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Development of a calibrating algorithm for Delta Robot's visual positioning based on artificial neural network

Wei Ding*, Jinan Gu, Shixi Tang, Zhenyang Shang, Enock A. Duodu, Changjun Zheng

Mechanical Information Research Center of Jiangsu University, Zhenjiang, 212013, PR China

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ABSTRACT

Delta robot with vision system can automatically control the end-actuator to accurately grasp moving objects on the conveyor belt. Establishment of the mapping relationship between the image feature space and the robot working space form a closed-loop chain for transformational link between the robot coordinate, camera coordinate and conveyor belt coordinate. The vision system calibration is a basic problem of robot vision research and implementation. The artificial neural networks (ANN) which has learning ability, adaptive ability and nonlinear function approximation ability can establish the nonlinear relationship between space points and pixel points to complete accurate calibration of the vision system. The convergence speed of calibration algorithm affects the real-time visual servo system. The calibration precision, generalization ability and calibration space of algorithm influence the robot grasping accuracy. Therefore, a new calibration technique for delta robot's vision system was presented in this paper. The algorithm combines ANN with Faugeras vision system calibration technology. The setting of the initial value, network structure and the choice of the activation function is based on the model of Faugeras vision system calibration algorithm, which makes the actual output of the network closer to the target output. Experiments proved that this algorithm has higher calibration accuracy and generalization ability compared with the conventional calibration algorithm, as well as faster convergence speed compared with the conventional artificial neural network structure in the case of high calibration accuracy.

1. Introduction

There are many factors that influence the process of imaging, such as radial distortion, tangential distortion, measurement error, etc. therefore the camera imaging model was turned into a complex nonlinear model. The mapping relationship between object point and image point has also become nonlinear. Many researchers have studied the camera imaging relations and proposed many new calibration methods. These methods can be divided into explicit calibration and implicit calibration. Explicit calibration method such as linear calibration method [1], nonlinear optimization method [2], Tsai two-step method [3] and self-calibration method [4], which is based on geometric properties of the imaging model, calculate internal parameters, external parameters and the distortion parameters to construct imaging model. However, these methods do not embrace all the nonlinear factors in the process of imaging. It can only choose one of the major factors, while ignoring other uncertain factors.

* Corresponding author.
E-mail address: ddyangzicheng@163.com (W. Ding).

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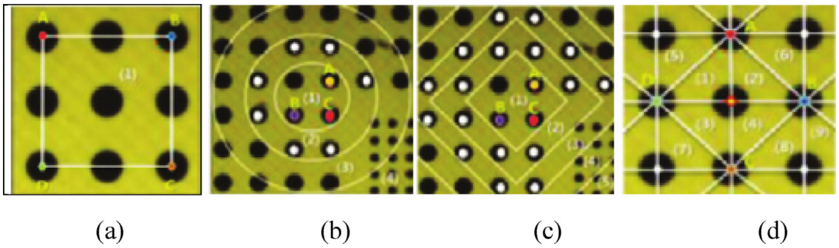


Fig. 1. Classification of training set (a) central zone, (b) circular pattern, (c) diamond pattern and (d) multiple equilateral triangles.

Meanwhile, this calibration technology, absolutely considers all kinds of nonlinear distortions based on the accurate mathematical model with definite physical meaning. These models have limitations including; (i) an effective model don't necessarily work in another system because the optical properties of camera may be different. For instance, two-step method proposed by Tsai has lower calibration accuracy than a simple linear method when the radial distortion is very low. Again, it is an indisputable fact that no precise model can perfectly represent a visual system. The more accurate modeling, the more complicated mathematical equations will be. For example, a model formulated by Weng [5] considers other kinds of distortion besides the radial distortion. However, one factor may cause a variety of distortion. Strong correlation between parameters can lead to the introduction of some significant parameters which can worsen the situation. Implicit calibration method, does not rely on certain mathematical model, but rather determines the nonlinear mapping relationship between image and object points through intermediate parameters. Implicit calibration method does not have the above limitations, and has better flexibility and wider application than the explicit calibration method. The camera calibration method based on artificial neural networks (ANN) belongs to one kind of implicit calibration methods. In view of the situation, this paper proposes an improved visual locating method based on ANN into a sorting visual positioning system of high-speed parallel Delta robot. This algorithm redefined the joint point between ANN and visual calibration, as well as an improvement in the calibration accuracy, generalization ability and convergence by modifying the conventional complex mathematical modeling.

