

ROBOT SENSOR CALIBRATION VIA NEURAL NETWORK AND PARTICLE SWARM OPTIMIZATION ENHANCED WITH CROSSOVER AND MUTATION

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Original scientific paper

In order to determine the position and orientation of an object in the wrist frame for robot, transform relation of hand-eye system should be estimated, which is described as rotational matrix and translational vector. A new approach integrating neural network and particle swarm optimization algorithm with crossover and mutation operation for robot sense calibration is proposed. First the neural network with rotational weight matrix is structured, where the weights are the elements of rotational part of homogeneous transform of the hand-eye system. Then the particle swarm optimization algorithm is integrated into the solving program, where the inertia weight factor and mutation probability are tuned self-adaptively according to the motion trajectory of particles in longitudinal direction and lateral direction. When the termination criterion is satisfied, the rotational matrix is obtained from the neural network's stable weights. Then the translational vector is solved, so the position and orientation of camera frame with respect to wrist frame is achieved. The proposed approach provides a new scheme for robot sense calibration with self-adaptive technique, which guarantees the orthogonality of solved rotational components of the homogeneous transform.

Keywords: *crossover and mutation particle swarm optimization, lateral direction, longitudinal direction, neural network with rotational matrix, robot sensor calibration*

Kalibracija senzora robota neuronskom mrežom i optimizacijom roja čestica poboljšana križanjem i mutacijom

Izvorni znanstveni članak

U cilju određivanja položaja i orijentacije nekog predmeta u zglobova za robot, treba procijeniti odnos transformacije sustava ruka-oko, što se opisuje kao rotacijska matrica i vektor translacije. Predlaže se novi pristup koji integrira neuronsku mrežu i algoritam optimalizacije roja čestica s operacijom križanja i mutacije za kalibraciju osjećaja robota. Najprije se strukturira neuronska mreža s matricom rotacijske težine gdje su težine elementi rotacijskog dijela homogenog prijenosa sustava ruka-oko. Tada se algoritam optimalizacije roja čestica integrira u program rješavanja, gdje se faktori težine inercije i vjerojatnosti mutacije sami podešavaju prema putanji gibanja čestica u longitudinalnom pravcu i lateralnom pravcu. Kad je zadovoljen kriterij terminacije, rotaciona matrica se dobiva iz nepromjenljivih težina neuronske mreže. Tada se rješava vektor translacije i postiže se položaj i orijentacija slike s kamere u odnosu na sliku sa zgloba. Predloženi pristup pruža novu šemu za kalibraciju robota tehnikom samo-adaptacije, što garantira ortogonalnost riješenih rotacijskih komponenti homogenog transformata.

Ključne riječi: *kalibracija senzora robota, lateralni pravac, longitudinalni pravac, neuronska mreža s rotacijskom matricom, optimalizacija roja čestica križanjem i mutacijom*

1 Introduction

The machine vision is widely used in robots, such as explosive ordnance disposal (EOD) robot, welding robot, assembly robot and so on. Much research has been done on using a sensor to locate a work-piece, and the three-dimensional position and orientation of a work-piece can be estimated by monocular vision, stereo vision, dense/sparse range sensing and so on. Monocular vision locates an object using a single view, and the object dimensions are assumed to be known a priori [1, 2]. Stereo vision uses two cameras instead of one so that the range information of feature points can be estimated [3, 4]. A dense range sensor scans a region of the world and there are as many sensed points as its resolution allows [5, 6, 7]. A sparse range sensor only scans a few points, and if the sensed points are not sufficient to locate the work piece, additional points will be sensed [8, 9, 10]. Tactile sensing is similar to sparse range sensing to obtain the same information of the sensed points [9, 10]. As for the 6 degree of freedom robot, if the sensor is mounted on the fifth link of the robot, its motion will be limited to 5 degree of freedom. Once the sensor position and orientation relative to the last link is found, it is straightforward to find the sensor position and orientation relation to other links with encoder readings and link specification, so that the position and orientation of work-pieces in the wrist frame for a robot can be determined with machine vision.

While the transform relation of camera frame with respect to wrist frame is estimated, the direct measurements are difficult, because there may be obstacles to obstruct the measurement path, the points of interests may be inside a solid and be unreachable, and the coordinate frames may differ in their orientations. On the other hand the camera frame is unreachable because its origin is at the focal point, inside the camera. Instead of direct measurement, we can compute the camera position by displacing the robot and observing the changes in the sensor frame. This method works for any sensors capable of finding the 3-dimensional position and orientation of an object. There are many researchers working on the hand-eye calibration, for example, Shiu and Park et al. solved homogenous transform equation to achieve the calibration of wrist-mounted robotic sensors with least square method by solving homogeneous transform equations of the form $AX=XB$ [11-13]. Yang et al. presented a new wrist-mounted robotic sensor calibration approach which utilized nominal rotation for camera frame to make rotation transform into translation, thus two translation motions and one rotation motion are needed, and only two feature points in the scene are required [14]. Y. Motai et al. utilized the Broyden-Fletcher-Goldfarb-Shanno optimization algorithm to obtain a solution which minimized the objective function $f(q) = \|e_2^{e1} R_h^e R_h^e - e_h^h R_h^{h1} R\|_2$ [15]. Zhang et al. adopted Kronecker product and particle swarm optimization to achieve the solution of rotation and translation

