Pergamon

0360-8352(94)00211-8

Computers ind. Engng Vol. 28, No. 3, pp. 593–603, 1995

0360-8352/95 \$9.50 + 0.00

A COMPARISON OF STATISTICAL REGRESSION AND NEURAL NETWORK METHODS IN MODELING MEASUREMENT ERRORS FOR COMPUTER VISION INSPECTION SYSTEMS

C. ALEC CHANG[1] and CHAO-TON SU[2]

[1]Department of Industrial Engineering, 113 EBW, University of Missouri-Columbia, Columbia, MO 65211, U.S.A. and [2]Department of Industrial Engineering and Management, National Chiao Tung University, Hsinchu 30050, Taiwan, Republic of China.

Abstract—This paper compares measurement error models for computer vision inspection systems based on the statistical regression method and a neural network-based method. Experimental results demonstrate that both of the models can effectively correct the dimensional measurements of geometric features on a part profile. It also shows that the statistical regression method can perform excellent tasks when the functions for models are carefully selected through statistical testing procedures. On the other hand, varieties of neural network architectures all have good performance when training data are collected carefully. The explicit nonlinear relationship in neural network architectures is very effective in building a general mapping model without specifying the functional forms in advance. While statistical regression methods will continue to play important roles in model building tasks, the neural network-based method will be a very powerful alternative for precision measurement using computer vision systems.

INTRODUCTION

Computer vision systems are ideal non-contact measurement and inspection systems for parts with a compound geometric profile. However, when a part is carried to such inspection systems by a plain conveyor belt, a different part position will cause a different effect of measurement distortion. This significant impact on the automated inspection system will lead to serious measurement errors. Also, the errors which are inherent in the boundary representation method affect its measurement accuracy. In order to get an accurate measurement of each geometric dimension on the part profile, the results of the initial measurements must be corrected.

There is some research concerning the calibration of camera distortion [1–6]. In 1983, Wagner [7] suggested that any resultant measurement value must contain an uncertainty of at least ± 1 pixel resolution value for each edge transition. Ho [8] found that the digitizing error of various geometric features can be expressed in terms of the dimensionless perimeter of the object. Etesami and Uicker [9] proposed a scheme using trigonometric functions based on Fourier series to model the machine part boundary contour. Chang *et al.* [10] developed a method to find more precise break points for boundary segmentation. They also explored the representation errors for the measurement of straight line edges, circular arcs and angles. Later, Chang *et al.* [11] developed an effective procedure to correct the error due to part orientation using the statistical regression method.

The artificial neural network is also a technology which has been successfully applied to the industry. Udo [12] surveyed potential applications of neural networks in manufacturing processes. Sasaki *et al.* [13] applied a neural network fed with optically generated features for the inspection of integrated circuit boards. Javed and Sanders [14] used a multi-layer neural network to devise a weld quality control monitor for zinc coated steel products. By using a back propagation neural network, Neubauer [15] developed an optical inspection system to detect and classify the defects on treated metal surfaces. Kroh *et al.* [16] developed a new neural network architecture for circular features recognition from binary images. Masory [17] proposed a neural network model to find the relationship between multi-sensor readings and actual tool wear measurements. Hou *et al.* [18] proposed an automated inspection system using a Hough Transform and a back propagation network for surface mount devices. Ker *et al.* [19] developed a neural network approach to check radii of circular parts and differentiate between good and defective products. Hwarng and Hubele

[20] presented a pattern recognition methodology for quality control charts based on the back propagation algorithm. This algorithm can be used to identify six types of unnatural patterns on $\bar{X}$ control charts, namely trends, cycles, stratification, systematic, mixtures and sudden shift. There were also works studying the connection of statistical regression models and neural networks. Wu [21] and Ball and Jurs [22] utilized a neural network method to estimate parameters of regression models. Holcomb and Morari [23] adopted partial least squares and a principle component analysis to improve performances in feedforward networks. By applying regression and artificial neural network methods to the autoclave curing process of composites, Joseph *et al.* [24] discussed the relative strengths and weakness for these two approaches.

When an industrial part is brought to the computer vision system, the profile of the part can be scanned by a camera. After the image has been digitized, boundary extraction methods can be applied to detect the edge points representing the part profile so that measurements can be made. The process to decompose the digital boundary into linear lines or non-linear curves at certain joints is boundary segmentation (also called break point detection). The break point detection method used in this paper is the K-curvature thresholding method. By calculating the change of the K-curvature of all edge points of the part profile, the break points of the profile can be detected with a proper threshold. After the break points are identified, the profile can be decomposed into several subsets of edge points. Then, each subset of edge points can be fitted by a proper geometric function. When the circular curves are fitted by a circle-fitting method, the radius size and the center of the circular arc can be found from function parameters directly. The length of a straight line edge can be measured by the distance between two intersection points. When the slopes of two intersecting straight lines are calculated by the line-fitting method, the angle between two intersecting lines can be derived.