2. The combination of calibration and artificial neural network

2.1. The similarity

In the field of robot vision, the research application of artificial neural network is extremely frequent [6–8]. In terms of production lines of Delta robot, the operation of the visual system to recognize objects on the conveyor belt and feedback the location information of the workpiece to the robot. Then, the robot controls the end-actuator to grasp the workpiece according to the feedback information. In the process of calibration, some parameters of the position relationship and the optical geometrical parameters of camera on some occasions does not need to be determined separately, but to calculate the implicit parameter matrix from the pixel coordinate and the corresponding points' coordinate in robot coordinate system. It has been theoretically proven that the ANN has the property to express arbitrary nonlinear mapping if it has the appropriate network topology structure and connection weights.

ANN has a certain commonality with respect to camera calibration. Firstly, both the ANN and camera deduce unknown parameter model from the known data and then deal with problem judging from the obtained model. Secondly, the camera imaging model is a nonlinear model while the ANN has strong nonlinear approximation ability and can adapt to the dynamic properties of the uncertain system. ANN has a good summary of system function and property through sample training and can solve the problems which are hard to depict for the mathematical model by taking advantage of the above feature. Therefore, it is achievable to apply ANN algorithm in the camera calibration technology according to the above argument. The camera calibration method based on artificial neural network can effectively overcome the measurement error of visual inspection (including the error of mathematical model, error of image acquisition, error during optical system adjustment and camera photosensitive error), which ensure an effective method to build a relationship between 2D image and 3D coordinates of objects.

2.2. Calibrating algorithms based on artificial neural network

Several scholars have used the ANN algorithm in different aspects to analyze the network performance.

2.3. The scale and distribution of training set

When training set reaches a certain scale, it can adequately reflects the properties of approximation function. Therefore, ANN after training acquires output with good precision and generalization ability. The total radial distortion in the image is proportional to the distance between the object points and the center point. Jun et al. [9] stated that the pixel coordinates of training set can be divided into two parts, the central and marginal regions as shown in Fig. 1(a) for application in different network. To large extent, experimental results show that the algorithm improves the precision of camera calibration. Again, Kwon [10] divided pixel coordinates into a series of concentric circles with the same radial distortion. As shown in Fig. 1(b), the

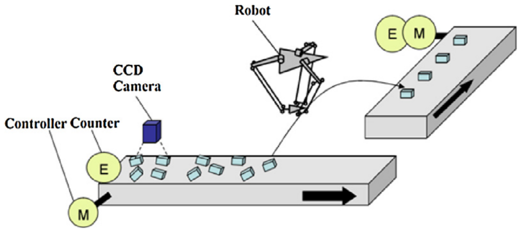


Fig. 2. Industrial environment of Delta robot.

construction of the corresponding artificial neural network for each region with the same radial distortion further improved the calibration accuracy. Actually, algorithm can be improved in radial distortion through transformational process. The report introduces fuzzy theory in the division of the training set, therefore considers the difference and continuity of the radial distortion at the same time. Experiment proved that transition between regions become smoother. The precision is higher than the former, but training convergence rate decline. Kwon [10] summarized the research on training set as shown in Fig. 1 The above algorithm can improve the calibration precision of the algorithm; however they only consider the radial distortion and ignore the other performance parameters of the network (Fig. 2).

2.2.1. The structure of ANN

Conventional artificial neural network algorithms such as the BP [11], RBF [12] and Support Vector Machine (SVM) [13] developed in recent years have optimized network structure through new algorithms to improve the final calibration precision. Through these attempts, the ultimate accuracy and speed of the calibration algorithm is greatly improved. However, the calibration space of these methods is small. When calibration space covered by template becomes small, these algorithms achieve high calibration precision. However, once the calibration space expanded to a certain range, the contradiction between precision and speed cannot be adjusted, yet the fatal flaw greatly limits the application range of the calibration algorithm.

2.2.2. Weight and bias

The topology structure and weights of neuron determines the function of the artificial neural network. It establishes the prototype by building a good network structure. This network can not realize the needed function through prototype. It therefore needs artificial neural network. The process of training makes network adjust weights and bias under the stimulation of the external environment, and react to external environment in a new way. It is significant natures of artificial neural network that can learn from the environment and improve their performance during learning. The artificial neural network achieves understanding and adaptation with the environment through over-learning.

