

The Application Research of Adaptive Ant Colony Optimization Algorithm on Intelligent Control System

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Abstract: A kind of intelligent control system based on fuzzy neural network optimized and trained by the adaptive ant colony optimization algorithm was proposed and constructed in this paper. The structure and the parameters of this intelligent control system were introduced. This intelligent control system used as joint servo controller is applied to the simulation research of robot control. Simulation has been carried out to evaluate the performance of proposed method and to compare the performance with optimization by conventional ant colony algorithm. The results show that the performance of trajectory tracking and the precision of robot control can be improved and have quick convergence based on adaptive ant colony algorithm in the training. This intelligent control method also has a good application prospects in other related fields. *Copyright © 2013 IFSA.*

Keywords: Intelligent control system, Adaptive ant colony algorithm, Robot, Fuzzy neural network.

1. Introduction

Intelligent control is the advanced stage of the development of automatic control, which provided a kind of effective theory and method to solve the control problem of complex systems that traditional control method is difficult to solve [1, 2]. At present, as the representative of the artificial intelligence theory and method, the rapid development of neural network and fuzzy logic provides strong guarantee for the control problem of multiple degrees of manipulator system [3].

In the traditional fuzzy control, fuzzy rules rely on expert experience, and lack of association and self learning ability [4, 5]. But, the neural network has a self-learning [6]. The fuzzy neural network (FNN) which combined by fuzzy logic system and artificial neural network not only can use fuzzy information effectively, but also has parallel processing and well-organized learning information. So it can overcome the single system inadequate [7]. The intelligent

control system, its parameters for training and learning by back propagation or the basic ant colony algorithm can get good control performance [8]. But the algorithm has long searching time and easy to stagnation. This paper proposes an intelligent FNN control method optimized and trained by an improved adaptive ant colony algorithm for a three joints robot system. A comparative study for the accuracy of tracking control and performance of convergence speed are present.

2. The Structure of Fuzzy Neural Network

The structure of fuzzy neural network controller is shown as in Fig. 1. The network is divided into three sub-networks. Each subnet represents a joint servo controller. The relationship between input and output of each layer of network are as follows.

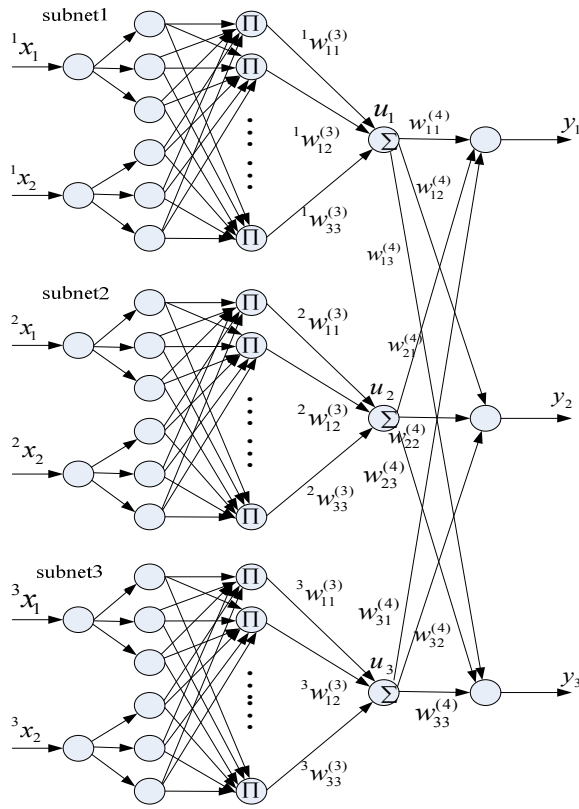


Fig. 1. The structure of fuzzy neural network.

1) The first layer is input (error and error change rate) into the network. Each of the input domains is $[-1, 1]$.

$${}^k out_i^{(1)} = {}^k in_i^{(1)} = {}^k x_i \quad (k = 1,2,3; i = 1,2), \quad (1)$$

${}^k in_j^{(i)}$ and ${}^k out_j^{(i)}$ express the input and output of neuronal j of layer i of subnet k separately. ${}^k x_i$ expresses input i of subnet k .