The premise of this research is that a part is delivered by a conveyor to the field of view of a camera but without a fixed part location and orientation. The purpose of this paper is to compare the statistical regression method and the neural network-based method in modeling dimensional measurement errors in computer vision inspection systems. Other boundary representation methods such as Hough Transform which tends to use tremendous amount of processing time for every operational cycle and Fourier Transform which is dealing with transformed domains are not included in the scope of this study [25, 26].

The basic profiles of an industrial part mainly consist of straight lines and circular arcs. The geometric features to be measured generally include the radius of a circular arc, the length of a straight line edge, and the angle formed by two straight lines. Two error correction procedures which utilize the statistical regression method and the neural network-based method for dimensional measurements are developed. These procedures are implemented in laboratory settings. Finally, their performances on error correction and characteristics of the statistical regression method and neural network-based method are compared.

ERROR CORRECTION PROCEDURES FOR DIMENSIONAL MEASUREMENTS BY COMPUTER VISIONS

Chang *et al.* [11] demonstrated that orientation is the major influencing factor on the measurement of the circular arc, length and angle after the image coordinate system is properly calibrated. Moreover, errors estimated from analytical models are mostly underestimated for the measurement of the radius, length and angle in laboratory experiments. There are errors due to minute shadow of parts, lighting variation and other unknown causes that cannot be easily approached analytically. In order to include all errors in the use of vision systems for error correction purposes, the empirical approach is proposed to formulate measurement correction models. This proposed framework is shown in Fig. 1. The stage of determining error correction models is the "learning process," while the stage in implementing the developed models in a computer vision system is the "operational process".

For measurement correction, the following relationship should be established in the learning process:

$$\varphi_\pi = f(\theta_\pi) \tag{1}$$

where φ_π is the ratio of the measured dimension to that of its corresponding true dimension of a geometric feature, and θ_π is the orientation of the part scanned. Then, the corrected estimate of true dimension, $\hat{\pi}_t$, can be obtained in the operational process by:

$$\hat{\pi}_t = \frac{\pi}{\varphi_\pi} \tag{2}$$

where π is the initial dimension of a geometric feature measured by a curve-fitting method.

The statistical regression method and the neural network-based method are then used to find the relationship between the geometric orientation and correction ratio. When these methods are applied, a set of input/output patterns should be obtained before the learning process. To collect an effective set of input/output data, one can position the rotary table within the field of view and place the part to be measured close to the center of the rotary table. By rotating the rotary table θ degrees in a counterclockwise (or clockwise) direction, where θ is a predetermined increment for the part orientation, one can scan the profile of the part at different orientations. When the coordinates of the edge points for each scanned image are obtained, the dimensions of the part can be computed. Thus, the observed dimension ratio can be obtained by

$$\varphi_{\pi_i} = \frac{\pi_i}{\pi_t} \tag{3}$$

where π_t is the true dimension and φ_{π_i} is the dimension ratio of ith observation with orientation θ_i.

(1) Modeling measurement errors by statistical regression

When the statistical regression method is applied to develop the required error correction models, orientation is used as an independent variable. The developed regression model will generate the

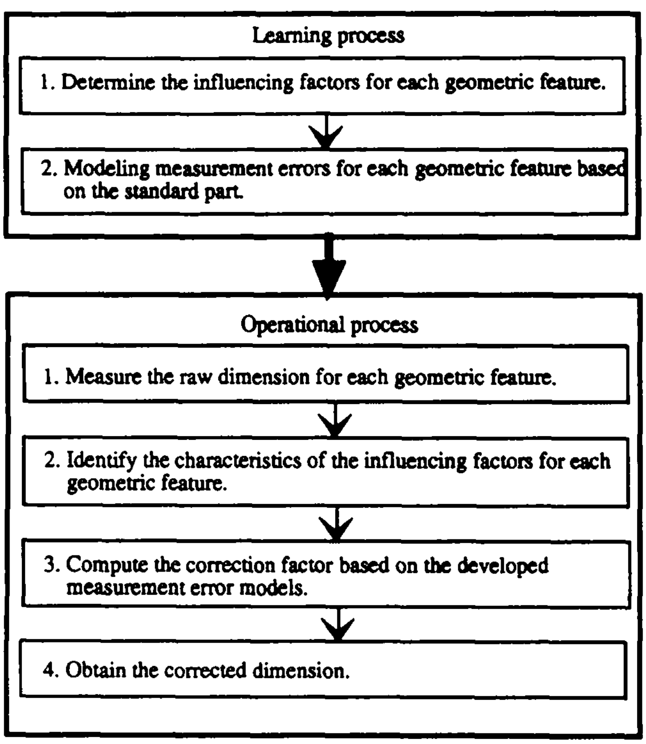


Fig. 1. The proposed error correction framework for the measurement of the part profile in computer vision inspection systems.

required correction ratio which is used as φ_π in equation (2). The proposed error correction procedure for dimension measurement of a part can be described as follows:

Procedure 1: Error correction by Statistical Regression Models

Learning process:

Step 1. Obtain a set of observed data, $(\varphi_{\pi_i}, \theta_{\pi_i})$, $i = 1, 2, \ldots, n$, where φ_{π_i} is the dimension ratio of the geometric feature with the orientation of θ_{π_i} degrees;
Step 2. Determine the specific functional form to be fitted based on the observed data;
Step 3. Find the regression models for observed dimension ratios and orientations for each geometric feature by using the least squares method.