Scholars have studied on the learning process of artificial neural network: (a) The improvement of error function and adaptive adjustment of learning rate (such as method of entropy function [14], conjugate gradient method [15] and simplex method [16]; (b) The use of optimization algorithm and parameter estimation theory in other field such as Kalman Filtering [17], Homotopy theory [18] and orthogonal projection algorithm [19]. There are still other improved algorithms which are designed specifically to overcome local minimum. Simulated annealing [20] and genetic algorithm [21] are both more effective method. The performance function of artificial neural network is not a function with only one variable x, but a function with all network variables (such as weights and bias). The number of variables is determined by the structure of the artificial neural network and is likely to be very large. An improved algorithm of its performance functions includes BP algorithm with variable optimal learning rate, conjugate gradient algorithm and Levenberg–Marquardt algorithm.

3. The new calibrating algorithm for delta robot's visual positioning based on artificial neural network

3.1. The traditional new calibrating algorithm

In this paper, the research object is the Delta robot which has the property of high speed and high precision. It can finish picking and placing various shapes of small products in the industrial feeding and unloading material. The mission of robot vision system is to recognize the workpiece which is needed to fetch on the conveyor belt and send its spatial position to the robot. The calibration of the relationship between the camera coordinate system, robot coordinate system and conveyor belt coordinate system is a premise of automatic control. Different occasions need different calibration model. The closer of the actual established model, higher the calibration accuracy. The complexity of the model is also need to be considered in the model establishment. However, when the model is relatively simple, calibration is easy to implement.

The conventional camera calibration need to use the two-dimensional or three-dimensional templates placed in a scene, and capture one or more pictures by the camera to determine the relationship between three-dimensional space-coordinates and the corresponding image pixel coordinates. As the camera of the vision system is not usually in the work space, conveyor belt and robot need to be calibrated respectively, and then comprehensively calibrated.

First of all, the relative coordinate transformation between the conveyor belt coordinate system and the robot coordinate system is needed to be considered with a formula:

$$P^R = H_C^R Trans \Delta L P^C \tag{1}$$

where P^R is the pose position and orientation of the object in the robot coordinate system, P^C is the pose position and orientation of the object in the conveyor belt coordinate system, $Trans\Delta L$ is scale factor of the conveyor belt installation error.

Secondly, the relative coordinate transformation between the pixel coordinate system and world coordinate system (namely conveyor belt coordinate system) is need to be calculated. The formula is shown below:

$$P^O = T_U^O T_W^U P^C \tag{2}$$

where $T_U^O$is the internal parameters of camera, $T_W^U$is the external parameters between camera coordinate system and conveyor belt coordinate system,$P^O$the pixel coordinate of object in the image.

Thirdly, the relative coordinate transformation between pixel coordinate system and robot coordinate system is to be calculated. For the Delta robot vision system is generally not in the work space, so the conveyor belt coordinate system as intermediaries is necessary for vision system calibration. The formula is shown below:

$$P^R = H_C^R Trans_{\Delta L} (T_W^U)^{-1} (T_U^O)^{-1} P^O \tag{3}$$

The conventional calibration algorithms have some limitations: (1) The multiple blocks and calibration board in the process of calibration in the model introduces systematic measurement error; (2) The camera belongs to the finished product and unavoidably exist error during installation; (3) The conventional calibration algorithm method ignored the distortion. Therefore, the conventional algorithm needs an improvement.

3.2. The new calibration algorithm based on improved artificial neural network

Considerable studies of calibration algorithm based on artificial neural network have been done by predecessors. However, most of research design algorithm parameters used to optimize artificial neural network performance includes network structure and learning rate. They improved the efficiency of calibration by optimizing artificial neural network. The network structure and hidden layer structure are acquired through experience and there is no theoretical foundation. This paper designed a new artificial neural network structure which is based on the calibration algorithm. In the process of calibration, linear performance parameters are assigned by linear parameters and nonlinear performance parameters which are calibrated using artificial neural network to fit the complicated nonlinear mapping relation. Compared to the conventional artificial neural network calibration algorithm, this algorithm reduces the search space and obtains more accurate approximation effect.