2) The second layer is the fuzzification layer. Each input has three fuzzy language word sets $\{N, Z, P\} = \{\text{"negative"}, \text{"zero"}, \text{"positive"}\}$. The membership function use the Gauss function below.

$${}^k out_{ij}^{(2)} = {}^k in_{ij}^{(2)} = \mu_{k, A_i^j}({}^k out_i^{(1)}) = \exp\left[-\frac{({}^k out_i^{(1)} - {}^k a_{ij})^2}{k b_{ij}^2}\right] \quad (k = 1,2,3; i = 1,2; j = 1,2,3), \quad (2)$$

where ${}^k A_i^j$ expresses the language set j of input i of subnet k , ${}^k A_i^j \in \{N, Z, P\}$, ${}^k a_{ij}$ and ${}^k b_{ij}$ are the center values and widths of ${}^k A_i^j$

3) The third layer expresses “and” operation. The multiplication is used for small operation.

$${}^k out_{ij}^{(3)} = {}^k in_{ij}^{(3)} = {}^k out_{1i}^{(2)} \cdot {}^k out_{2j}^{(2)}, \quad (3)$$

where $k = 1,2,3; i = 1,2,3; j = 1,2,3$.

4) The fourth layer expresses the defuzzification process. The weighted average judging method can be used here.

$${}^k in^{(4)} = \sum_{i,j=1}^3 ({}^k out_{ij}^{(3)} \cdot {}^k w_{ij}^{(3)}) \quad (k = 1,2,3), \quad (4)$$

$$u_k = {}^k out^{(4)} = \frac{{}^k in^{(4)}}{\sum_{i,j=1}^3 {}^k out_{ij}^{(4)}} \quad (k = 1,2,3), \quad (5)$$

${}^k w_{ij}^{(3)}$ are the weights of the network. The initial values are each control rule of output variables corresponding to the language set center values.

5) The fifth layer expresses the coupling between joints function.

$$y_l = \sum_{k=1}^3 (u_k \cdot w_{kl}^{(4)}) \quad (l = 1,2,3), \quad (6)$$

$w_{kl}^{(4)}$ are the weights of the network. The physical meaning is the coupling effect between joints. The values of training include $w_{kl}^{(4)}$, ${}^k w_{ij}^{(3)}$ and Gauss function parameters ${}^k a_{ij}$, ${}^k b_{ij}$.

3. Optimization Based on Ant Colony Algorithm

The basic idea of optimizing fuzzy neural network by ant colony algorithm comes from the literature [9]: the number of the network parameters need to be optimized is M , represented as p_1, p_2, \dots, p_M . For any one parameter $p_i (1 \leq i \leq M)$, set it to a value within the scope of N random non-zero value, and form set I_{p_i} . Then, each ant of the ant colony selects one weight in the set I_{p_i} , and selects a group of network weights in all sets. The ant number is h . Each ant selects one element from each set according to each element $p_j (I_{p_i})$ in the set that corresponds to the pheromones and state transition probabilities. The process of each ant's choosing element is independent. When an ant has selected elements in all sets, it is to reach the food source (selected a group of fuzzy neural network weights and thresholds), and then adjust the information of elements in the sets. This process is run repeatedly until the evolutionary trend is not obvious or reaches a given number of iterations. The optimizing and training procedure of fuzzy neural network based on ant colony fuzzy are as follows.

1) Initialization: Set time $t=0$ and the maximum cycle number $N_{c_{\max}}$; Set each element's information as the set $\tau_j(I_{p_i}) = \tau_0$. Where, τ_0 is a constant. The pheromone increment is $\Delta\tau_j(I_{p_i}) = 0$. There is no clear theoretical method to the number of ant to determine. According to experts, it usually should meet $M/h=1.5$. Where, M is the number of parameters to be optimized and h is the ant number. The pheromone volatilization factor is $\rho = 0.4$ in this paper.

2) Start all ants. In the light of set I_{p_i} , ant K calculates the state transfer probability according to the following equation.

$$P_r(\tau_j^k(I_{p_i})) = \frac{\tau_j^k(I_{p_i})}{\sum_{g=1}^N \tau_g(I_{p_i})}, \quad (7)$$

3) Repeat the steps (2) until all ants reach the target source.