simultaneously [16]. M. X. Li dealt with the kinematics calibration for an active head-eye system by non-linear optimization solution for the rotational components of the head-eye relation [17]. F. Dornaika and R. Horaud proposed a non-linear constrained minimization optimization method to solve the rotational and transformational components of the hand-eye system's homogeneous transform simultaneously [18]. There is a research report on calibration of wrist-mounted robot sensors by integrating a neural network with basic genetic algorithm. Although it may be the first report on hand-eye calibration by neural network with orthogonal matrix, however the weight vectors of the neural network should be transformed according to the cross product principle to get orthogonal vectors and to form rotational matrix, and it is complicated and miscellaneous for computing [19]. Based on the above researches, in the paper we proposed a novel approach to realize the robot sensor calibration, according to the requirements of hand-eye calibration for a manipulator. Our contributions are in the following: first a neural network with rotational weights matrix is structured, where the weights matrices are the rotational components of the eye-in-hand's homogeneous transform; then a novel approach i.e. particle swarm optimization with enhancement of crossover and mutation (abbr. as PSOECM) is proposed, where motion trajectories of particles are analysed in longitudinal direction and lateral direction, so the inertia weights of particle swarm optimization (abbr. as PSO) and mutation probability are tuned self-adaptively.

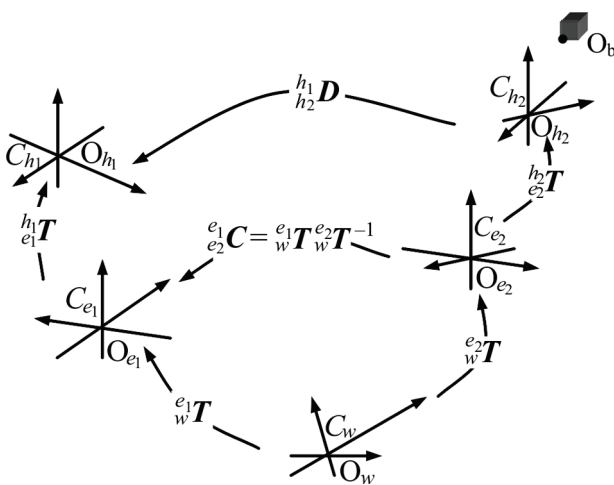


Figure 1 Machine vision system of manipulator

The paper is organized as follows. First the hand-eye relation i.e. the position and orientation of a wrist-mounted sensor with respect to the robot wrist frame is analysed and inferred in the next section. Then some properties of rotational matrix are explored, and the general solution algorithm to the rotational components of a solvable homogeneous transform equation of the form ${}_{e2}^e C {}_{h1}^e T = {}_h^e T {}_{h2}^e T$ is discussed in Section 3. In Section 4, hybrid neural network and particle swarm optimization is proposed, where the neural network is designed with rotational weight matrix, and the particle swarm optimization algorithm with crossover and mutation operation is adopted. Then the robot sensor calibration experiment is demonstrated and the position and

orientation of camera frame with respect to wrist frame are estimated with the proposed approach in Section 5. Finally, conclusions, further work and direction in this field are given in Section 6.

2 Hand-eye relation and homogeneous transform model

As shown in Fig. 1, C_{h1} and C_{h2} are the wrist frame before and after motion respectively, C_{e1} and C_{e2} are the camera frame before and after motion respectively; C_w is the world frame. The position and orientation of the camera frame with respect to the wrist frame is invariant before and after motion; and we let ${}^h_e T = {}_{e1}^h T = {}_{e2}^h T$. Assume the relations of the camera frame C_{e1} and C_{e2} with respect to the world frame C_w are ${}_{w}^{e1} T$ and ${}_{w}^{e2} T$; thus the relation of C_{e2} with respect to C_{e1} is ${}_{e1}^{e2} C = {}_{w}^{e1} T {}_{w}^{e2} T^{-1}$. The position and orientation of the wrist frame C_{h2} with respect to C_{h1} can be read from the manipulator's controller, which is described as ${}_{h1}^{h2} D$. Thus the transform relations of C_{e1} , C_{h1} , C_{e2} and C_{h2} are described as follows,

$${}_{e2}^{e1} C {}_{h1}^e T = {}_h^e T {}_{h2}^e D \tag{1}$$

Eq. (1) is the homogeneous transform equation for hand-eye system of manipulator. With rotational matrix R and translational vector P , Eq. (1) can be rewritten as follows

$$\begin{bmatrix} {}_{e2}^{e1} R & {}_{e2}^{e1} P_{oe2} \\ \mathbf{0} & 1 \end{bmatrix} \begin{bmatrix} {}_h^e R & {}_h^e P_h \\ \mathbf{0} & 1 \end{bmatrix} = \begin{bmatrix} {}_h^e R & {}_h^e P_h \\ \mathbf{0} & 1 \end{bmatrix} \begin{bmatrix} {}_{h2}^{h1} R & {}_{h2}^{h1} P_{oh2} \\ \mathbf{0} & 1 \end{bmatrix}, \tag{2}$$

where $\mathbf{0}$ is a row of 3 zeros. By multiplying out and equating the first row of Eq. (2), we have,

$${}_{e2}^{e1} R {}_h^e R = {}_h^e R {}_{h2}^{h1} R, \tag{3}$$

$${}_{e2}^{e1} R {}_h^e P_h + {}_{e2}^{e1} P_{oe2} = {}_h^e R {}_{h2}^{h1} P_{oh2} + {}_h^e P_h. \tag{4}$$

3 Rotational matrix and solving conditions for uniqueness

Rotational matrix, such as ${}_h^e R$ can be expressed as a rotation of angle θ around an axis $k = k_x \vec{i} + k_y \vec{j} + k_z \vec{k}$, that is [20]

$$R(k, \theta) = e^{k_x \theta}, \tag{5}$$

where k_x is a skew-symmetric matrix, that is

$$k_x = \begin{bmatrix} 0 & -k_z & k_y \\ k_z & 0 & -k_x \\ -k_y & k_x & 0 \end{bmatrix}.$$