According to the Kolrnogorov Theorem, the artificial neural network has the characteristic of expressing arbitrary nonlinear mapping. This calibration algorithm has dual hidden layer structure. The pixel coordinate system object is converted into camera coordinate based on pin-hole camera model. The camera coordinates is converted into the coordinates in robot coordinate system based on the external parameter matrix. The deriving formula is shown as below:

$$P^R = Trans_{\Delta L} (T_W^{U'})^{-1} (T_U^O)^{-1} P^O \tag{4}$$

In Eq. (4), $T_W^{U'}$ refers to the external parameters matrix between pixel coordinate system and the robot coordinate system.

3.2.1. The derivation of artificial neural network structure based on calibration algorithm

The transformational relationship between pixel coordinates and the corresponding points in the camera coordinate system is nonlinear transformation because there exits nonlinear distortion factors. The transformational formula is shown as below:

$$\begin{bmatrix} \frac{xc}{zc} \\ \frac{yc}{zc} \\ 1 \end{bmatrix} = \begin{bmatrix} kx & ks & u0 \\ 0 & ky & v0 \\ 0 & 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} r11 & r12 & t1 \\ r21 & r22 & t2 \\ r31 & r32 & t3 \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \tag{5}$$

where (xc, yc, zc) is the coordinate of object point in the camera coordinate system, (u, v) is pixel coordinate of object point, $kx$is the amplification coefficient on X-axis, ky is the amplification coefficient on Y-axis, ks is coupling coefficient.

The partial learning neural network is constructed as shown in Fig. 3. The value of (u, v) is the input of neural network. The value of (xc, yc, zc) is the output of neural network. The activation function is the hyperbolic tangent sigmoid function. $rij(i = 1, 2; j = 1, 2, 3)$ is neural connection weight, $tn(n = 1, 2, 3)$ is neuron threshold values.

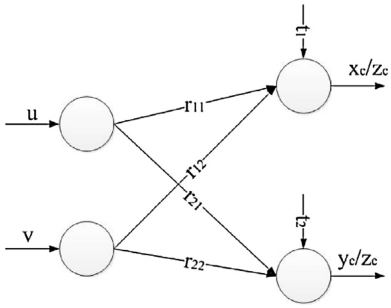


Fig. 3. Partial structure of the new artificial neural network.

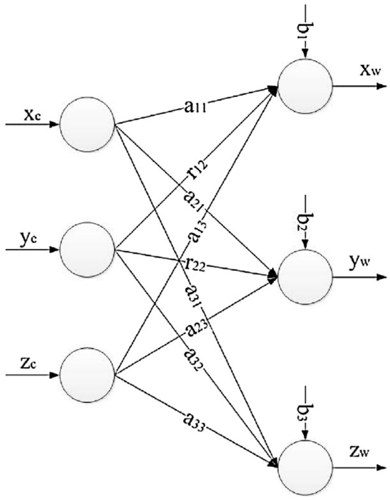


Fig. 4. Partial structure of the new artificial neural network.

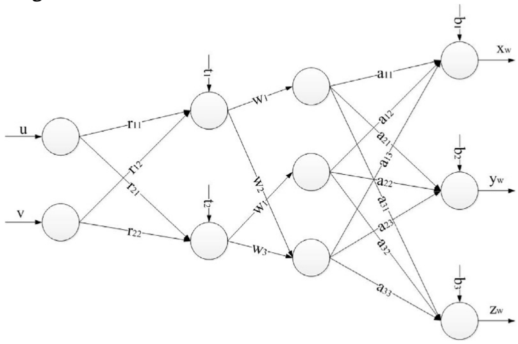


Fig. 5. The overall structure of the new artificial neural network.