4) Set $t \leftarrow t + 1$; Calculate output value and error of neural network by using weights which each ant chose; Record the current optimal solution. The path information is updated based on the following equations.

$$\tau_j(I_{p_i})(t+1) = (1-\rho)\tau_j(I_{p_i})(t) + \Delta\tau_j(I_{p_i}), \quad (8)$$

$$\Delta\tau_j(I_{p_i}) = \sum_{k=1}^{40} \Delta\tau_j^k(I_{p_i}), \quad (9)$$

$$\Delta\tau_j^k(I_{p_i}) = \begin{cases} \frac{Q}{e^k} & \text{ant } k \text{ select element } p_j(I_{p_i}), \\ 0 & \text{or} \end{cases} \quad (10)$$

where e^k is the neural network output error when use a set of weights which ant k select, which is defined as $e^k = |O - O_q|$. In which, O and O_q represent this fuzzy neural network actual output and the desired output. The smaller error e^k is, the more pheromone increased. $\rho(0 \leq \rho < 1)$ expresses pheromone volatilization coefficient and Q is pheromone constant.

5) If all the ant converges to a path or cycle number $N_c \geq N_{\max}$, then the loop is complete and output the results, or jumps to the step (2).

4. Adaptive Ant Colony Algorithm Principle and Method

In the process of constructing the solution, the ant colony algorithm is mainly depends on the combination of the information feedback principle

and a heuristic algorithm. The random selection strategy makes the evolutionary speed of this algorithm slower. The principle of positive feedback aims at improving the performance of a better solution, but easy to stagnation. This is the shortcomings of the basic ant colony algorithm. One of the basic ideas for improvement is to apply adaptive regulation strategy in the state transition probability, pheromone and information of ant colony algorithm. To a certain extent, we can overcome some shortcomings of the basic ant colony algorithm.

4.1. Adaptive Selection Strategy

In order to solve the problem of the basic ant colony algorithm that using a random selection strategy makes evolution speed slowly, we use a selection strategy of deterministic selection and random selection combining and dynamically adjust the certainty choice probability in the search process. When the evolution developed to a certain generation, the direction of evolution has been basically established. Then, dynamic adjustment is done for the path information. We should reduce the difference amount of information on the best and worst path and increase appropriately the probability of random selection. Therefore, the solution space of the more complete search is facilitated to get. These can overcome the deficiency of the basic ant colony algorithm effectively.

As mentioned above, ant k from city i to choose the next city j by the selecting formula below.

$$j = \begin{cases} \arg \max_{s \in allowed} \{[\tau_{is}(t)]^\alpha [\eta_{is}(t)]^\beta\} & \text{if } p \leq p_0 \\ \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum_{s \in allowed(i)} [\tau_{is}(t)]^\alpha [\eta_{is}(t)]^\beta} & \text{else} \end{cases}, \quad (11)$$

where $p_0 \in (0,1)$, which is predetermined by a deterministic choice probability value. p is uniformly distributed random number of $(0,1)$. The experimental results show that algorithm using the adaptive selection and dynamic adjustment strategy not only can accelerate the convergence rate and save the searching time but also can avoid premature stagnation. It is very useful and favorable for the large-scale optimization problems to find a better solution.

4.2. Adaptive Update Strategy for Pheromone

In the basic ant colony algorithm, pheromone ρ is directly related to the global search ability and convergence speed. When solving the large scale problem or the number of ants in many cases, if the pheromone volatilization ρ is too large, the global

searching ability of the algorithm can be reduced; if reduced ρ , the global searching ability of the algorithm will increase, but the algorithm convergence speed will be slower. Based on these, this paper adopts an adaptive adjusting pheromone control strategy, which assumes that the initial value of ρ is $\rho(t_0) = 1$. When the obtained solution by ant colony algorithm searching in N cycle was not significantly improved, ρ is updated as following adaptively.

$$\rho(t) = \begin{cases} 0.95\rho(t-N) & \text{if } 0.95\rho(t-N) \geq \rho_{\min} \\ \rho_{\min} & \text{else} \end{cases}, \quad (12)$$

where ρ_{\min} is the minimum value of ρ . It can prevent ρ too small and reduce convergence speed. At the same time, in order to improve ant colony algorithm global search ability and improve its search speed, at each end of the loop to derive the optimal solution and save them.