Operational process:

Step 1. Measure the raw dimension, π, for each geometric feature;
Step 2. Estimate the orientations of each geometric feature;
Step 3. Present the orientations of each geometric feature to the regression models and compute the estimated correction ratio, φ_π;
Step 4. Obtain the corrected dimension, $\hat{\pi}_t = \pi/\varphi_\pi$, for each geometric feature.

Once the limits of the correction ratio are predicted, the prediction interval of the corrected dimension can be estimated.

(2) Modeling measurement errors by neural network

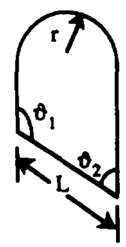
The back propagation network is used to find the relationship between φ_π and θ_π, where φ_π is the dimension ratio and θ_π is the orientation of the scanned feature π. In back propagation neural network, the value of the target pattern should be between 0 and 1. In addition, if the value of the input pattern is >3, the value of the sigmoid function will be close to 1, and if the value of the input pattern is < -3, the value of the sigmoid function will be close to 0. Too many input patterns which have values >3 or < -3 will block the weight changing of the back propagation algorithm. In this study, when an architecture of neural network is defined, the orientations of each geometric feature are fed to the input layer. The output layer has several nodes, each corresponding to the dimension ratio of each geometric feature. However, the observation of the target pattern is very close to 1 (approx. 0.950–1.120) and the observation of the input pattern is between 0 and 360. Therefore, based on the above guidelines, data sets should be scaled and shifted. In order to obtain a set of suitable training patterns to speed network learning, the observed dimension ratio is subtracted by 0.5 and its corresponding orientation is divided by 100 which would maintain the input values around 0 to 3. Once a set of training patterns are obtained and the learning rate and momentum coefficient are determined for a selected architecture, the required mapping function can be estimated. The value of the total sum of squared error for all patterns (SSE) is used as an index for the performance of the trained network. If SSE reaches a stable condition or is less than some criterion, the network training can be terminated.

Based on the discussion above, the modeling procedure by the back propagation network can be summarized as follows:

Procedure 2: Error correction by Neural Network Models

Learning process:

Step 1. Obtain a set of observed data, $(\varphi_{\pi_i}, \theta_{\pi_i})$, $i = 1, 2, \ldots, s$, where φ_{π_i} is the dimension ratio of the geometric feature with the orientation of θ_{π_i} degrees;
Step 2. Transform the observed data sets into a set of training patterns $(\mathbf{x}_i, \mathbf{t}_i)$, $i = 1, 2, \ldots, s$, where $(x_i, t_i) = (\varphi_{\pi_i}/100, \theta_{\pi_i} - 0.5)$;
Step 3. Determine the learning rate and the momentum coefficient based on the training patterns $(\mathbf{x}_i, \mathbf{t}_i)$, $i = 1, 2, \ldots, s$;
Step 4. Choose a set of network architectures. Train each network until the difference of the SSE of two successive iterations is less than a predetermined tolerance;
Step 5. Choose a trained network with the smallest SSE.



The averages of the mechanical measuring results:

$r = 0.375''$

$L = 0.9010'' \pm 0.0002''$

$\vartheta_1 = 123.59° \pm 0.03°$

$\vartheta_2 = 56.22° \pm 0.03°$

Fig. 2. A test part (material: aluminum, thickness: 0.0260″ ± 0.0005″).

Operational process:

Step 1. Measure the raw dimension, π, for each geometric feature;
Step 2. Estimate the orientations of each geometric feature, θ_π;
Step 3. Set $\theta'_\pi = \theta_\pi/100$;
Step 4. Present θ'_π to the trained network which is selected from Step 5 in the learning process and compute the output φ'_π;
Step 5. Obtain the corrected dimension, $\hat{\pi}_t = \pi/\varphi_\pi$, for each geometric feature, where $\varphi_\pi = \varphi'_\pi + 0.5$.