The transformational relationship between camera coordinate system and robot coordinate system is linear transformation, and the formula is shown as:

$$\begin{bmatrix} xw \\ yw \\ zw \\ 1 \end{bmatrix} = Trans\Delta L \left[T_W^{U'}\right]^{-1} \begin{bmatrix} xc \\ yc \\ zc \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & \Delta L \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} R & p \\ 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} xc \\ yc \\ zc \\ 1 \end{bmatrix} = \begin{bmatrix} a11 & a12 & a13 & b1 \\ a21 & a22 & a23 & b2 \\ a31 & a32 & a33 & b3 \\ a41 & a42 & a43 & b4 \end{bmatrix} \begin{bmatrix} xc \\ yc \\ zc \\ 1 \end{bmatrix} \tag{6}$$

Where $\Delta L$is the scaling factor of moving distance between the conveyor belt encoder and robot, R is the direction vector of robotic space axis in camera coordinate system,p is the origin of robotic space axis in camera coordinate system, (xc, yc, zc) refers to the coordinate of object point in camera coordinate system, (xw, yw, zw)represent the coordinate of object point in robot coordinate system. As presented in Fig. 4, $(xc, yc, zc)$is the input of the neural network, $(xw, yw, zw)$is the output of the neural network where the activation function is linear function, $aij(i = 1, 2, 3, 4; j = 1, 2, 3)$ is neural connection weight, $bn(n = 1, 2, 3)$ is neuron threshold value.

Hence, the general neural network structure of the Delta robot calibration algorithm is shown in Fig. 5. As each initial weight and bias of this neural network has a corresponding physical implication, the neural network with four layers can fully

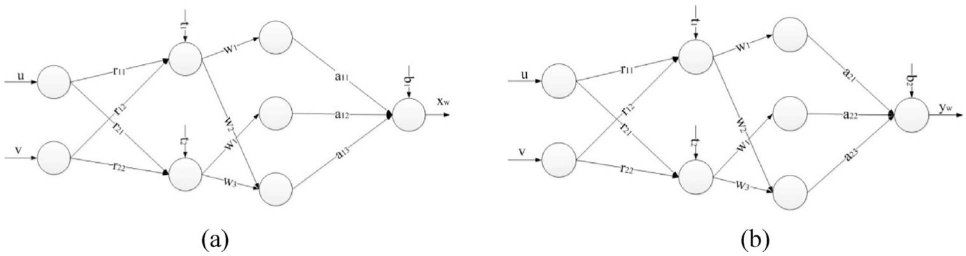


Fig. 6. The new distributed neural network structure.

reflect the approximation function capability. Since the network structure is closer to the real model, the neural network has faster convergence, higher training precision and stronger generalization ability. This network can calculate the coordinates of object point in the robot coordinate system based on the input the pixel coordinates of object point.

Speed is important in Delta robot production line among the process of batch sorting. Again, the same batch of workpiece often has the same height. Besides find from the above network, the mapping relationship between pixel point and the output object point coordinates of Xw and Yw is different which may affect the efficiency when they are trained in the same artificial neural network. In order to further improve the precision and speed of the neural network, parallel processing is needed, and the final network structure is presented in Fig. 6. The new distributed neural network structure in the direction of Xw-axis and the new distributed neural network structure in the direction of Yw-axis are shown in Fig. 6(a) and (b), respectively.

3.2.2. The derivation of algorithm based on the new model

The input dimension of neural network is 2 and the output dimension is 1. Assuming that the number of training samples is equal to N, the weight between input layer and hidden layer is rij, weight between hidden layer and output layer is aij, the weight among hidden layers is wij. The whole sample error of neural networks is shown in the following formula:

$$J = \frac{1}{2}\sum_{p=1}^{N}\sum_{j=1}^{3}(tpj - ypj) \tag{7}$$

Where *tpj*denotes the expected output of neuron j and sample P,*ypj* is corresponding actual output. In order to decrease error, the weight of neural network is needed to be adjusted based on gradient algorithm, and expressed as follow:

$$\Delta rij = -\eta\frac{\partial J}{\partial rij} \tag{8}$$

$$\Delta aij = -\eta\frac{\partial J}{\Delta aij} \tag{9}$$

$$\Delta wij = -\eta\frac{\partial J}{\Delta wij} \tag{10}$$

Where η is learning rate ($\eta > 0$).

Assuming that s represents the number of iterations, the weight iteration formula of neural network can be deduced as follows:

$$rij(s+1) = rij(s) + \Delta rij \tag{11}$$

$$aij(s+1) = aij(s) + \Delta aij \tag{12}$$

$$wij(s+1) = wij(s) + \Delta wij \tag{13}$$

The weight is adjusted through iterative formula. The forward and reverse weight is repeated until the entire sample error of J meet the requirement of accuracy or reach the maximum cycle times.

