure and parameters for the neural network have been discussed in detail.In the assembly quality prediction process; it has been demonstrated that the method is characterized by the advantages of high accuracy and high reliability.

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