IMPLEMENTATION AND VALIDATION

These two proposed procedures were implemented on the ITEX 100 Image Processing System with a personal computer connected to a camera. These experiments were carried out in a laboratory where the temperature is maintained at 20°C. To reduce the distortion in the ITEX 100 System, the image coordinates are calibrated first. Four features of a precision test part as shown in Fig. 2 are measured. Because the error correction models are part-dependent, they are fitted in the learning stage. Forty sets of observed data for the test part in different orientations are collected. Using the proposed Procedures 1 and 2, the error correction models of the test part are presented as follows:

(1) Statistical regression models

After several pilot studies, it is determined that cos θ and sin θ are to be used as the independent variables, where θ is the orientation of a geometric feature. By applying the least squares method, error correction models for the test part are built as follows:

$$\varphi_r = 0.963856 + 0.017924 \cos^2 \theta_r \tag{4}$$

$$\varphi_L = 0.9690754 + 0.005576 \sin \theta_L + 0.024086 \cos^2 \theta_L + 0.009085 \sin \theta_L \cos \theta_L \tag{5}$$

$$\varphi_{\vartheta_1} = 0.997877 + 0.001611 \cos \theta_L + 0.006872 \cos^2 \theta_L + 0.015025 \sin \theta_L \cos \theta_L \tag{6}$$

$$\varphi_{\vartheta_2} = 1.002895 - 0.005887 \sin \theta_L - 0.014004 \cos^2 \theta_L - 0.023232 \sin \theta_L \cos \theta_L \tag{7}$$

where φ_r, φ_L, φ_{ϑ_1}, and φ_{ϑ_2} are the ratios of radius, length, angle 1 and angle 2, respectively. θ_r is the orientation of the circular arc and θ_L is the orientation of the straight line edge, angle 1 and angle 2. Note that a same orientation can be specified for all adjoining geometric features.

(2) Neural network-based models

These four geometric features on the sample part associate with one of the two orientation angles. Therefore a neural network can be structured with two input patterns and four target patterns. Thus $(\theta_r/100, \theta_L/100)^t$ is used for the input layer and $(\varphi_r - 0.5, \varphi_L - 0.5, \varphi_{\vartheta_1} - 0.5, \varphi_{\vartheta_2} - 0.5)^t$ is used for the output layer. The Parallel Distributed Processing Software (PDP) with a back propagation learning algorithm is used for the network training [27].

Through several pilot runs, the learning rate and the momentum coefficient are set at 0.20 and 0.90 from a pilot study. Several different network's architectures have been tried. Results of network 2-3-3-4 as shown in Fig. 3 demonstrates the best performance. Accordingly, the model

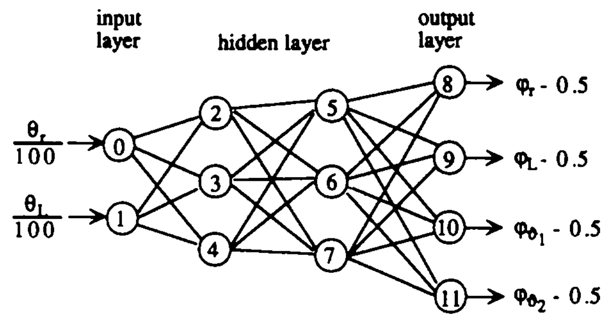


Fig. 3. The architecture of network 2–3–3–4.

of network 2–3–3–4 is chosen to estimate the required correction ratios when a new input pattern $(\theta_r/100, \theta_L/100)^t$ of an incoming part is given.

The neural network-based correction models for the ratios of radius, length, angle 1 and angle 2 of the test part are summarized as follows:

$$\varphi_r = 0.5 + [1 + \exp(-\mathrm{net}_{p8})]^{-1} \quad (8)$$

$$\varphi_L = 0.5 + [1 + \exp(-\mathrm{net}_{p9})]^{-1} \quad (9)$$

$$\varphi_{\vartheta_1} = 0.5 + [1 + \exp(-\mathrm{net}_{p10})]^{-1} \quad (10)$$

$$\varphi_{\vartheta_2} = 0.5 + [1 + \exp(-\mathrm{net}_{p11})]^{-1} \quad (11)$$

where $\mathrm{net}_{pi} = \Sigma_j w_{ij} a_{pj} + b_{i,j}$ belongs to previous layer based on network 2–3–3–4 (Fig. 3), $a_{p0} = \theta_r/100$ and $a_{p1} = \theta_L/100$ for $a_{pi} = (1 + \exp(-\mathrm{net}_{pi}))^{-1}$ $(i = 2, 3, \ldots, 11)$. θ_r is the orientation of the circular arc and θ_L is the orientation of the straight line edge, angle 1 and angle 2. The weights and biases of this network model, w_{ij} and b_i, are listed in Table 1.

(3) A comparison

To compare performances of these two error correction procedures, the test part is scanned another 20 times so that an additional 20 sets of edge points are obtained in different orientations. The orientations of these 20 scans are listed in Table 2. A statistical summary of the implementation results from the error correction by using procedure 1 and procedure 2 is shown in Table 3. Compared to their true dimensions, the absolute measurement errors are also listed correspondingly.