4. Experiments

4.1. The calculation of initial value based on Faugeras

The calibration of robot vision system involves the transformation of multiple coordinate systems. As shown in Fig. 7, W represents the world coordinate system which is used to describe the position of object point in robot's three dimensional coordinate system, Q represents the camera coordinate system which is established for the deduction and understanding of the calibration model. O represents pixel coordinate system, whose origin is left vertex of the image,

The transformational projection matrix between the image coordinate system and robot coordinate system is as shown in the following formula:

$$si\begin{bmatrix} ui \\ vi \\ 1 \end{bmatrix} = \begin{bmatrix} m11 & m12 & m13 & m14 \\ m21 & m22 & m23 & m24 \\ m31 & m32 & m33 & m34 \end{bmatrix}\begin{bmatrix} Xwi \\ Ywi \\ Zwi \\ 1 \end{bmatrix} \tag{14}$$

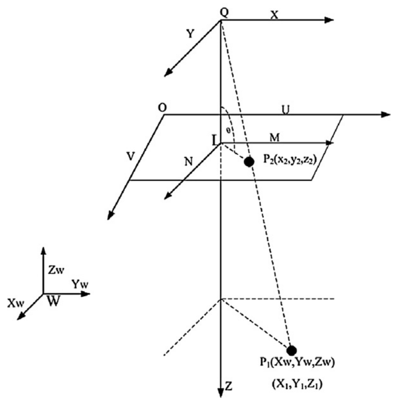


Fig. 7. The relationship between robot coordinate system, camera coordinate system and pixel coordinate system.

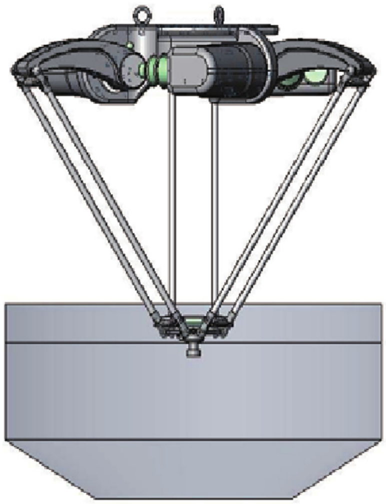


Fig. 8. The moving range of robot.

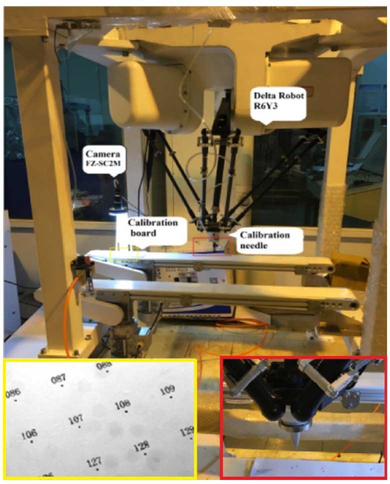
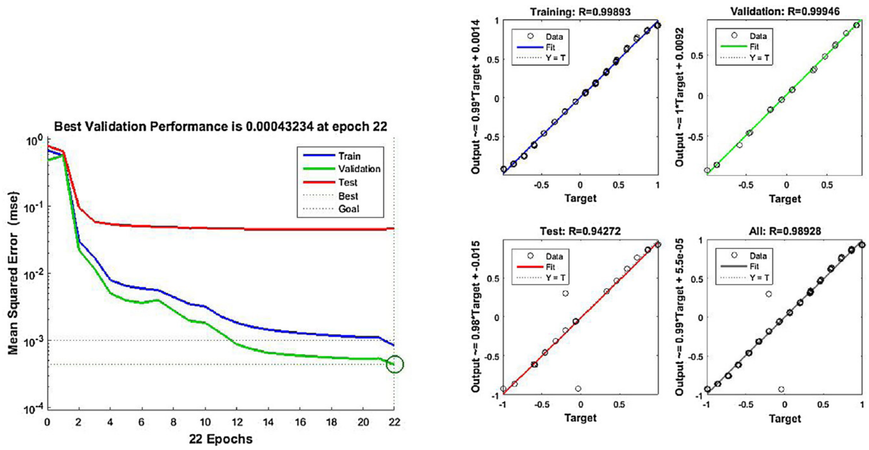


Fig. 9. Delta robot with vision system.