When update pheromone at each end of the loop, if update all the pheromone on the path for all ants traversed, it is easy to cause the results of algorithm to oscillate and not easy to converge. If just update the pheromone of ant colony algorithm on the current optimal search path, then it is further strengthened for the positive feedback effect and it is easy to cause the search process quickly fall into a local optimal solution. In order to overcome the above problem of ant colony algorithm, this paper select championship competition in the pheromone updating strategy. L ants that search the best results in the circular are selected and the corresponding sections of their pheromones in the path traversed are modified.

4.3. Dynamic Adaptive Adjust of Pheromone Constant

Information interaction of ant colony algorithm is mainly through the pheromone to complete. The process of convergence to the optimal solution is the process of information positive feedback. The principle of positive feedback is to enhance the better solution, but prone to stagnation. In view of the characteristics of ant colony algorithm, this paper proposes a dynamic method to modify pheromone constant according to the state of searching. This algorithm uses time-varying functions $Q(t)$ instead of pheromone constant Q . The formula of pheromone increment is given by:

$$\Delta\tau_j^k(I_{p_i}) = f(t) = \frac{Q(t)}{e^k}, \quad (13)$$

In which, time varying function is shown as follows.

$$Q(t) = \begin{cases} Q_1 & \text{if } t \leq T_1 \\ Q_2 & \text{if } T_1 < t \leq T_2 \\ Q_3 & \text{if } T_2 < t \leq T_3 \end{cases}, \quad (14)$$

where Q_i corresponding to different functions of different values.

5. Simulation of Special Robot

The model of special robot studied in this paper is shown in Fig. 2.

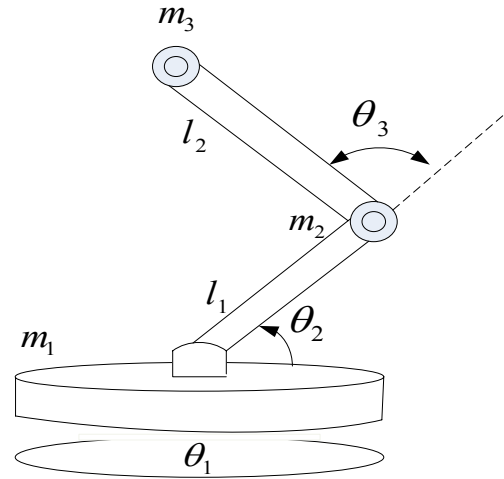


Fig. 2. The model of special robot.

The model is consists of the rotary chassis which height could ignore compared with the length of the mechanical arm and two mechanical arms. The mechanical arm which connects with rotary chassis called major arm, its length is l_1 . And the other mechanical arm called basic arm, its length is l_2 . All three joints are rotational joint. Suppose that the mass distribution of each mechanical arm is concentrated in the end of mechanical arm. The mass of major arm is m_2 , the mass of basic arm is m_3 , and the mass of rotary chassis is m_1 . Then the dynamic equations of special robot by using iterative formula of Newton-Euler are established. The detailed derivation can be seen in literature [10].

$$\tau = M(\Theta)\ddot{\Theta} + V(\Theta, \dot{\Theta}) + G(\Theta), \quad (15)$$

$$\text{where } \tau = \begin{bmatrix} \tau_1 \\ \tau_2 \\ \tau_3 \end{bmatrix}, \quad \Theta = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix},$$

$$M(\Theta) = \begin{bmatrix} m_3 l_2^2 \cos^2(\theta_2 + \theta_3) & & & \\ +2m_3 l_1 l_2 \cos \theta_2 \cos(\theta_2 + \theta_3) & 0 & & 0 \\ +(m_2 + m_3) l_1^2 \cos^2 \theta_2 + J & & & \\ 0 & m_3 l_2^2 + 2m_3 l_1 l_2 \cos \theta_3 + (m_2 + m_3) l_1^2 & m_3 l_2^2 + m_3 l_1 l_2 \cos \theta_3 & \\ 0 & m_3 l_2^2 + m_3 l_1 l_2 \cos \theta_3 & m_3 l_2^2 & \end{bmatrix}$$