Fisher has shown that the eigen-values of k_x are $-j$, j and 0, and these eigen-values are distinct, so k_x in Eq. (5) can be diagonalized. Let it be the diagonalizing matrix whose columns contain independent eigen-vectors, so the

skew-symmetric matrix can be rewritten as follows,

$$\mathbf{k}_x = \mathbf{E} \begin{bmatrix} -j & 0 & 0 \\ 0 & j & 0 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{E}. \tag{6}$$

According to Taylor's expansion we have Eq. (7).

$$e^{\mathbf{k}_x \theta} = \sum_{i=0}^{\infty} \frac{(\mathbf{k}_x \theta)^i}{i!} = \mathbf{I}_3 + \left(\frac{\theta}{1!} \mathbf{E} \begin{bmatrix} -j & 0 & 0 \\ 0 & j & 0 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{E}^{-1} - \frac{\theta^3}{3!} \mathbf{E} \begin{bmatrix} -j & 0 & 0 \\ 0 & j & 0 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{E}^{-1} + \dots + (-1)^{n-1} \frac{\theta^{2n-1}}{(2n-1)!} \mathbf{E} \begin{bmatrix} -j & 0 & 0 \\ 0 & j & 0 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{E}^{-1} \right) + \left(-\frac{\theta^2}{2!} \mathbf{E} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{E}^{-1} + \frac{\theta^4}{4!} \mathbf{E} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{E}^{-1} - \dots + (-1)^{n-1} \frac{\theta^{2n}}{(2n)!} \mathbf{E} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{E}^{-1} \right). \tag{7}$$

According to the Taylor's expansion of $\sin \theta$ and $\cos \theta$, by simplifying we have

$$e^{\mathbf{k}_x \theta} = \mathbf{E} \begin{bmatrix} e^{-j\theta} & 0 & 0 \\ 0 & e^{j\theta} & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{E}^{-1}, \tag{8}$$

where $e^{-j\theta}$, $e^{j\theta}$ and 1 are eigen-values of ${}^e_h \mathbf{R}$, and eigen-vector (the third column of \mathbf{E}) of ${}^e_h \mathbf{R}$ corresponding to eigen-value of constant 1 is rotational axis \mathbf{k} .

According to Eq. (3) we have ${}^{e1}_{e2} \mathbf{R} = {}^e_h \mathbf{R} \cdot {}^{h1}_{h2} \mathbf{R} \cdot {}^e_h \mathbf{R}^{-1}$, so ${}^{e1}_{e2} \mathbf{R}$ and ${}^{h1}_{h2} \mathbf{R}$ are similar matrices, and their rotational angles are equal. Let it be θ , and assume \mathbf{k}_e and \mathbf{k}_h are their rotational axes, thus

$$\mathbf{R}(\mathbf{k}_e, \theta) = ({}^e_h \mathbf{R} \mathbf{E}) \begin{bmatrix} e^{-j\theta} & 0 & 0 \\ 0 & e^{j\theta} & 0 \\ 0 & 0 & 1 \end{bmatrix} ({}^e_h \mathbf{R} \mathbf{E})^{-1}, \tag{9}$$

where \mathbf{k}_h and \mathbf{k}_e axes are the 3rd column of \mathbf{E} and ${}^e_h \mathbf{R} \mathbf{E}$ respectively, thus we have

$$\mathbf{k}_e = {}^e_h \mathbf{R} \mathbf{k}_h. \tag{10}$$

From the above we know that if ${}^e_h \mathbf{R}$ is a solution to Eq. (3), which must meet $\mathbf{k}_e = {}^e_h \mathbf{R} \mathbf{k}_h$; in turn, if ${}^e_h \mathbf{R}$ meets $\mathbf{k}_e = {}^e_h \mathbf{R} \mathbf{k}_h$, which is a solution to Eq. (3). That means that any ${}^e_h \mathbf{R}$ meets Eq. (3) can rotate \mathbf{k}_h to \mathbf{k}_e .

Lemma 1: If \mathbf{R} is a rotational matrix and $\mathbf{R} \text{rot}(\mathbf{k}_i, \theta) = \text{rot}(\mathbf{k}_i, \theta) \mathbf{R}$, and $\theta \neq 0$ (or π), then $\mathbf{R} = \text{rot}(\mathbf{k}_i, \beta)$, where β is arbitrary.

According to Eq. (3), there must exist some rotational matrix \mathbf{R}' meet

$${}^{e1}_{e2} \mathbf{R} \cdot \mathbf{R}' = \mathbf{R}' \cdot {}^{h1}_{h2} \mathbf{R}. \tag{11}$$

Assume \mathbf{R}_1 is a particular solution to Eq. (3), so ${}^{h1}_{h2} \mathbf{R} = \mathbf{R}_1^{-1} \cdot {}^{e1}_{e2} \mathbf{R} \mathbf{R}_1$. Plugging it into Eq. (11), we have

$$\mathbf{R}'^{-1} \cdot {}^{e1}_{e2} \mathbf{R} \cdot \mathbf{R}' = \mathbf{R}'^{-1} \cdot {}^{e1}_{e2} \mathbf{R} \cdot \mathbf{R}_1. \tag{12}$$

Rewrite ${}^{e1}_{e2} \mathbf{R}$ as $\text{rot}(\mathbf{k}_e, \theta)$ and rearrange, Eq. (12) can be rewritten as follows,

$$\text{rot}(\mathbf{k}_e, \theta) \cdot \mathbf{R}' \cdot \mathbf{R}'^{-1} = \mathbf{R}' \cdot \mathbf{R}'^{-1} \cdot \text{rot}(\mathbf{k}_e, \theta). \tag{13}$$

