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Optimization of robot path planning based on improved BP algorithm

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Abstract: *Path planning is one of the key problems of welding robots. In the face of increasing accuracy and efficiency requirements in the manufacturing industry, the importance of robot path planning has also increased. For welding robots, short welding time and stable welding process are generally required. In this paper, genetic algorithm is used to optimize BP neural network algorithm, so as to obtain better weights and thresholds, so as to obtain better solutions in path planning. After simulation and verification in MATLAB, the results show that, the optimized BP neural network algorithm effectively improves the efficiency of the algorithm and optimizes the ability of finding the global optimal path.*

Keywords: *Improved BP neural network algorithm; Welding robot; Path planning; Genetic algorithm*

1. Introduction

Since entering the 21st century, with the accelerating process of industrialization, welding robots have been gradually introduced into industrial production in order to improve production efficiency and market competition[1]. In the last century, in the 1960s, there were robots abroad, and after half a century, the research on path planning has been very mature. The domestic research in related fields is relatively late, but due to everyone's attention and application in production, people's research on path planning is very hot, and the development of application is also very fast. In automobile welding, there are about 4000 ~ 6500 solder joints in a white body, more than half of which are welded by welding robots. However, the welding effect of different welding paths is different, which leads to a key problem of welding robots -- path planning. Since its emergence, this problem has attracted a large number of scholars to further study the path planning of robots. Literature[2] adopted the improved B-spline interpolation method to optimize the joint space of the robot, which not only improved the accuracy of the robot passing the solder joints, but also made the motion process more stable. In literature [3], Levi Flight and particle swarm optimization algorithm were combined to increase the population diversity, improve the optimization performance of the algorithm, and realize path planning through discretization, aiming at the shortest overall path length. Literature [4-5] fuses the improved A* algorithm and DWA algorithm. The improved fusion algorithm has high search efficiency and real-time obstacle avoidance ability while ensuring the optimal global path. Literature [6] introduces the K-means algorithm in the partition-based clustering method to improve particle swarm optimization and cluster particles to improve accuracy and stability and achieve better path effect. In literature[7], by introducing reversal operators, adding insertion operators and deletion operators to adaptive genetic algorithm, a new adaptive strategy is proposed to adjust crossover and mutation probabilities, so as to better avoid falling into local optimality and improve the optimization efficiency of the algorithm. Based on the artificial potential field method based on algorithm fusion, literature [7]solves some problems of artificial potential field method in robot path planning.

When solving the basic BP neural network algorithm parameters, it is easy to fall into local minima, the learning convergence speed is relatively slow, and the structure of the neural network is easy to be uncertain. In this paper, genetic algorithm is selected to optimize the BP neural network algorithm, and the optimized BP neural network algorithm is applied to the welding path planning of the car door. It is of great significance for the welding robot to find a reasonable, shortest and stable path.

2. Mathematical engineering problems

In this paper, a single robot welded the car door of the body in white is taken as the research object (Figure 1), and an optimal path is found by improving the BP neural network algorithm to connect the messy solder joints. Through finishing, it is found that all solder joints are on the same plane, so that the algorithm processing is reduced from three-dimensional space to two-dimensional space, which greatly reduces the difficulty of the algorithm.

Figure 1: Body in white

General welding requirements of welding robots: starting from the starting point, through the pre-designed path, the process of sequentially welding all solder joints back to the starting point without collision. The solution of this process is very similar to the Traveling salesman problem (TSP) proposed by Dantzig et al in 1959. After so many years of development, the solution of TSP has made great progress. After data processing, the three-dimensional data is reduced to a point on a two-dimensional plane, so the mathematical model can be established: Let the set of solder joints be S=$\{S_1, S_2, S_3, \dots, S_n\}$, Where $S_1, S_2, S_3, \dots, S_n$ represents the two-dimensional plane coordinates of each solder joint. $S_1 = (x_1, y_1), S_2 = (x_2, y_2), \dots, S_n = (x_n, y_n)$, The distance between solder joint i and solder joint j is set to l_{ij},

$$l_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \qquad \text{(Where i and j satisfy 1≤i and j≤ n)} \qquad (1)$$

3. Combination of bp neural network algorithm and genetic algorithm

3.1 Basic algorithms

In 1986, Rumelhart, McClelland and others proposed BP (Back Propagation) network, which is mainly used to train multi-layer feedforward networks through error back propagation algorithm, and now it has become one of the mainstream models.

