International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 5 Issue 6 ǁ June. 2017 ǁ PP. 48-53

Welding Path Planning of welding Robot Based on Improved Ant Colony Algorithm

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ABSTRACT: The basic ant colony algorithm in the welding robot path planning, in the search process, prone to search for too long, low efficiency, easy to fall into the local optimal and other issues. In this paper, the basic ant colony algorithm is improved, and the Adadelta algorithm is introduced. By combining the basic ant colony algorithm and Adadelta algorithm, the probability of selecting the next solder joint in the ant search process is increased and the randomness is increased. The algorithm updated the parameters to improve the ant pheromone update, and improved the pheromone volatilization coefficient, using the adaptive way to update the pheromone. The results show that the improved ant colony algorithm is more efficient than the basic ant colony algorithm, the algorithm is more efficient and the convergence rate is faster, and the algorithm is better than the basic ant colony algorithm. The shortest path is the shortest. The results show that the improved ant colony algorithm improves the efficiency of the algorithm, and improves the problem of the basic ant colony algorithm in the welding path planning of the welding robot. The convergence speed is faster and the search result is better.

I. INTRODUCTION

With the development of the economy and the strong support of the government, the demand for robots in various industries is getting higher and higher. In the automobile, motorcycle, ship, engineering equipment and other manufacturing industry, the role of welding robot is growing. In general, an ordinary car's white body has 4200-6300 welding points, only to the welding robot as the core of the production line, in order to complete the mass production and technological reform. The application of welding robots is becoming more and more extensive, and more and more scholars and researchers are engaged in the research of key technologies of welding robots. For welding robots, the planning of welding tasks is particularly important, so the welding path planning is one of the key research. The welding path planning of the spot welding robot is the most important step in the welding process. If the welding path can be planned reasonably, the working time of the robot can be reduced, the working efficiency of the robot can be improved and the production cost can be reduced. In [1], an evolutionary algorithm based on the introduction of new genetic operators is proposed to optimize the robot path. In [2], it is pointed out that when the number of solder joints is small, the dynamic programming is better than other optimization algorithms, but when the solder joint increases, it will often cause no solution. In [3], a double global optimal genetic algorithm is proposed to optimize the path length of welding robot. In [4], a new algorithm is proposed, which is based on TSP (traveled salesman problem) elastic network and neural network to solve the deformation problem of welding robot path planning. In this paper, the combination of Adadelta algorithm and ant colony algorithm is used to increase the randomness of pheromone to avoid the local optimization of the algorithm, so as to improve the performance of the algorithm and realize the path planning by discretizing the objective function.

Welding Path Planning Task Description

Welding robot welding path planning is in fact: to meet the constraints, to find an optimal welding path. The most important thing about the path planning of a welding robot is the path planning of the welding point. How to find a path that traverses all the solder joints is the key [5]. In the welding process, may also have to take into account the welding torch, the workpiece and fixture interference problem, for these problems, you can increase the method of virtual solder joints to solve [6]. In general, there are many ways to complete the welding task, according to different purposes to select the appropriate route, some tend to consume less, some are more inclined to take less time, and some tend to the shortest path, the main study The planning path is the shortest. The purpose of the welding robot path planning is to provide the robot with a solder joint order in these solder joints. Simplify the shortest path planning into traveler problems, treat all solder joints as a city, where travelers travel from the starting point, traverse all the cities, and then return to the starting point for the shortest path planning problem.

With N solder joints, the set of N solder joints is $C=\{c_1,c_2,c_3,\cdots,c_N\}$,The distance between each two solder joints is $d(c_i, c_j) \geq 0$,among them $c_i, c_j \in C(1 \leq i, j \leq N)$,The length of the target function to achieve the minimum path length of the solder sequence $\left(c_{\varphi(1)}, c_{\varphi(2)}, c_{\varphi(3)}, \cdots, c_{\varphi(N)}\right)$,that is:

$$s = \sum_{i=1}^{N=1} d\left(c_{\varphi(i)}, c_{\varphi(i+1)}\right) + d\left(c_{\varphi(N)}, c_{\varphi(1)}\right), \qquad (1)$$

S is the total length of the welding path. How to make S the smallest, while reducing the path planning time, improve efficiency is the key to path planning.