Thus $\text{rot}(\mathbf{k}_e, \theta)$ and $\mathbf{R}' \cdot \mathbf{R}'^{-1}$ are commutative. If the rotational angle θ is neither 0 nor π . From lemma 1, the rotational axis of $\mathbf{R}' \cdot \mathbf{R}'^{-1}$ must be parallel or anti-parallel to \mathbf{k}_e . So there must exist a β such that $\mathbf{R}' \cdot \mathbf{R}'^{-1} = \text{Rot}(\mathbf{k}_e, \beta)$. Thus the general solution to ${}^{e1}_{e2} \mathbf{R} \cdot {}^e_h \mathbf{R} = {}^e_h \mathbf{R} \cdot {}^{h1}_{h2} \mathbf{R}$ can be obtained as follows,

$$\mathbf{R} = \text{rot}(\mathbf{k}_e, \beta) \mathbf{R}_1, \tag{14}$$

where \mathbf{R}_1 is a particular solution to the Eq. (3), and β is an arbitrary angle. Thus the unique solution cannot be obtained for the Eq. (3) as there is a freedom degree.

While the translational vector ${}^e \mathbf{P}_h$ is solved, Eq. (4) can be written as

$$({}^{e1}_{e2} \mathbf{R} - \mathbf{I}) \cdot {}^e \mathbf{P}_h = {}^e_h \mathbf{R} \cdot {}^{h1}_{oh2} \mathbf{P}_{oh2} - {}^{e1}_{oe2} \mathbf{P}_{oe2}. \tag{15}$$

According to the properties of the eigen-values and eigen vectors of rotational matrix, we have

$${}^{e1}_{e2} \mathbf{R} - \mathbf{I} = \mathbf{E} \begin{bmatrix} e^{-j\theta} - 1 & 0 & 0 \\ 0 & e^{j\theta} - 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{E}. \tag{16}$$

From Eq. (16) we know that the rank of $({}^{e1}_{e2} \mathbf{R} - \mathbf{I})$ is 2, so there may be no solution or there are infinite number of solutions to ${}^e \mathbf{P}_h$. The first case is ruled out since the physical system guarantees the existence of a solution.

The solution must exist and consist of all the vectors in the null space of $\begin{pmatrix} e^1 \\ e^2 \end{pmatrix} \mathbf{R} - \mathbf{I}$ translated by a particular solution to Eq. (15). The null space of $\begin{pmatrix} e^1 \\ e^2 \end{pmatrix} \mathbf{R} - \mathbf{I}$ has a dimension of 3-rank $\begin{pmatrix} e^1 \\ e^2 \end{pmatrix} \mathbf{R} - \mathbf{I}$, so there is one freedom degree for solution to be determined.

As there are a rotational freedom degree and a translational freedom degree while the ${}^e_h \mathbf{R}$ and ${}^e \mathbf{P}_h$ are solved according to Eqs. (10) and (15), in order to solve the ${}^e_h \mathbf{T}$ uniquely, it is necessary to let manipulator two movements and form a system of two homogeneous transform equations of the form: ${}^{e1} \mathbf{C}_h^e {}^e_h \mathbf{T} = {}^{e1} \mathbf{T}_h {}^{h1} \mathbf{D}$, and

${}^{e2} \mathbf{C}_h^e {}^e_h \mathbf{T} = {}^{e2} \mathbf{T}_h {}^{h2} \mathbf{D}$. So a closed-form solution to the eye-in-hand system can be obtained.

4 Solving with combination of neural network and particle swarm optimization

4.1 Neural network structured with rotational weight matrix

Rotational weight matrix such as ${}^e_h \mathbf{R}$ has 9 unknown parameters, however only 3 parameters of them are independent, which can be expressed as a rotation by angle θ about arbitrary axis $\mathbf{k} = k_x \vec{i} + k_y \vec{j} + k_z \vec{k}$, that is

$$\mathbf{R}(\mathbf{k}, \theta) = \begin{bmatrix} k_x k_x (1 - \cos \theta) + \cos \theta & k_y k_x (1 - \cos \theta) - k_z \sin \theta & k_z k_x (1 - \cos \theta) + k_y \sin \theta \\ k_x k_y (1 - \cos \theta) + k_z \sin \theta & k_y k_y (1 - \cos \theta) + \cos \theta & k_z k_y (1 - \cos \theta) - k_x \sin \theta \\ k_x k_z (1 - \cos \theta) - k_y \sin \theta & k_y k_z (1 - \cos \theta) + k_x \sin \theta & k_z k_z (1 - \cos \theta) + \cos \theta \end{bmatrix}. \tag{17}$$

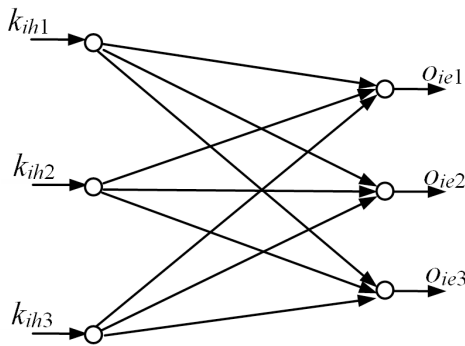


Figure 2 Neural network with rotational matrix

According to the Eq. (10), i.e. $\mathbf{k}_e = {}^e_h \mathbf{R} \cdot \mathbf{k}_h$, a neural network with rotational matrix is structured and shown in Fig. 2. Let weight matrix $\mathbf{R} = [\mathbf{n}, \mathbf{o}, \mathbf{a}]$, where normal vector $\mathbf{n} = [r_{11}, r_{21}, r_{31}]^T$, orientation vector $\mathbf{o} = [r_{12}, r_{22}, r_{32}]^T$, and approach vector $\mathbf{a} = [r_{13}, r_{23}, r_{33}]^T$. The inputs of the network are elements of $\mathbf{k}_{ih} = [k_{ih1}, k_{ih2}, k_{ih3}]^T$, and the outputs can be obtained through forward channel computing, which constitute the vector $\mathbf{o}_{ie} = [o_{ie1}, o_{ie2}, o_{ie3}]^T$, that is $\mathbf{o}_{ie} = {}^e_h \mathbf{R} \mathbf{k}_{ih}$. And the expected values of the network are the elements of rotational axis $\mathbf{k}_{ie} = [k_{ie1}, k_{ie2}, k_{ie3}]^T$. In the light of the solving objective, let the performance index of system be