BP neural network algorithm is a supervised learning algorithm using forward propagation and back propagation. The main flow of the algorithm is as follows: Input the data to be learned, that is, the sample, and use forward propagation and back propagation to make a large amount of adjustment training on the learning sample to reduce the algorithm's bias, so that the obtained output and our expected target are within the error range. When the algorithm's error score is less than expected, the training is finished and the algorithm's weight and bias are retained. The specific process is as follows: suppose that the input layer contains n neurons, the hidden layer contains p neurons, and the output layer contains q neurons. The symbolic meaning is shown in Table 1.

Table 1: Meaning of symbols

Input vector	$x = (x_1, x_2, \dots, x_n)$
Hidden layer input vector	$h_i = (h_{i1}, h_{i2}, \dots, h_{ip})$
Hidden layer output vector	$h_o = (h_{o1}, h_{o2}, \dots, h_{op})$
Output layer input vector	$y_i = (y_{i1}, y_{i2}, \dots, y_{iq})$
Output layer output vector	$y_o = (y_{o1}, y_{o2}, \dots, y_{oq})$
Expected output vector	$d_o = (d_1, d_2, \dots, d_q)$
Error function	$e = \frac{1}{2}\sum_{o=1}^{q}(d_o(k) - y_{oo}(k))^2$

Step 1: Calculate the input and output of each neuron in the algorithm.

$$h_{ih}(k) = \sum_{i=0}^{n} w_{hi} x_i(k) \quad h = 1,2,\dots,p \tag{2}$$

$$h_{oh}(k) = f\left(h_{ih}(k)\right) \quad h = 1,2,\dots,p \tag{3}$$

$$y_{io}(k) = \sum_{h=0}^{p} w_{oh} h_{oh}(k) \quad o = 1,2,\dots,q \tag{4}$$

$$y_{oo}(k) = f\left(y_{io}(k)\right) \quad o = 1,2,\dots,q \tag{5}$$

Step 2: Solve the partial derivatives of each neuron in the output layer according to the error between the output and the expectation.

$$\frac{\partial e}{\partial w_{oh}} = \frac{\partial e}{\partial y_{io}} \cdot \frac{\partial y_{io}}{\partial w_{oh}} = -\delta_o(k) h_{oh}(k) \tag{6}$$

Step 3: Weight, $\delta_o(k)$, hidden layer output to solve the error function of the hidden layer of each neuron partial derivative.

$$\frac{\partial e}{\partial w_{hi}} = \frac{\partial e}{\partial h_{ih}(k)} \cdot \frac{\partial h_{ih}(k)}{\partial w_{hi}} = -\delta_h(k) x_i(k) \tag{7}$$

Step 4: $\delta_o(k)$, hidden layer output to optimize w_{oh}.

$$\Delta w_{oh}(k) = -\mu \frac{\partial e}{\partial w_{oh}} = \mu \delta_o(k) h_{oh}(k) \tag{8}$$

$$w_{oh}^{N+1} = w_{oh}^{N} + \mu \delta_o(k) h_{oh}(k) \ \text{(Where μ is the learning rate)} \tag{9}$$

Step 5: $\delta_h(k)$, input layer input to optimize the weight.

$$\Delta w_{hi}(k) = -\mu \frac{\partial e}{\partial w_{hi}} = \delta_h(k) x_i(k) \tag{10}$$

$$w_{hi}^{N+1} = w_{hi}^{N} + \mu \delta_h(k) x_i(k) \tag{11}$$

Step 6: Solve the global error.

$$E = \frac{1}{2m} \sum_{k=1}^{m} \sum_{o=1}^{q} (d_o(k) - y_o(k))^2 \tag{12}$$

Step 7: According to the error solved, compare the error with the expected target to see whether the accuracy is in line with it. If it is in line with it or the learning times of the algorithm reaches the upper limit, the BP neural network algorithm is terminated; otherwise, the sample and the expected target are selected again and the algorithm is input to continue learning.

In the last century, John holland in the United States proposed the genetic algorithm, which was a search algorithm established by using Darwin's natural selection and population genetic mechanism in biology. This algorithm mainly solved the optimal solution through selection, crossover and mutation and other processes.