The traditional spot welding robot, welding robot path planning is the use of traditional teaching methods, in order to improve the accuracy of the work, often need to constantly debug, to adjust the accuracy. This method is relatively large workload, and the efficiency is particularly low, debugging is also more laborious, is not conducive to artificial intelligence. With the advent of the era of artificial intelligence, intelligent algorithms are developing faster and faster, providing a better solution for these optimization problems.

II. PATH PLANNING BASED ON IMPROVED ANT COLONY ALGORITHM

2.1 basic ant colony algorithm

Ant colony optimization (ACO) is also called ant algorithm, the role of this algorithm is to find the optimal path in the probability of the algorithm. Ant colony algorithm of the general idea [7]: is the natural ants looking for a process of food, ants are group-type animals, looking for food, and not just an ant to find food, but a group, and between each ants Have the information to pass.

Each ants in the search for food when they do not know where the food, assuming that an ant to find food, and this time the ants will be to the surrounding environment to release a relatively easy to evaporate the secretion of pheromone to achieve, this The secretions are called pheromones. As time goes on, the pheromone volatilization will gradually disappear and the size of the pheromone concentration represents the distance from the food. Because of the role of pheromone, more and more ants will find food, but some ants do not repeat the same way as other ants, they choose not the same way, if some ants choose the road path than the other Of the road path is shorter, then as time goes by, more and more ants are attracted to this short road up, after a period of time, will come out a shortest path road is repeated by most of the ants.

If $b_i(t)$is the number of ants in the element (solder) at t time, $\tau_{ij}(t)$is the information of the path(i, j) at t time.N is the total number of solder joints.m is the total number of ants in the ant colon. $L = \{l_{ij} | c_i, c_j \subset C\}$ is the collection C of elements in a collection of two elements. $T = \{\tau_{ij}(t) | c_i, c_i \subset C\}$ is the set of the amount of information remaining on the two lines of the element (solder) in the set C at time t.At the initial time t = 0,The m ants randomly put n solder joints in the m solder joints, at the initial moment, the amount of information on each road are the same.If $\tau_{ij}(0) = const$,The optimization process of the basic ant colony algorithm is realized by the directed graph $g = (C, L, T)$.

In the process of finding the food, the ant will determine the direction of the act according to the amount of information on the various roads. In order to avoid some meaningful path planning, each ant will generate a taboo table $tabu$,This table is used to preserve all the path points where the ants have chosen to travel in parallel. At time t, the transition probability P of the ant k from the solder i to the solder j is:

$$P_{ij}^k(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum\limits_{s \subset A_k} [\tau_{is}(t)]^\alpha [\eta_{is}(t)]^\beta}, & j \in A_k \\ 0, & others \end{cases} \qquad (2)$$

Where $A_k = \{C - tabu_k\}$ represents the set of all the solder pieces of the ant k alone. When the ant k traverses all the solder joints, the path of the ant k is the feasible solution to the problem.In the formula (2), α is the information heuristic factor, the greater the value of α , the greater the possibility that the ant k chooses the path of the other ants, the stronger the association between the ants. β is the expected heuristic factor, and its value is larger, the closer the state transition probability is to the greedy rule. $\eta_{ij}(t)$ is the heuristic function, which indicates the expected degree of the ant moving from the solder i to the solder joint j. In the greedy algorithm, the reciprocal of the distance（d_{ij}） between the joint i and the solder joint j is often taken,that is:

$$\eta_{ij}(t)=\frac{1}{d_{ij}} \tag{3}$$

For each ants, the smaller the d_{ij}, the greater the $P_{ij}^{k}(t)$.In order to prevent the residual pheromone too much lead to the role of inspiration information is not obvious, in each of an ant finish a solder joint or successfully all the solder joints are traversed after the update pheromone, in the new pheromone update After the old pheromone is becoming weaker.So, at time $(t+n)$, the pheromone on path (i, j) can be updated as follows:

$$\tau_{ij}(t+n)=(1-\rho)\tau_{ij}(t)+\Delta\tau_{ij}(t) \tag{4}$$

$$\Delta\tau_{ij}(t)=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t) \tag{5}$$

In the formula, ρ is the volatilization coefficient of pheromone, and $1-\rho$ represents the residual factor of pheromone, where $0<\rho<1$. $\Delta\tau_{ij}(t)$ represents the increment of pheromone on a successful full path, $\Delta\tau_{ij}(0)=0$ when t = 0, and $\Delta\tau_{ij}^{k}(t)$ represents the amount of information remaining on this full path.