$$E_i = \frac{1}{2} \sum_{j=1}^3 (k_{iej} - o_{iej})^2, \quad i = 1, 2, \dots, 48.$$

Thus if the neural network comes to the global optimization balance position, the rotational components of the homogeneous transform of the eye-in-hand system can be estimated from the network weights as Eq. (10) is transformed into Fig. 2 [21, 22].

4.2 Integration with crossover and mutation particle swarm optimization algorithm

While the rotational matrix of hand-eye system is fitted, we integrate the neural network with particle

swarm optimization (PSO) algorithm, which is a stochastic optimization algorithm. The swarm consists of 48 particles, which move around in a 3 dimensional searching space at variant velocities according to individual experience and swarm experience, and adjust their velocities and positions dynamically. The elements of particles' position are k_x , k_y , and θ ; The objective function is the performance index of the structured neural network; the search space of k_x and k_y is $[-1, 1]$; and the search space of θ is $[0; 3, 14]$. In the iteration, if $k_x^2 + k_y^2 \leq 1$, and $k_z = \pm \sqrt{1 - k_x^2 - k_y^2}$. As for positive or negative, it is chosen according to which one makes performance index smaller; else let $k_z = rand(\cdot)$, then the rotational axis is normalized to form a unit vector; and the above operation can be taken as constrained mutation operation for the rotational axis, which don't influence the particles' evolution direction to optimization solutions basically. Each particle is composed of three elements such as k_x , k_y , and θ is taken as a potential solution to a problem. Assume the position of the i^{th} particle is represented as $\mathbf{x}_i = (x_{i1}, x_{i2}, x_{i3})$, the best previous encountered position of the i^{th} particle is denoted its individual best position $\mathbf{p}_{li} = (p_{li1}, p_{li2}, p_{li3})$, its value called p_{best} is the smallest value of i^{th} particle by far. The best value of all individual p_{best} values is denoted the global best position $\mathbf{p}_g = (g_{i1}, g_{i2}, g_{i3})$ up to now, and called g_{best} ; a velocity along each dimension is represented as $\mathbf{v}_i = (v_{i1}, v_{i2}, v_{i3})$. The velocity updating equation is formulated as follows,

$$\mathbf{v}_i(t+1) = \omega \mathbf{v}_i(t) + c_1 r_1 (\mathbf{p}_{li} \otimes \mathbf{x}_i(t)) + c_2 r_2 (\mathbf{p}_g(t) \otimes \mathbf{x}_i(t)). \tag{18}$$

where \otimes denotes crossover operation, and the velocity vector has three components. The first one is the inertia term which keeps the particle move to next position, and plays the role of balancing the global and local searches. A large inertia weight facilitates a global search while a small inertia weight favor local search with high ability. The second one is the cognitive component, which is its

own thoughts and experience. The third one is the social component, which represents the messages shared all particles swarm and guide to the global best. c_1 and c_2 are the two acceleration coefficients, and are both set to values of 2,0 in the experiment. r_1 and r_2 are random numbers in the range of $[0, 1]$ [23]. The crossover probability for velocity updating is 1. And the crossover operation is carried out with arithmetic crossover that produces two complimentary linear combinations of the parents: that is $p_{li}(t) \otimes x_i(t) = r_1 p_{li}(t) + (1 - r_1)x_i(t)$, $p_g(t) \otimes x_i(t) = (1 - r_1)p_g(t) + r_1 x_i(t)$, and where $r_1 \in [0; 1]$, is a random number.

Then the position of particles is updated as follows,

$$x_i(t+1) = x_i(t) + v_i(t+1). \quad (19)$$

At the same time, a mutation operation is introduced into the position adjustment, which services for introducing a noise into the information of a particle, so that variety of the swarm can be guaranteed. One variable of position vector is selected randomly, so the non-uniform mutation operation for the selected variable is dealt with according to p_m as follows,

$$x_m(t) = \begin{cases} x_m(t-1) + (b_i - x_m(t-1))f(t) & \text{if } 0 \leq \lambda_1 < 0,5 \\ x_m(t-1) - (x_m(t-1) - a_i)f(t) & \text{if } 0,5 < \lambda_1 \leq 1 \end{cases}. \quad (20)$$

where function $f(t) = \lambda_2 \left(1 - \frac{t}{T}\right)^b$, and shape parameter $b = 2$, which determines the non-uniform degree of the operation. λ_1, λ_2 are uniform random numbers between $(0, 1)$; $x_m(t)$ and $x_m(t-1)$ are the m^{th} variables of the vector $x_i(t)$ at the t^{th} generation and $(t-1)^{\text{th}}$ generation, a_i and b_i are the lower and upper bound of $x_m(t)$, which are set 0 and 1 in the experiment; t is the current generation, and T is the maximum number of generations.