The algorithm cleverly uses the theory of biology, improves it and transplants it to the computer, establishes a mathematical model, and uses the huge computing power of the computer to quickly calculate the process of chromosome crossing and mutation in and out of biology. The initial sample is gradually screened through the introduction of fitness in the objective function, and excellent individuals will be left for each screening, and excellent individuals will be screened for the next round, and so on until the desired target is selected or the iteration upper limit is reached.

3.2 Improved BP neural network algorithm

Although the traditional BP neural network algorithm can make use of the increasingly huge computing power of modern computers when processing a large amount of data, it can still solve the final result, but due to the shortcomings of the BP neural network algorithm, such as slow convergence speed and local minimization, the result may not be the best. After understanding, this paper optimizes BP neural network algorithm by using the characteristics of genetic algorithm expansibility and easy combination with other algorithms.

Genetic algorithm optimization of BP neural network algorithm is mainly to optimize three parts of the neural network. The first part is the structure of the BP neural network algorithm, which is determined by the number of learning samples, and then the number of parameters of the neural network structure is optimized by genetic algorithm, and finally the coding length of the population is obtained. The second part is to optimize the weight and threshold of the BP neural network algorithm by genetic algorithm.

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After the completion of the first step, that is, after the structure of the neural network algorithm is determined, the number of the weight and threshold can be known, and the number between the weight and threshold can be initialized by the general reality [-0.5, 0.5]. This paper introduces genetic algorithm mainly to optimize the weight and threshold of BP neural network algorithm. The third part is the training and prediction of the improved BP neural network algorithm. After these three steps, the defects of the BP neural network algorithm have been significantly improved, and the obtained results are greatly optimized and more in line with the ideal goal.

3.3 Algorithm flow

The flow chart of BP neural network algorithm optimized by genetic algorithm is shown in Figure 2.

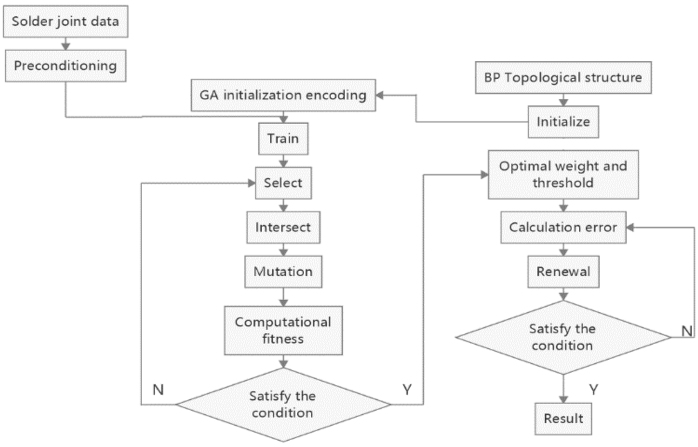

Figure 2: Flow chart of optimized BP algorithm

The specific process: (1) all the obtained solder joint data are sorted into the improved BP algorithm; (2)The topology of BP neural network is determined, so that the initial BP neural network weight and threshold length are obtained, which are passed to the genetic algorithm for initial value coding; (3) The error obtained by BP neural network training is taken as the fitness value; (4) Genetic algorithm for selection, crossover, mutation operations; (5) Calculate the fitness value until the error of BP algorithm is the optimal fitness function of genetic algorithm, and then pass the conditions to BP neural network as the optimal weight and threshold, otherwise, repeat the selection, crossover, variation, and calculation of fitness value; (6)BP neural network obtains the optimal weight value and threshold value, calculates the error, and updates the weight value and threshold value; (7)When the error is less than 9%, the output simulation results, that is, the best welding route, otherwise return to continue to calculate the error, weight, threshold update and judgment operation, until the error is less than 9% or the number of iterations is maximized, so as to end.

4. MATLAB verification

Table 2 Algorithm simulation results

Algorithm name	Distance data /mm(rounded)		
GA	15351	15557	15472
	15528	15559	15478
	15409	15390	15411
BP	15075	15011	15015
	15014	14931	15045
	15054	15048	14926
GP-BP	13930	13900	13794
	13921	13956	13901
	13931	13936	13909

This paper takes single-robot welding of the car door of the body in white as the research object, and uses the software MATLAB to verify the BP neural network algorithm improved by genetic algorithm, and verifies the feasibility of the improved algorithm in the path planning of the welding robot, and it is of great significance to find the optimal path. The solder joint data are respectively imported into genetic

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algorithm, BP neural network algorithm and optimized BP algorithm, and the simulation results obtained are shown in Table 2.