Where (ui, vi) represents the coordinate of an object point Pi in the pixel coordinate system, (Xwi, Ywi, Zwi) denotes the position vector of an object point Pi in the robot coordinate system, the coefficient of si represents Z-axis coordinate in the camera coordinate system, the matrix (3×4) in the middle represents transformation matrix between the pixel coordinate system and the robot coordinate system.



(a) (b)

Fig. 10. Training results of Y coordinate.

The 2n linear equations are originated from the selected n object points on calibration template, where the linear equation can be presented in the matrix form as follow:

$$\begin{bmatrix} Xw1 & Yw1 & Zw1 & 1 & 0 & 0 & 0 & 0 & -u1Xw1 & -u1Yw1 & -u1Zw1 \\ 0 & 0 & 0 & 0 & Xw1 & Yw1 & Zw1 & 1 & -v1Xw1 & -v1Yw1 & -v1Zw1 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ Xwn & Ywn & Zwn & 1 & 0 & 0 & 0 & 0 & -unXwn & -unYwn & -unZwn \\ 0 & 0 & 0 & 0 & Xwn & Ywn & Zwn & 1 & -vnXwn & -vnYwn & -vnZwn \end{bmatrix} \begin{bmatrix} \frac{m11}{m34} \\ \frac{m12}{m34} \\ \frac{m13}{m34} \\ \frac{m14}{m34} \\ \frac{m21}{m34} \\ \frac{m22}{m34} \\ \frac{m23}{m34} \\ \frac{m24}{m34} \\ \frac{m31}{m34} \\ \frac{m32}{m34} \\ \frac{m33}{m34} \end{bmatrix} = \begin{bmatrix} u1 \\ v1 \\ \cdots \\ un \\ vn \end{bmatrix} \tag{15}$$

There are 11 unknowns in the above equation and can be modified in the following relation:

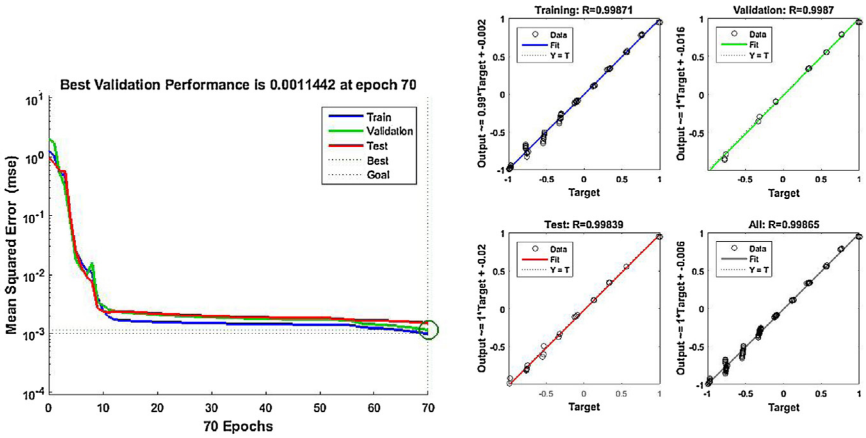
$$Am = b \tag{16}$$

This method always needs dozens of object point during the process of calibration; therefore the number of equations is much larger than the number of unknowns. We used the least squares method to reduce the error.

$$m = (A^T A)^{-1} A^T b \tag{17}$$

The above algorithm represents nonlinear optimization, and computing precision can satisfy almost all situations. However, the influence of the lens distortion has not been taken into account. The ignorance of the lens distortion is not desirable especially for 3d measurement.

The workspace and experimental environment are as shown in Figs. 8 and 9, respectively. The experimental steps are as follows: Firstly, select a set of object points and obtain their coordinates (Xwi, Ywi, Zwi) in robot coordinate system. Secondly, move the object points beneath the camera and the moving distance of encoder (ΔL), then calculate the current pixel coordinates (ui,vi) of object points obtained from the CCD camera and the corresponding coordinates in robot coordinate system (Xwi + ΔL,Ywi,Zwi) due to the movement of the conveyor belt. ΔLequals to 569.9 mm, is obtained by experimental measurements. Finally, construct overdetermined system between the robot coordinate system and pixel coordinate system



(a) (b)

Fig. 11. Training results of Y coordinate.

Table 1
Error of comparison between the Faugeras and the new ANN.