According to the strategy of pheromone renewal, Dorigo M. proposed three different basic ant colony algorithm models, namely Ant-Quantity system model, Ant-Cycle system model and ant System model (Ant-Density system) model, the main difference between the different models is not the same as $\Delta\tau_{ij}^{k}(t)$.

In theAnt-Cyclesystem model:

$$\Delta\tau_{ij}^{k}(t)=\begin{cases}\dfrac{Q}{L_k} & tour(i, j)\in tour_k \\ 0 & otherwise\end{cases} \tag{6}$$

In the formula, Q represents the intensity of the pheromone, and L_k represents the length of the ant k in the complete path of success.

In contrast, in the Ant-Quantity system model, the distance between the solder joints is related:

$$\Delta\tau_{ij}^{k}(t)=\begin{cases}\dfrac{Q}{d_{ij}} & tour(i, j)\in tour_k \\ 0 & otherwise\end{cases} \tag{7}$$

In the Ant-Density system:

$$\Delta\tau_{ij}^{k}(t)=\begin{cases}Q & tour(i, j)\in tour_k \\ 0 & otherwise\end{cases} \tag{8}$$

Both the ant and em model are pheromones updated with local information after the one-step action is completed, and the ant colony system updates the pheromone on the path after the ant completes a complete path, using the overall information The In solving the traveling salesman problem, the ant system model is obviously better than the other two algorithms, so it is usually used as a model of the basic algorithm of ant colony.

2.2Adadelta Algorithm

The Adadelta algorithm is derived from the Adagrad algorithm. Adagrad is a gradient-based algorithm that allows learning rate adaptive parameters to be significantly updated for low frequency parameters and small updates to high frequency parameters because Adagrad is well suited for sparse data, Adagrad Which greatly improves the robustness of the stochastic gradient descent algorithm. But the Adagrad algorithm has a major weakness, that is, it adds a squared gradient to the denominator because each time it is added to a positive number, the cumulative and the training stage has been increasing, which leads to the learning rate becoming smaller and eventually changing The infinitesimal, as in equation (9). It is because of this fatal flaw, which gave birth to the Adadelta algorithm.The basic idea of the Adagrad algorithm is as follows:

$$\Delta x_t = -\frac{\eta}{\sqrt{\sum_{\tau=1}^{t}(g_\tau)^2}}.g_t \qquad (9)$$

Where x is the parameter, t is the timing, Δ is the update, η is the learning rate, and g is the gradient. The Adadelta algorithm is an extension of the Adagrad algorithm to alleviate the Adagrad learning rate monotonically decreasing algorithm. The Adadelta algorithm does not accumulate all the time gradients in the past, but limits the accumulation time to the interval of the window size. The basic idea of AdaDelta is to use the first order method to approximate the second order Newton method. 1988 Becker and LeCun proposed a method of approximating the inverse matrix using matrix diagonal elements:

$$\Delta x_t = -\frac{1}{|diag(H_t)| + \mu}.g_t \qquad (10)$$

Diag refers to the diagonal matrix of the constructed Hessian matrix, and μ is a constant term, preventing the denominator from being zero. In 2012, Schaul et al. Borrowed Adagrad's approach and proposed a more accurate approximation:

$$\Delta x_t = -\frac{1}{|diag(H_t)|}\frac{E|g_t - w:t|^2}{E|g_t{}^2 - w:t|}.g_t \qquad (11)$$