$$V(\Theta, \dot{\Theta}) = \begin{bmatrix} -2m_3 l_2^2 \dot{\theta}_1 \dot{\theta}_2 \sin(\theta_2 + \theta_3) \cos(\theta_2 + \theta_3) - 2m_3 l_2^2 \dot{\theta}_1 \dot{\theta}_3 \sin(\theta_2 + \theta_3) \cos(\theta_2 + \theta_3) \\ -2m_3 l_1 l_2 \dot{\theta}_1 \dot{\theta}_2 \sin \theta_2 \cos(\theta_2 + \theta_3) - 2m_3 l_1 l_2 \dot{\theta}_1 \dot{\theta}_3 \cos \theta_2 \sin(\theta_2 + \theta_3) \\ -2m_3 l_1 l_2 \dot{\theta}_1 \dot{\theta}_3 \cos \theta_2 \sin(\theta_2 + \theta_3) - 2(m_2 + m_3) l_1^2 \dot{\theta}_1 \dot{\theta}_2 \sin \theta_2 \cos \theta_2 \\ m_3 l_2^2 \dot{\theta}_1^2 \sin(\theta_2 + \theta_3) \cos(\theta_2 + \theta_3) + m_3 l_1 l_2 \dot{\theta}_2^2 \sin \theta_3 + m_3 l_1 l_2 \dot{\theta}_1^2 \cos \theta_2 \sin(\theta_2 + \theta_3) \\ -m_3 l_1 l_2 \dot{\theta}_1^2 \cos^2(\theta_2 + \theta_3) \sin \theta_3 - m_3 l_1 l_2 (\dot{\theta}_2 + \dot{\theta}_3)^2 \sin \theta_3 \\ +m_3 l_1 l_2 \dot{\theta}_1^2 \sin(\theta_2 + \theta_3) \cos(\theta_2 + \theta_3) \cos \theta_3 + (m_2 + m_3) l_1^2 \dot{\theta}_1^2 \sin \theta_2 \cos \theta_2 \\ m_3 l_2^2 \dot{\theta}_1^2 \sin(\theta_2 + \theta_3) \cos(\theta_2 + \theta_3) + m_3 l_1 l_2 \dot{\theta}_2^2 \sin \theta_3 + m_3 l_1 l_2 \dot{\theta}_1^2 \sin(\theta_2 + \theta_3) \cos \theta_2 \end{bmatrix}$$

$$G(\Theta) = \begin{bmatrix} 0 \\ m_3 g l_2 \cos(\theta_2 + \theta_3) + (m_2 + m_3) g l_1 \cos \theta_2 \\ m_3 g l_2 \cos(\theta_2 + \theta_3) \end{bmatrix}, \quad Q(t) = \begin{cases} 0.5 & 0 < t \leq 50 \\ 1.0 & 50 < t \leq 100 \\ 1.5 & 100 < t \end{cases}, \quad (16)$$

where t_1, t_2 and t_3 represent joint torques of the three joints, l_1, l_2 represent the length of two mechanical arms. According to the hypothesis, the mass of major arm and basic arm were concentrated in the end of mechanical arm. So the centroid inertia tensor of two mechanical arms are 0, the centroid inertia tensor of rotating chassis is J . θ_1, θ_2 and θ_3 represent joint angular positions of the three joints. $M(\Theta)$ represents inertial matrix. Each element reflects the inertia moment between joints. $V(\Theta, \dot{\Theta})$ represents Centrifugal and Coriolis force. Three components reflect the influence by Centrifugal and Coriolis force. $G(\Theta)$ represents gravity. Three components are the rotary chassis and the two mechanical arms for their respective joint shaft torque.

The parameters of the fuzzy neural network for training include the center and width values of Gauss function which are in the second layer of the network for a total of 36, 27 weight parameters of third layer and 9 weight parameters of fourth layer, therefore the number of parameters $m = 72$. The value range of network parameter p_i is $[-1.2, 1.2]$, each parameter sets 40 values. The number of ants is $h=48$. The pheromone volatilization factor is $\rho=0.98$. $N = 5$ means that when the solution obtained by searching is no obvious improvement in the 5 cycle, then use formula (13) to update pheromone. The minimum pheromone value is $\rho_{\min} = 0.5$. $L = 6$ means that every cycle only update the best quality of the former 6 ant path pheromones. The time-varying pheromone functions are as follows.