Table 1. (a) The weights of network 2–3–3–4

j–i	w_{ij}	j–i	w_{ij}
0–2	−0.697784	4–7	−1.711437
0–3	−0.589492	5–8	−1.431301
0–4	3.979731	5–9	1.261130
1–2	4.863389	5–10	1.573830
1–3	−0.506309	5–11	−2.428989
1–4	−0.438711	6–8	1.009104
2–5	−0.850405	6–9	1.040810
2–6	0.718835	6–10	−0.277697
2–7	−1.436456	6–11	0.011072
3–5	−2.264152	7–8	1.369623
3–6	−1.819924	7–9	1.755147
3–7	0.740621	7–10	−0.264766
4–5	−0.957300	7–11	−0.253761
4–6	1.044890		

Table 1. (b) The biases of network 2–3–3–4

i	b_i	i	b_i
2	−1.481065	7	0.507747
3	1.456667	8	−0.383967
4	−2.849992	9	−1.338276
5	1.551175	10	−0.333596
6	−0.671860	11	0.838023

Table 2. Twenty different orientations of the test part

No.	θ_r	θ_L	No.	θ_r	θ_L
1	16.7499	162.7700	11	186.4145	332.8866
2	46.7057	192.1600	12	211.9046	357.6542
3	51.7330	197.1156	13	226.9896	12.2848
4	56.6248	202.1813	14	236.9372	22.3381
5	66.3256	212.0437	15	256.6371	41.9351
6	86.1563	232.1433	16	261.8560	46.9985
7	121.0246	267.5440	17	316.1019	102.5291
8	136.0842	282.9632	18	326.1614	112.6399
9	141.0935	287.9212	19	336.2495	122.7072
10	145.9828	292.6986	20	346.1750	132.6138

Note: θ_r is the orientation of the circular arc and θ_L is the orientation of the straight line edge, angle 1 and angle 2.

A statistical test is conducted to decide whether the absolute measurement errors from the neural network-based method are different from those using the statistical regression method. This is to test the hypothesis

$$\mathrm{H}_0\colon\ \mu_{N_\pi} = \mu_{R_\pi}, \quad \pi \in \{r, L, \vartheta_1, \vartheta_2\}$$

against the alternative

$$\mathrm{H}_a\colon\ \mu_{N_\pi} \neq \mu_{R_\pi}$$

where N_π and R_π denote the absolute measurement error using the neural network-based method and the statistical regression method for each geometric feature, respectively. μ_{N_π} and μ_{R_π} are the means of N_π and R_π, respectively. Since the distribution of absolute measurement errors passed a normality test, the following t distribution is applied

$$t^* = \frac{\bar{X}_{N_\pi} - \bar{X}_{R_\pi}}{\sqrt{\dfrac{s^2_{N_\pi} + s^2_{R_\pi}}{n}}}, \quad v = \frac{(s^2_{N_\pi} + s^2_{R_\pi})^2}{s^4_{N_\pi} + s^4_{R_\pi}}(n-1) \tag{12}$$

where $\bar{X}_{N_\pi}$, $\bar{X}_{R_\pi}$, and $s^2_{N_\pi}$, $s^2_{R_\pi}$ are simple means and variances, n is the sample size and v is the degree of freedom for which a round-off integer is used.

For the radius measurement,

$$t^* = \frac{0.0007 - 0.0006}{\sqrt{\dfrac{0.0027^2 + 0.0028^2}{20}}} = 0.115, \quad v = 38.$$

Although the error correction model for the radius measurement based on the statistical regression method performs better, this result is not statistically significant with $\alpha = 0.05$ level [$t(0.975, 38) = 2.025$]. Thus, the hypothesis of H_a is injected, i.e. μ_{N_r} is not different from μ_{R_r} statistically. Therefore, we conclude that the error correction results of radius for procedure 1 (statistical regression models) and procedure 2 (neural network-based models) are not significantly

Table 3. The statistical summary of corrected dimensional measurements

Features	Methods	Before correction: Measured dimension	Before correction: Absolute measurement error	Procedure 1 Statistical regression: Corrected dimension	Procedure 1 Statistical regression: Absolute measurement error	Procedure 2 Neural network: Corrected dimension	Procedure 2 Neural network: Absolute measurement error
Radius	$\bar{X}$	0.3654″	0.0096	0.3756	0.0006	0.3757	0.0007
	s	0.0029		0.0027		0.0028	
Length	$\bar{X}$	0.88654″	0.01446	0.90306	0.00206	0.90324	0.00224
	s	0.00861		0.00445		0.00370	
Angle 1	$\bar{X}$	123·810	0.22	123.609	0.019	123.588	0.002
	s	0.761		0.200		0.246	
Angle 2	$\bar{X}$	56.012	0.208	56.270	0.050	56.254	0.034
	s	0.580		0.160		0.166	

Note: $\bar{X}$ and s are the sample mean and standard deviation of 20 observations.