2.3 Improved ant colony algorithm

The traditional ant algorithm has positive feedback, strong robustness and global optimum. However, the ant colony algorithm has a strong randomness in the search process in order to get an ideal path in the search process. The fast convergence of the group algorithm also requires a high certainty in the process of ant colony search. Randomness and certainty are the key factors in the performance of the algorithm, both inseparable, but full of contradictions. Therefore, the ant colony algorithm has the search speed is relatively slow, easier to fall into the local optimal shortcomings, in order to improve the performance of ant colony algorithm, we must solve the balance between the two problems. In this paper, the Adadelta algorithm is combined with the basic ant colony algorithm to improve the randomness, convergence speed, local optimal problem and the balance between them. The traditional ant colony algorithm is improved as follows:

(1) increase the randomness, modify the probability of ants to the next solder joint. Because the traditional ant colony algorithm to choose the next solder joint mainly depends on the concentration of pheromones and the distance between the two solder joints, and pheromone concentration and the length of the distance between the solder joints set the parameters can only be experienced, so the early The workload is relatively large, the optimization process is relatively slow, easy to fall into the local optimal. In this paper, the Adadelta algorithm is introduced to introduce the concept of gradient, and the gradient is used to change the probability of solder joint selection, so as to increase the randomness of solder joint selection. As in equation (12).

$$P'^{k}_{ij}(t) = \begin{cases} \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum_{s \subset A_k}[\tau_{is}(t)]^\alpha [\eta_{is}(t)]^\beta}.|g_t| \ , & j \in A_k, |g_t| \le 1 \\ \dfrac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum_{s \subset A_k}[\tau_{is}(t)]^\alpha [\eta_{is}(t)]^\beta}.\dfrac{1}{|g_t|} \ , & j \in A_k, |g_t| > 1 \end{cases} \\ 0, \qquad \qquad others \end{cases} \qquad (12)$$

(2)Improvement of pheromone update rules. In the traditional ant colony algorithm, when the population completes a cycle, all the ants will be pheromone updates, which can not fully reflect the guiding role of the optimal path, and some poor information will interfere with the next generation of population search , Some of the pheromone pheromone after the role of positive feedback, it may lead to the ant colony algorithm search process into a precocious phenomenon, that is easy to fall into the local optimal solution, the introduction of Adadelta algorithm, the use of changes in parameters to the ant colony algorithm The pheromone update in each cycle, adding more enlightening information, infiltrating the gradient change parameter, changing the parameters at the different stages of the ant search to change the amount of information released, thus vigorously updating the useful pheromone , To abandon the inferior pheromone. As shown in equation (13).

$$\Delta\tau_{ij}^{k}(t)=\begin{cases}\dfrac{Q}{L_k+\kappa|\Delta x_t|} & tour(i,j)\in tour_k \\ 0 & otherwise\end{cases} \tag{13}$$

III. SIMULATION ANALYSIS

In this paper, the results of improved ant colony algorithm and basic ant colony algorithm are simulated by MATLAB 2015a simulation software, and the results of path planning are compared. Figure 1 is a car door welding point diagram, where the black point is the need to weld the point, we even from which to take 77 solder joints to do the simulation.

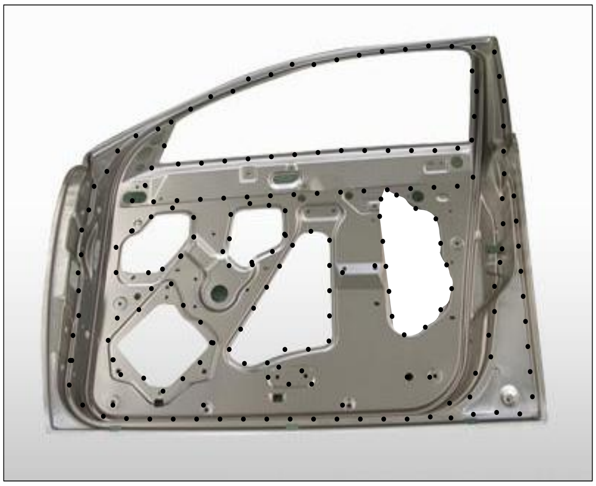

Figure 1 a door welding map

Figure 2 is the basic ant colony algorithm of the welding path planning results, and ultimately get the welding path of the shortest path length of 28223.3607. Figure 3 is the result of the welder path planning of the improved ant colony algorithm described herein. The shortest path length is 27402.3503. In MATLAB simulation, the shortest path of the solder joint welding order:
76-33-53-29-56-55-54-64-57-58-34-20-77-35-67-74-72-73-71-17-68-70-69-60-59-66-65-61-62-63-31-30-27-51-50-52-49-28-48-32-44-45-10-3-46-15-14-1-12-47-13-11-23-16-18-5-19-37-38-36-25-6-24-39-7-2-4-40-41-75-8-42-43-9-22-26- 21-76.