Through fuzzy expert control, the sample values were gotten. By using the basic ant colony algorithm and adaptive ant colony algorithm to learn and train, when convergence error is set at 0.05, the basic ant colony algorithm takes on average 206 iterations of training and the adaptive ant colony algorithm need only be trained 146 iterations. Then the two trained controller separately control to meet the requirement of trajectory tracking.

In this paper, the parameters of the special robot are as follows: The moment of inertia of the rotary chassis is $J = 0.5 kgm^2$. The main arm and the basic arm quality respectively is: $m_2 = 15kg$, $m_3 = 20kg$. The length of arms respectively are $l_1 = 0.6m$ and $l_2 = 0.8m$. Initial conditions for $\theta_1(0) = 0 rad$, $\theta_2(0) = 0 rad$, $\theta_3(0) = 0 rad$, $\dot{\theta}_1(0) = \dot{\theta}_2(0) = \dot{\theta}_3(0) = 0 rad/s$. The desired trajectory of the rotary chassis, the main arm and the basic arm is $\theta(t) = \sin(2\pi t)$, and sampling period is 0.001 second. Neglecting the friction and disturbance, quantitative factors are set as $k_{e1} = 50$, $k_{e2} = k_{e3} = 200$, and $k_{ec1} = k_{ec2} = k_{ec3} = 1$. Torque proportional factors are set as $k_{u1} = 2050$, $k_{u2} = 3300$, $k_{u3} = 1500$.

The control simulation of special robot is in the MATLAB environment. The structure of the control system is shown in Fig. 3. In Fig. 3, θ_{d1} , θ_{d2} and θ_{d3} are the desired positions of three joints, θ_1, θ_2 and θ_3 are the actual positions of the three

joints, e_1 , e_2 and e_3 are the position errors of the three joints, ec_1 , ec_2 and ec_3 are the error rates of change, t_1 , t_2 and t_3 are the torques of three joints. Fuzzy neural network is used as the joint servo controller.

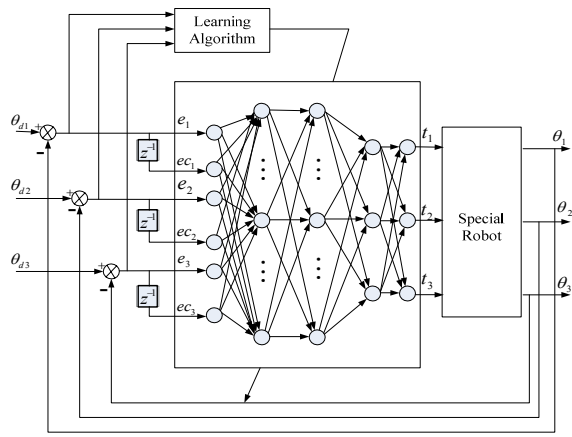


Fig. 3. The structure of the control system.

Simulation results show from Fig. 4 to Fig. 9. The Fig. 4, Fig. 5 and Fig. 6 are tracking curves for rotary chassis, the main arm and the basic arm of special robot. The Fig. 7, Fig. 8 and Fig. 9 give three joints trajectory tracking error curves of special robot.

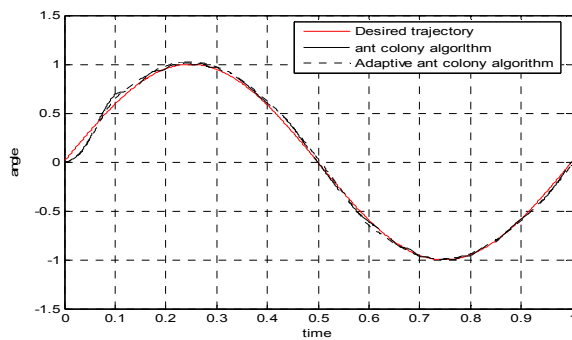


Fig. 4. The position tracking curve of rotary chassis.

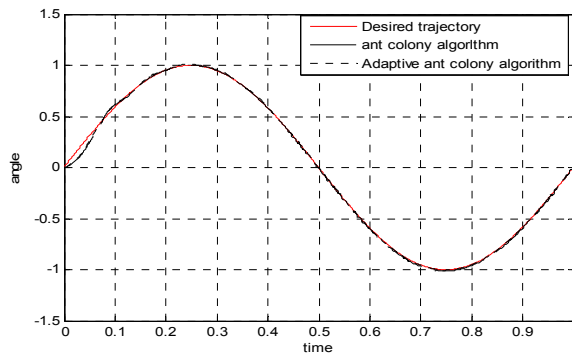


Fig. 5. The position tracking curve of major arm.