It can be seen from the simulation results that the optimized GA-BP, GA and BP are obviously better. On average, GA-BP is about 7.3% higher than BP and about 10% higher than GA, and the average value can generally reflect the optimal algorithm effect. In terms of variance, the variance of GA-BP is the smallest among the three algorithms, and the difference is relatively large, which also reflects that the optimization ability of the optimized algorithm is relatively stable, and the improvement of the maximum and minimum values is not much different from the average value.

Figure 3 shows the fitness curve. In the experiment, the fitness value ranges from 0 to 50 under 100 iterations. When the iteration number starts from 40, the fitness value of the genetic algorithm is at the optimal solution in the whole process, indicating that the genetic algorithm has provided the best weight and threshold for the BP neural network algorithm stably since 40 iterations. It lays a good foundation for searching welding path planning behind BP neural network algorithm.

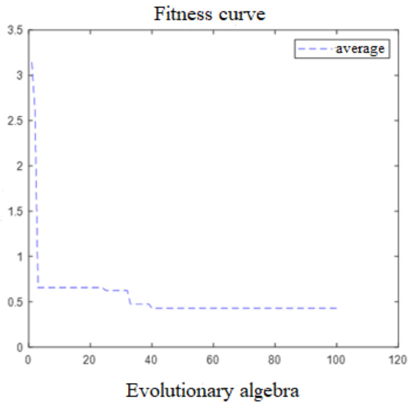

Figure 3: Fitness curve

Figure 4 shows the percentage of prediction error of the neural network. It can be clearly found from the figure that the maximum error is only 6% once, and other errors are all less than 6%, and are basically within 3%. The accuracy rate can be roughly determined above 97% from the figure, which is in line with the accuracy requirements of the experiment in this paper. It can be shown from the side that it is feasible to improve BP neural network algorithm by genetic algorithm to ind the path of welding robot.

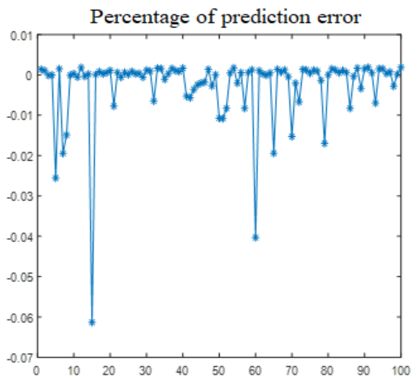

Figure 4: Prediction error

Figure 5 shows the path optimized by the improved algorithm, in which the best path is 14-12-13-11-22-15-5-6-7-2-4-8-9-10-3-17-16-18-23-24-19-20-21-25-27-26-29-30-28-1, and the shortest distance is 13794.6189mm. Based on the above three MATLAB experiment diagrams, it can be seen that the improvement of BP neural network algorithm by genetic algorithm has a great effect on the path planning of welding robots, and the error is relatively small, which is conducive to improving production efficiency.

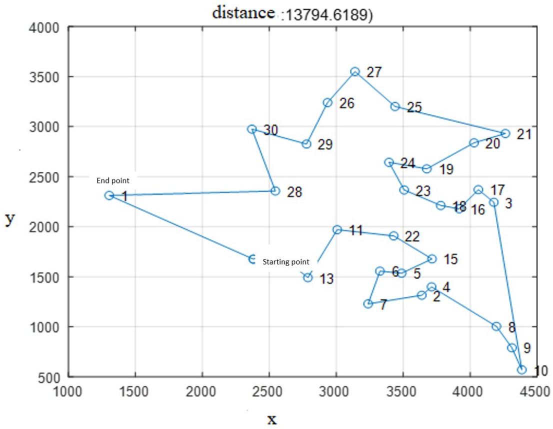

Figure 5: Optimizing the path

5. Conclusion

In this paper, the welding path planning of a single robot is studied. The weight and threshold values in the BP neural network are optimized by genetic algorithm to find the individual with the shortest welding path of the robot, so as to make up for the defect that the BP neural network is easy to fall into the local minimum. The improved algorithm is verified by MATLAB, and it can be seen from the simulation results that the improved BP algorithm improves the ability of the welding robot to find the optimal path in path planning.

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