Table 4. t^* values between absolute errors from the neural network-based method and the statistical regression method

Feature	Radius	Length	Angle 1	Angle 2
t^*	0.115	−0.139	−0.240	−0.362
$t^*_{critical}$	$t(0.975, 38) = 2.025$	$t(0.025, 34) = -2.034$	$t(0.975, 37) = 2.027$	$t(0.975, 38) = 2.025$

Note: t^* values are used to test whether the absolute measurement errors of the neural network-based method are different from those of the statistical regression method.

different. Calculated t^* values to test the absolute measurement errors of the neural network based models and the statistical regression based models for error correction are listed in Table 4. It is also concluded that the measurement results of length and angle for procedures 1 and 2 are not significantly different.

Dimensional measurements with respect to part orientation before and after error correction by these two methods are shown in Fig. 4. Both error correction results using regression models and neural network models demonstrate a very good performance for corrected dimensional measurements using computer visions.

DISCUSSION

When the statistical regression method is used, the specific functional form must be specified in advance. In this study, the sine and cosine transformations on θ (orientation) are used for regression relation between radius ratio, length ratio, angle ratio and orientations. In general, the form of the fitting function should be chosen carefully when the statistical regression method is applied. For

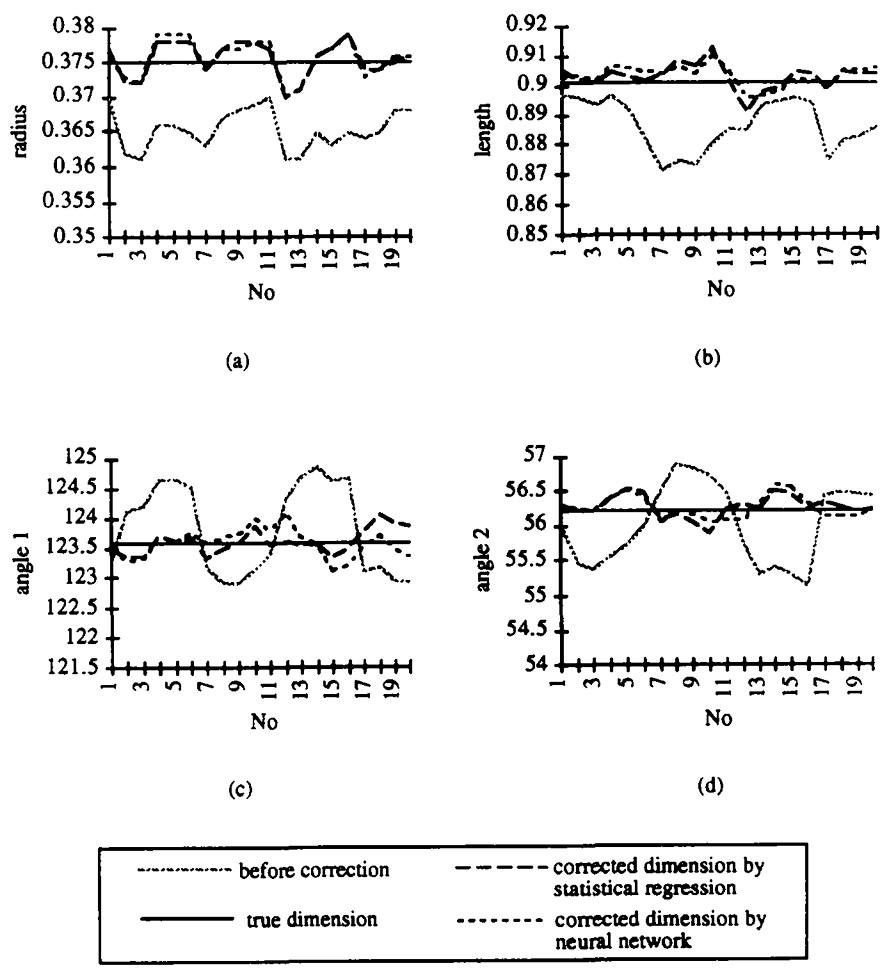


Fig. 4. Measurement results for the test part.

Table 5. Total sum of squared errors of six networks

Network	epoch	SSE
2–4–4	35,500	0.00165
2–6–4	24,000	0.00151
2–8–4	38,500	0.00145
2–2–2–4	30,000	0.00360
2–3–3–4	30,000	0.00140
2–4–4–4	31,500	0.00176

Note: the back propagation procedure is said to be operated one epoch when the forward and backward passes are swept through the whole training patterns one time.

example, if one of the following simple models is selected for the radius measurement instead of using equation (4):

$$\varphi_r = 0.973765 - 0.0001528\theta_r \tag{13}$$

$$\varphi_r = 0.973321 + 0.000556 \cos \theta_r - 0.000257 \sin \theta_r \tag{14}$$

where θ_r is the orientation (measured in radians) based on the center, its performance to reduce measurement errors is not satisfactory. Fortunately, a required testing process in the statistical regression method will reject both models by a common criterion of $\alpha = 0.05$ for F values. The probability values of F (PROB > F) for equations (13) and (14) are 0.8207 and 0.9341, respectively. This statistical testing and screening process usually leads to acceptable models with satisfactory performances. As long as the form of the fitting function is determined properly, the statistical regression method can effectively find the mapping coefficients. From Table 4, one can see that the statistical regression models from equations (4) to (7) perform slightly better. This is due to a very careful selection of these equation formats by observing error patterns from initial measurements.