4.3 Parameters tuning of particle swarm optimization

4.3.1 Evolution speed factor and square deviation factor of particles

1) Evolution speed factor

In longitudinal direction, the direction and degree of evolution can be forecasted by individual evolution speed factor, as the derivative term can forecast signal variations in a proportional-integral-derivative (PID) controller. The performance of the particle evolution process of the PSO is measured with evolution speed factor, which is expressed as follows,

$$e = \frac{1}{N} \sum_{i=1}^N \left(\min \left(1, \frac{E_i(t-1) - E_i(t)}{E_i(t-1) + r_3 \varepsilon_1} \right) \right), \quad (21)$$

where $E_i(t-1)$ and $E_i(t)$ are objective function of system at the $(t-1)^{\text{th}}$ and t^{th} generation for i^{th} particle, which can be obtained from the performance index of the neural network; $N = 48$, which is the number of

population; r_3 is random number between $(0, 1)$, ε_1 is a small constant nearly approximate to zero taken as an offset bias value, in case $E_i(t-1)$ equals to zero; in this experiment, let $\varepsilon_1 = 1 \times 10^{-14}$. And $0 < e \leq 1$; the smaller the e is, the slower the evolution speed is. While $e = 0$, the algorithm stagnates or the optimal solution is found [24].

2) Square deviation factor of particles

In lateral direction, if the particles' diversity decreases too soon during the iteration, the algorithm may not search the global optimization solution for the system. In order to represent the particles' diversity, a so-called square deviation factor of particles is introduced, which describes the particles' distribution. In the experiment the square deviation of particles is given by the following equation by,

$$\sigma_t = \frac{1}{N} \sum_{i=1}^N (E(x_i(t)) - E_v)^2, \quad (22)$$

where E_v is the average number of particles' objective function $E(x_i(t))$, i.e. $E_v = \frac{1}{N} \sum_{i=1}^N E(x_i(t))$. In view of normalization processing, the square deviation factor of the particles can be written as follows,

$$\psi_t = \frac{\sigma_t}{\max(\sigma_1, \sigma_2, \dots, \sigma_t)}. \quad (23)$$

It is obvious that $0 \leq \psi_t < 1$; and the bigger the ψ_t is, the more the diversity of the particles is [25].

4.3.2 Self-adaptive tuning of inertia weight and mutation probability

According to the motion trajectory characteristic of particles, the suitable coefficient ω can find the global optimum within a reasonable number of iterations. If the evolution speed of individuals is fast, the algorithm can search optimization solution at large scope. On the other hand, if the square deviation factor of individuals is small, the algorithm will be trapped in local optimization position easily [26]. In order to obtain the global optimization solution we proposed an innovative approach. According to the characteristic of the individual's motion trajectory from the lateral direction and longitudinal direction, at the beginning, inertia weight factor ω and mutation probability p_m should increase along with the increasing of gathering degree of individuals, and increase along with decreasing of individuals evolution speed accordingly. On the other hand, to guarantee the convergence of algorithm, the inertia weight factor ω and mutation probability p_m should adopt smaller value for particles with higher fitness degree while the iteration achieved into the neighbourhood of the global optimization position. ω and p_m are modified dynamically as follows,

$$\omega = \omega_{e\omega} e^{\frac{(e_t-0,6)^2}{2 \times 0,38^2}} + \omega_{\sigma\omega} e^{\frac{(\sigma_t-0,14)^2}{2 \times 0,16^2}}, \tag{24}$$

$$p_m = \omega_{em} e^{\frac{(e_t-0,5)^2}{2 \times 0,64^2}} + \omega_{\sigma m} e^{\frac{(\sigma_t-0,15)^2}{2 \times 0,2^2}}, \tag{25}$$

where $\omega_{e\omega}, \omega_{em}, \omega_{\sigma\omega}$ and $\omega_{\sigma m}$ are the coefficients of evolution speed factor and square deviation factor of particles; their ranges are defined as $0 < \omega_{e\omega}, \omega_{em} < 1, 0 < \omega_{\sigma\omega}, \omega_{\sigma m} < 1$. In the experiment, let $\omega_{e\omega} = 0,8, \omega_{em} = 0,04, \omega_{\sigma\omega} = 0,5$ and $\omega_{\sigma m} = 0,05$. Self-adaptive tunings of inertia weight factor ω and mutation probability p_m are shown in Fig. 3, where SDF denotes the square deviation factor of particles, and ESF denotes the evolution speed factor. As for the inertia weight factor, From the Eq. (24) and Fig. 3, we can see that the evolution speed factor play larger influence in large value, i.e. at larger evolution velocity of particle. At the same time, in order to make particles to search the optimization solution at larger scope, the inertia weight factor increase along evolution process until the evolution speed factor is smaller 0,6 at the initial phase of iteration.

On the other hand, when the program process at the state that the square deviation factor of particles is at the neighbourhood of 0,14, the square deviation factor play larger role for inertia weight factor, which decrease sharply so as to improve the diversity of particles. And when the program come to the neighbourhood of global optimization solution, in order to guarantee the convergence of algorithm, let the inertia weight factor decrease sharply while the square deviation factor of particles is smaller, in this experiment, when the $\sigma_t < 0,14$. As can be seen from Fig. 3 and Eq. (25), it is similar for the self-adaptive adjusting of mutation probability p_m .