	Pixel coordinates		Robot coordinate(mm)		Faugeras		New ANN	
	u	v	Xw	Yw	X1	Y1	X2	Y2
1	307	205	619.62	176.51	616.64	178.88	621.32	176.34
2	399	205	609.84	176.51	606.52	178.94	610.74	176.42
3	1235	298	518.66	187.48	510.75	189.44	518.04	186.72
4	1329	298	508.68	188	499.64	189.55	507.53	186.94
5	955	1053	549.75	267.17	539.72	268.33	551.08	265.48
6	1051	1053	539.54	267.17	528.5	268.84	540.61	265.49
mse					0.535		0.109	

and calculate the optimal approximation solution of the implicit parameters, internal parameters and external parameters as indicated in the following formula:

$$\begin{aligned} M &= \begin{bmatrix} m11 & m12 & m13 & m14 \\ m21 & m22 & m23 & m24 \\ m31 & m32 & m33 & m34 \end{bmatrix} = \begin{bmatrix} 1.939\times10^{-14} & -8.404\times10^{-17} & 1.897\times10^{-14} & 0 \\ 7.217\times10^{-17} & -2.047\times10^{-14} & -4.804\times10^{-15} & 0 \\ 9.066\times10^{-19} & -1.007\times10^{-18} & 0.0015 & 1 \end{bmatrix} \\ &= \begin{bmatrix} 2.923\times10^{-17} & 0 & 2.861\times10^{-17} & 0 \\ 0 & 3.087\times10^{-17} & -7.243\times10^{-18} & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 663.19 & -2.8750 & 649.033 & -0.979 \\ 2.338 & -663.196 & -155.631 & 0.235 \\ 9.066\times10^{-19} & -1.007\times10^{-18} & 0.0015 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{aligned} \tag{18}$$

4.2. The new calibration algorithm based on the new neural network

One hundred and sixty (160) series of experimental data obtained from Harris corner extraction method which was respectively used for training and testing. The new neural network formulated in this paper is a four layer distributed architecture. Accurate initial weights and biases accelerate the convergence and avoid the premature of network. The output error is set as 0.001 and the training results obtained are shown in Figs. 10 and 11.

The error of comparison between the Faugeras and the new ANN is shown in Table 1.

5. Analysis and conclusion

The experimental result indicated that the new structure and algorithm of this paper has a faster convergence speed compared to the traditional neural network algorithm. Among them, the training error of X-axis extended to 0.001 mm after 22 couples of iterations, and the training error of Y-axis stretched to 0.001 mm after 70 couples of iterations. This implies that the construction of a network structure in conformity with the actual model can greatly improve the working efficiency of the artificial neural network.

Compared with the traditional algorithm of Faugeras, although the computing speed is slightly superior to the algorithm, however, the calibration precision is substantially lower than the algorithm in this paper. Also, when the validation data is beyond the scope of training data, the generalization ability of the new neural network is higher than the traditional calibration algorithm. This phenomenon may occur due to many causes, including (1) in linear model of Faugeras, the implicit matrix is determined by four camera internal parameters, the rotation matrix R and translational matrix t. The implicit matrix has 10 independent variables with 11 equations. We can draw a conclusion that the11 parameters are not independent and there exists a constraint relation between variables which has not been factored in the algorithm model. The calculation results may have an error when the input data is inaccurate because the distribution of the error between the parameters also doesn't follow the constraint relation. (2) The actual model in the real scene is far more complicated than the ideal model. There may be an existence of angular deviation between the conveyor belt coordinate system and the robot coordinate system which is often ignored.

The proposed calibration model in this paper is based on the traditional Delta robot calibration algorithm. The linear relationship in the traditional algorithm could be used to calculate the initial value of the new artificial neural network. The nonlinear relationship in the traditional algorithm is used in the new artificial neural network to iterate. Compared with the traditional algorithm, this algorithm simplifies the process of calibration and improves the calibration precision and generalization of the algorithm. Compared with the traditional neural network algorithm, this new artificial neural network design in this paper is based on traditional algorithm and structure which is closer to the real model, therefore has a splitting velocity of convergence. Further work will focus on the combination with other intelligent algorithms to optimize the learning efficiency in order to reduce the sample error that can enhance the searching capability of the network and efficiency.

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