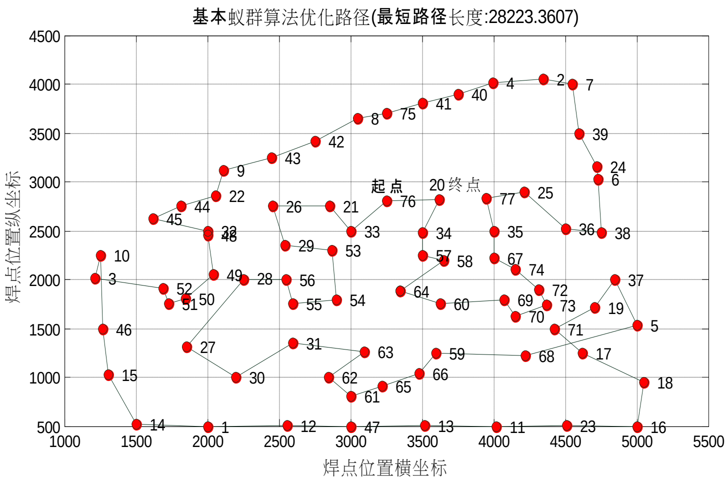

Figure 2 Basic ant colony algorithm planning results

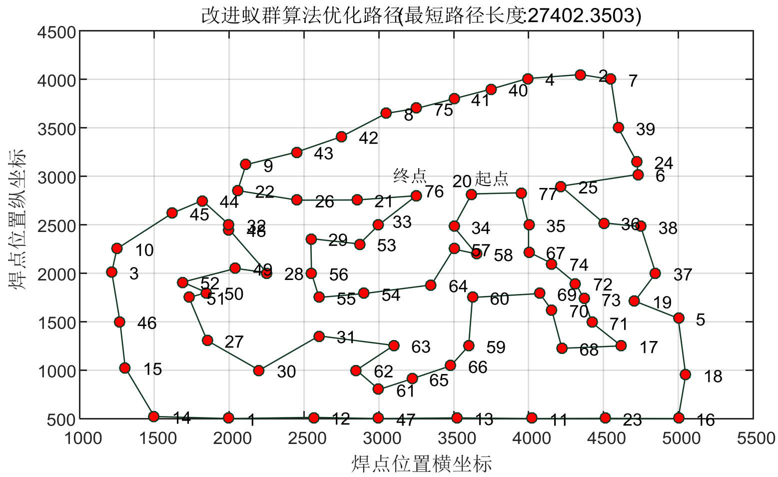

Figure 3 improved ant colony algorithm planning results

Compared with the basic ant colony algorithm and the improved ant colony algorithm, the improved ant colony algorithm is better than the basic ant colony algorithm. The shortest path length of the improved ant colony algorithm is much smaller than that of the basic ant colony algorithm.

IV. CONCLUDING REMARKS

The path planning of welding robot welding point is an important step of spot welding robot work, and the result of planning will directly affect the efficiency of welding. It is time-consuming and laborious to plan the welding sequence by hand, and it is not easy to find satisfactory path planning results. When using the basic ant colony algorithm to weld the robot to do the welding path planning, it is easy to fall into the local optimum, and the search process is relatively slow, the efficiency is relatively low. In this paper, the Advertta algorithm is combined with the basic ant colony algorithm to improve the randomness of ant search and improve the way of pheromone updating. The pheromone volatilization coefficient is improved to be adaptive, which greatly improves the performance of the algorithm. The results of MATLAB simulation show that the improved ant colony algorithm can effectively improve the basic ant colony algorithm, accelerate the search speed and convergence speed of the algorithm, and improve the shortest path length of the algorithm.

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