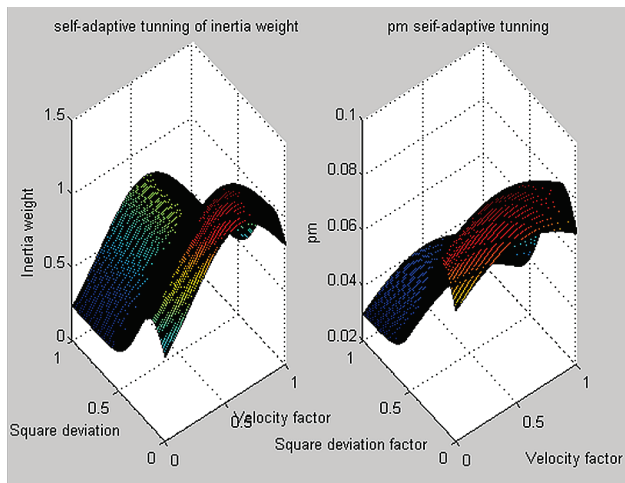


Figure 3 Self-adaptive tuning of ω and p_m

4.4 Chart-flow of solving program

The implementation steps of solving program is shown as follows:

Step 1. Initializing the position and velocity vector of each particle randomly, where the rotational axis is initialized with 3 random numbers, then to obtained unit

vector by normalized processing. The rotational angle is initialized with a random function, which is between 0 and $3,14$; so the rotational axis and rotational angle consist of a particle's position, which is a vector with 3 elements; and other 47 particles' positions are initialized similarly. The other constant parameters are set as follows: acceleration coefficients $c_1=c_2=2$, the iteration is 320, population size is 48, the offset bias value $\varepsilon_1 = 1 \times 10^{-14}$.

Step 2. Calculating the fitness value of each particle, which is obtained from performance index of the neural network, that is $f(x_i) = \frac{1}{E_i - r_4 \times 1 \times 10^{-14}}$, where the E_i is performance index of the neural network, r_4 is random number between (0, 1).

Step 3. For each particle, comparing its fitness value $f(x_i)$ with the value of fitness individual experienced best position p_{li} , if $f(x_i) > p_{li}$, let $p_{besti} = f(x_i)$ and $p_{li} = x_i$. And comparing its fitness value with the global best p_{gbest} position's, if $f(x_i) > p_g$, let $p_g = f(x_i)$ and $p_g = x_i$.

Step 4. Computing the evolution speed factor and square deviation of fitness according to the Eq. (24) and (25), then obtained the inertia weight ω and the mutation probability p_m .

Step 5. Updating of the current particle's velocity and position according to the Eqs. (18) and (19).

Step 6. According to the mutation probability P_m , and generating a random number $r \in [0,1)$, if $r < p_m$, the mutation operator is carried on with Eq. (20); or go to Step 7.

Step 7. Setting iteration=iteration+1, if iteration<320, going back to Step 2, else, the best result will be obtained.

5 Calibration experiment and precision analysis

5.1 Hand-eye calibration experiment

The robot sensor calibration experiment is carried out in eye-in-hand system of robot, which consists of a 6-degree-of-freedom manipulators and a camera. As there are two freedom degrees to be determined while ${}^e_h T$ is solved according to Eq. (1), so let the manipulator move 3 times, ${}^e_2 C = {}^e_1 T \cdot {}^e_2 T \cdot {}^e_3 T^{-1}$, ${}^e_3 C = {}^e_2 T \cdot {}^e_3 T \cdot {}^e_4 T^{-1}$ and ${}^e_4 C = {}^e_3 T \cdot {}^e_4 T \cdot {}^e_1 T^{-1}$ are obtained according to camera's extrinsic parameters ${}^e_1 T, {}^e_2 T, \dots, {}^e_4 T$, which are shown as follows [27 ÷ 29],

$${}^e_2 C = \begin{bmatrix} 0,9759 & -0,2149 & 0,0382 & -0,4203 \\ 0,2139 & 0,9765 & 0,0274 & 4,0629 \\ -0,0432 & -0,0186 & 0,9989 & 40,9565 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$${}^e_3 C = \begin{bmatrix} 0,9468 & -0,2657 & 0,1813 & 46,7499 \\ 0,2629 & 0,9640 & 0,0397 & 28,7530 \\ -0,1853 & 0,0101 & 0,9826 & 76,4267 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$${}^{e3}_{e4}C = \begin{bmatrix} 0,7568 & -0,6037 & 0,2508 & 49,6182 \\ 0,6536 & 0,6925 & -0,3054 & 60,6975 \\ 0,0107 & 0,3950 & 0,9186 & 49,3622 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Their rotational axes are $K_{e1} = [-0,1048, 0,1855, 0,9770]^T$, $K_{e2} = [-0,0459, 0,5693, 0,8209]^T$, and $K_{e3} = [0,4801, 0,1646, 0,8617]^T$; and their rotational angles are $12,6751^\circ$, $18,7843^\circ$ and $46,8492^\circ$, respectively.

On the other hand, the relations of position and orientation of wrist frames at four positions, that is ${}^{h1}_{h2}D, {}^{h2}_{h3}D, {}^{h3}_{h4}D$ are obtained from the controller, we have

$${}^{h1}_{h2}D = \begin{bmatrix} 0,9803 & -0,0524 & 0,1905 & 22,3217 \\ 0,0709 & 0,9933 & 0,0915 & 31,8272 \\ -0,1844 & 0,1031 & 0,9774 & 13,6549 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$${}^{h2}_{h3}D = \begin{bmatrix} 0,9795 & -0,0685 & 0,1896 & 47,6352 \\ 0,1144 & 0,9633 & -0,2428 & 29,6315 \\ -0,1660 & 0,2595 & 0,9514 & 81,6971 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$${}^{h3}_{h4}D = \begin{bmatrix} 0,7136 & -0,5047 & 0,4859 & 43,6257 \\ 0,6195 & 0,7784 & -0,1013 & 12,3647 \\ -0,3271 & 0,3733 & 0,8681 & 72,2146 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Their rotational axes are $K_{h1} = [0,4422, 0,8521, 0,2801]^T$, $K_{h2} = [0,7823, 0,5539, 0,2850]^T$ and $K_{h3} = [0,3236, 0,5545, 0,7667]^T$; and their rotational angles are $12,7103^\circ$, $18,7251^\circ$ and $47,1532^\circ$ respectively.