A principal strength of the neural network approach over the statistical regression method is that the neural network is explicitly nonlinear through hidden layers. It is a more general mapping procedure that a specific function format is not required in model building. Moreover, the performance is not sensitive to different network's architectures in this study. The performances of six different networks are listed in Table 5. Among them, network 2–3–3–4 has the smallest SSE and network 2–2–2–4 has the largest SSE. In this study, each of the six trained networks gives improved measurement results. That is to say, the neural network-based method will give satisfactory results for the error correction of dimensional measurements in general. But SSE cannot be directly linked with performance of network models. There are no uniform screening processes for network models before they are actually implemented. A performance checking is required before a model can be adopted as the error correction model in inspection processes.

A possible drawback of the neural network approach is that is usually requires many training data and tremendous numbers of iterations to complete learning. The building of the neural network-based models in this study takes advantage of the factorial design concept. These data are collected by rotating the sample part with a constant incremental angle. Although the use of a factorial design concept for data collection is not necessary, the amount of training data required for building good network models will be greatly reduced. Moreover, the influencing factors in this study have been selected by the statistical method (ANOVA) for model fitting. Thus, the input variables for neural network training have been reduced to one influencing factor [11]. Another major difference is that the confidence intervals of estimated coefficients and responses from models can be specified for the statistical regression method based on statistical variations. The neural network-based method has to utilize a tedious sensitivity analysis for this task. The different characteristics of the statistical regression method and the neural network-based method for modeling measurement errors are summarized in Table 6.

CONCLUSION

With the advent of computer vision inspection, a proper error correction of dimensional measurements is essential. Two error correction procedures using the statistical regression and the neural network-based methods for dimensional measurements in computer vision systems are

Table 6. Characteristics of statistical regression and neural network-based methods

Statistical regression method	Neural network-based method
1. Performance is very sensitive to the selection of functional forms for models. The best regression model performs slightly better than neural network models. (It is not statistically significant in this research)	1. Performance is not sensitive to the selection of network architecture. All reasonable models in this research reduce measurement errors greatly and they perform better than most regression models except the best ones
2. It is harder to handle nonlinear relationships. The users must have specified function formats for models to be fitted	2. It is explicitly nonlinear. The users can handle varieties of nonlinear relationships thorugh hidden layers without specified function formats
3. The model selection process is self-sustained through statistical testing procedures. Improper models would be screened out by statistical tests before checking actual performance of models	3. SSE is a common criterion for selecting a best network architecture. Its process does not have a self-sustained screening criterion to identify low quality models before checking actual performance in error correction tasks
4. Data collection for model fitting can be very effective through the factorial design concept	4. The excellent results of neural network models in this research are partially due to the utilization of statistical experimental design methods to collect learning data
5. A simple universal statistical criterion for prediction intervals can be specified	5. Tedious sensitivity analyses must be utilized to specify prediction intervals
6. It can accommodate a limited data set for model fitting through larger prediction	6. In general, it requires a large number of input/output patterns for training
7. It requires much less computing time for model fitting	7. Training time is long
8. Industrial practitioners can easily grasp the practical meaning of models and coefficients	8. Industrial practitioners may have difficulty grasping the practical meaning of weights and biases in networks

implemented and compared in this paper. Experimental results show that both of these two procedures can be used for the purpose of correcting measurement errors. These two proposed procedures for modeling measurement errors can assist quality control practitioners utilizing computer vision systems for measurement and inspection tasks. Both of these procedures are applicable to different geometric features, such as the correction of estimated vertex of the parabola, foci of ellipse, and foci and vertices of hyperbola. They should be also applicable to correct the estimation of coefficients for curves with higher degrees.

In order to adopt the regression method effectively, the form of the fitting function should be defined in advance, i.e. the specific form of a correction function must be chosen first and then a fitting is carried out according to the minimal sum of square errors. On the other hand, if the form of the fitting function cannot be specified, then the neural network-based method is suggested. When the learning rate, momentum coefficient and number of nodes in the hidden layers are carefully chosen, the back propagation network does not require any *a priori* information and can map the input patterns to the output patterns properly.