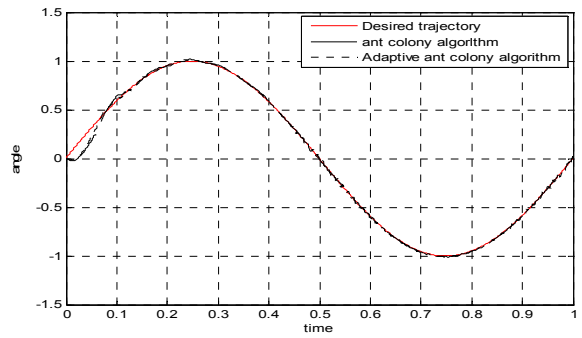


Fig. 6. The position tracking curve of basic arm.

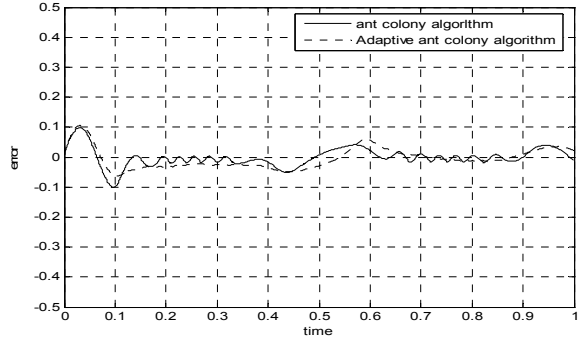


Fig. 7. The tracking error curve of rotary chassis.

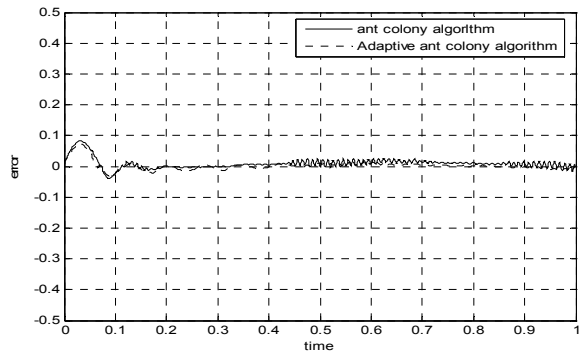


Fig. 8. The tracking error curve of major arm.

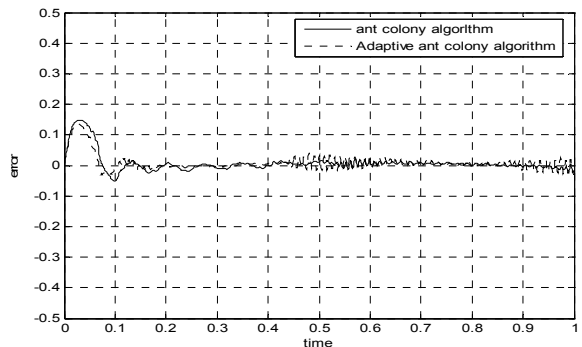


Fig. 9. The tracking error curve of basic arm.

In Fig. 4, Fig. 5 and Fig. 6, the red solid line represents the desired trajectory, the black solid line and the dotted line represent respectively the position

tracking curves of FNN control optimized and trained by basic ant colony algorithm and adaptive ant colony algorithm for special robot system. In Fig. 7, Fig. 8 and Fig. 9, the solid line and dotted line represent respectively the tracking error curves of FNN control optimized and trained by basic ant colony algorithm and adaptive ant colony algorithm for special robot system. The results showed that the fuzzy neural network optimized by the adaptive ant colony algorithm has faster convergence speed than by ant colony algorithm, and has better tracking performance and stability.

6. Conclusions

In view of the insufficiency of the basic ant colony algorithm, adaptive adjustment factors are used to improve the optimization algorithm. An adaptive ant colony algorithm was introduced into the optimization and training of fuzzy neural controller. The simulation results show that the FNN controller based on adaptive ant colony algorithm has better performance than the traditional basic ant colony algorithm for special robot. The FNN controller based on adaptive ant colony optimization algorithm for parameter training converges faster, and has better tracking accuracy.

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