In the experiment, according to the orthogonal vector characteristic, let $k_{4e} = k_{1e} \times k_{2e}$, $k_{5e} = k_{2e} \times k_{3e}$, $k_{4h} = k_{1h} \times k_{2h}$, and $k_{5h} = k_{2h} \times k_{3h}$. In the solving program, the input vectors are $k_{1e}, k_{2e}, \dots, k_{5e}$, and their corresponding desired vectors are $k_{1h}, k_{2h}, k_{3h}, k_{4h}, k_{5h}$ respectively. While the termination criterion is satisfied, a global extremum is obtained, that is the rotational angle θ is $123,7178^\circ$, and the rotational axis $k = 0,5057\vec{i} + 0,3888\vec{j} + 0,7702\vec{k}$, i.e. the rotational matrix can be obtained according to the stable weights as follows,

$${}^e_hR = \begin{bmatrix} -0,1574 & -0,3349 & 0,9290 \\ 0,9463 & -0,3201 & 0,0450 \\ 0,2823 & 0,8862 & 0,3673 \end{bmatrix}$$

Then in the light of least square method, the translational vector is obtained as follows,

$${}^eP_h = [26,6562; 20,8910; 102,0396]^T$$

If the traditional data processing approach such as least square method is adopted, the robot sensor calibration is achieved as follows [30],

$${}^e_hR = \begin{bmatrix} -0,1531 & -0,3271 & 0,9049 \\ 0,9491 & -0,3098 & 0,0422 \\ 0,2866 & 0,8813 & 0,3669 \end{bmatrix},$$

$${}^eP_h = [26,9997; 22,3209; 100,2951]^T$$

5.2 Precision analysis of calibration

While precision analysis of eye-in-hand system is carried out, let $T_{eri} = {}^{ei}_{e(i+1)}C \cdot {}^e_hT^{-e} \cdot {}^{hi}_{h(i+1)}D$ as precision performance indexes. The errors T_{eri} are shown in Tab. 1 for the proposed approach, i.e. the hybrid neural network and particle swarm optimization with the crossover and mutation (NNPSOwCM), and the least square method (LSM). It is shown that NNPSOwCM has higher precision than LSM.

5.3 Orthogonality analysis

The rotational matrix R consists of three unit vectors n , o and a , according to the least square method, the results of dot product of two elements in the estimated rotational matrix's are: $n^T o = 0,0086$, $o^T a = 0,0143$, and $a^T n = 0,0067$. According to the proposed approach, those are: $n^T o = -1,1102 \times 10^{-16}$, $o^T a = -2,2204 \times 10^{-16}$, and $a^T n = -1,9429 \times 10^{-16}$. As can be seen from the above analysis, the proposed approach that is NNPSOwCM can guarantee the orthogonality of the rotational matrix.

Table 1 Precision performance indexes of two methods

	T_{er1}	T_{er2}	T_{er3}
NNPSOwCM	$\begin{bmatrix} 0,0032 & 0,0044 & 0,0023 & -0,1652 \\ 0,0014 & 0,0030 & -0,0008 & 0,5185 \\ -0,0006 & 0,0023 & -0,0058 & -0,2184 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} -0,0026 & -0,0006 & -0,0010 & -0,1929 \\ -0,0007 & 0,0001 & 0,0023 & -0,2127 \\ -0,0008 & -0,0000 & 0,0014 & 0,2108 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} 0,0041 & -0,0035 & 0,0041 & 0,0357 \\ 0,0040 & -0,0012 & -0,0051 & -0,0440 \\ 0,0011 & -0,0004 & 0,0012 & -0,2035 \\ 0 & 0 & 0 & 0 \end{bmatrix}$
LSM	$\begin{bmatrix} -0,0023 & 0,0046 & 0,0028 & -0,5635 \\ 0,0012 & 0,0048 & -0,0056 & 0,1583 \\ -0,0005 & 0,0020 & -0,0059 & -0,1932 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} -0,0076 & 0,0022 & 0,0007 & 0,6236 \\ -0,0011 & 0,0028 & -0,0022 & -0,4527 \\ -0,0011 & -0,0011 & 0,0038 & 0,1599 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} -0,0091 & 0,0000 & 0,0071 & 0,1063 \\ -0,0019 & 0,0069 & -0,0206 & 0,2257 \\ 0,0061 & 0,0054 & -0,0051 & 0,4060 \\ 0 & 0 & 0 & 0 \end{bmatrix}$

6 Conclusions

In this paper, a new approach i.e. integrating neural network with rotational matrix and particle swarm optimization algorithm for the solution of the rotational components of the homogeneous transform of the hand-eye system is proposed, where the neural network is structured according to solving requirement of the rotational components of the homogeneous transform of the hand-eye relation. And an improved particle swarm optimization is adopted, where the crossover and mutation operation is used to update the velocity and position for particles, and the crossover probability is 1, and the inertia weight factor and the mutation probability is tuning adaptively according to the feature of particles' motion trajectory in longitudinal direction and lateral direction. So the relation of position and orientation of camera mounted in hand with respect to manipulator wrist is realized. Precision analysis shows that the proposed approach can meet the precision requirement in practice; and has advantages of simplicity and clarity, and guarantees the orthogonality of the three column vectors of estimated rotational matrix.

In the future, in the light of the feature of rotational matrix of camera's extrinsic parameters, we would like to develop a monocular vision system that makes the optical axis of camera be perpendicular to the test platform.

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