REFERENCES

1. A. A. Rodriguez, J. R. Mandeville and F. Y. Wu. System calibration and part alignment for inspection of 2D electronic circuit patterns. *SPIE 1332, Optical Testing and Metrology III: Recent Advances in Industrial Optical Inspection*, pp. 25–35 (1990).
2. A. W. Burner, W. L. Snow, M. R. Shortis and W. K. Goad. Laboratory calibration and characterization of video cameras. *SPIE 1395, Close-Range Photogrammetry Meets Machine Vision*, pp. 664–671 (1990).
3. Y. R. Shiau and B. C. Jiang. Determine a vision system's 3D coordinate measurement capability using taguchi methods. *Int. J. Prod. Res.* **29**, 1101–1122 (1991).
4. L. L. Wang and W. H. Tsai. Camera calibration by vanishing lines for 3-D computer visions. *IEEE Trans. Pattern Anal. Mach. Intell.* **13**, 370–376 (1991).
5. R. Mohr and E. Arbogast. It can be done without camera calibration. *Pattern Recogn. Lett.* **12**, 39–43 (1991).
6. Z. C. Lai. The calibration of a stereo vision system with two camera. *1992 IPPR Conference on Computer Vision, Graphics and Image Processing*, Taiwan, pp. 41–48 (1992).
7. G. G. Wagner. Vision methodology as it applies to industrial inspection applications. *Gauging: Practical Design and Application*, pp. 410–418. Society of Manufacturing Engineers (SME) (1983).
8. C. S. Ho. Precision of digital vision systems. *IEEE Trans. Pattern Anal. Mach. Intell.* **PAMI-5**, 593–601 (1983).

9. F. Etesami and J. J. Uicker. Automatic dimensional inspection of machine part cross sections using Fourier analysis. *Computer Vision Graph. Image Process.* **29**, 216–247 (1985).
10. C. A. Chang, L. H. Chen and J. I. Ker. Efficient measurement procedures for compound part profile by computer vision. *Computers Ind. Engng* **21**, 375–377 (1991).
11. C. A. Chang, L. G. David, L. H. Chen and C. T. Su. Error correction models for measurement and inspections in computer vision systems. *2nd Industrial Engineering Research Conference Proceedings*, pp. 629–633 (1993).
12. G. J. Udo, Neural networks applications in manufacturing process. *Computers Ind. Engng* **23**, 97–100 (1992).
13. K. Sasaki, D. Casasent and S. Natarajan. Neural net selection of features for defect inspection. *Proc. SPIE Int. Soc. Opt. Engng.* **1384**, 228–233 (1991).
14. M. A. Javed and S. A. C. Sanders. Neural networks based learning and adaptive control for manufacturing systems. *Proceedings of the IEEE/RSJ International Workshop on Intelligent Robots and Systems-IROS '91*, pp. 242–246. IEEE Service Center, Piscataway, NJ (1992).
15. C. Neubauer. Fast detection and classification of defects on treated metal surfaces using a backpropagation neural network. *1991 IEEE International Joint Conference on Neural Networks*, pp. 1148–1153. IEEE Service Center, Piscataway, NJ (1991).
16. J. R. Kroh, T. S. Durrani and R. Chapman. Neural network architecture for circular features extraction in binary patterns. *Electron. Lett.* **27**, 1879–1880 (1991).
17. O. Masory. Monitoring machining processes using multi-sensor readings fused by artificial neural network. *J. Mater. Process. Technol.* **28**, 231–240 (1991).
18. T. H. Hou, L. Lin and P. D. Scott. A neural network based automated inspection system with an application to surface mount devices. *Int. J. Prod. Res.* **31**, 1171–1187 (1993).
19. J. I. Ker, M. Lynch and A. Kalale. A neural network approach to machine vision based radius inspection. *Intell. Engng Syst. Artif. Neural Networks* **2**, 541–546 (1992).
20. H. B. Hwarng and N. F. Hubele. Back-propagation pattern recognition for $\bar{X}$ control charts: methodology and performance. *Computers ind. Engng* **24**, 219–235 (1993).
21. F. Y. Wu. Applications of neural network in regression analysis. *Computers ind. Engng* **23**, 93–95 (1992).
22. J. W. Ball and P. C. Jurs. Automated selection of regression models using neural networks for ^{13}C NMR spectral predictions. *Analyt. Chem.* **64**, 379–386 (1993).
23. T. R. Holcomb and M. Morari. PLS/neural networks. *Computers chem. Engng* **16**, 393–411 (1992).
24. B. Joseph, F. H. Wang and D. S. Shieh. Exploratory data analysis: a comparison of statistical methods with artificial neural networks. *Computers chem. Engng* **16**, 413–423 (1992).
25. C. A. Chang and K.-H. Hsieh. Object identification and profile inspection by computer vision systems in multiple objects scenario. *Proceedings the Third Industrial Engineering Research Conference*, Atlanta, pp. 503–508 (1994).
26. C. A. Chang. Precision measurement and automated inspection for part profile by computer vision and CMM. *Proceedings, 13th Modern Engineering and Technology Seminar*, Taipei, Vol. 6, pp. 59–75 (1990).
27. J. L. McClelland and D. E. Rumelhart. *Explorations in Parallel Distributed Processing*. MIT Press, Cambridge, MA (1991).