Scholar Publishing Group
Machine Learning Theory and Practice
https://doi.org/10.38007/ML.2021.020204
ISSN 2790-0983 Vol. 2, Issue 2: 32-45

Path Planning and Positioning Technology of Cotton Picking Robot in Complex Cotton Field

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Keywords: Complex Cotton Field Environment, Cotton Picking Robot, Path Planning, Cotton Peach Positioning, Machine Vision Positioning

Abstract: Agricultural robot will become a powerful tool to save a lot of human resources in the future, which can reduce the labor intensity and cost of workers, and improve the efficiency of picking operations. The purpose of this paper is to study the path planning and positioning technology of cotton picking robot based on the complex cotton field environment. Firstly, based on the research of common path planning technology, according to the known degree of the target to the environment, the common path planning algorithms are roughly divided into two categories: global and local planning, and its characteristics, advantages and disadvantages in application are briefly analyzed. The parallel binocular vision measurement system is selected as the positioning tool of the cotton peach to simulate the complex cotton field environment. The experimental results show that after error compensation, the measurement errors in the X and Z directions are within 5mm. The measurement error prediction model for the vision system well expresses the nonlinear model between the original measurement value and the measurement error. The global optimization rate of hybrid particle swarm optimization algorithm is 50%, but the result is the most unstable; the global optimization rate of basic genetic algorithm is 20%, the global optimization rate of multi population genetic algorithm is 70%, the global optimization rate of improved multi population genetic algorithm is 90%, the global optimization rate and speed of improved multi population genetic algorithm are the best of the several algorithms studied in this paper, Therefore, this algorithm is used to optimize the path in practical application.

1. Introduction

Cotton industry, like most agricultural fields, is a labor-intensive industry. The traditional planting mode needs to invest a lot of manpower and material resources in the whole harvest cycle. Due to the development of social economy, the human cost accounts for a higher and higher proportion. Therefore, the shortage of labor force and the traditional cotton planting mode need a lot of manpower to form a sharp contrast, which eventually brings about The result is that the income of cotton industry is not high and the enthusiasm of cotton farmers is not high. Therefore, it is the general trend for the development of cotton industry to vigorously promote mechanized cotton picking.

Traditional agricultural machinery gradually began to develop in the direction of high automation and intelligence, which marks the direction of agricultural production turning to automation and intelligence. Picking has always been the most labor-intensive, energy-consuming and time-consuming link in agricultural production. Picking takes a long time, has strong seasonality, labor intensity, and high labor cost. Picking operation accounts for about 40% of the whole production process. Especially in today's society with rapid development of all walks of life, more and more other industries attract the original agricultural labor force of our country, and the trend of population aging is prominent, which leads to the lack of a large number of agricultural labor force in agricultural production, and the cost of agricultural production is also greatly increased. Therefore, it is of great significance to develop and study the agricultural robot represented by cotton picking machine.

Luo, Lufeng based on the analysis of the current situation of cotton picker in China, put forward a design scheme of intelligent cotton picker robot (ICPR) based on machine vision, including motion control subsystem and machine vision subsystem. The former takes Anchuan MP2100 as the core, based on the interface module of seed-vpm642 and 2-CCD camera, and the identification of mature cotton is the key task of the robot application Firstly, through statistical experiments and analysis, an optimized segmentation algorithm is proposed to study the cotton image recognition method based on color difference. The results show that the recognition effect of this method is good and the recognition speed is improved [1]. The agricultural sector urgently needs engineering achievements such as automation, information technology and recent robotics. D. Wang proposed a new algorithm to extract features, model and match in cotton image processing. They are artificial intelligence for robot vision, image processing for segmentation, feature measurement of invariants, dimensions and shapes, texture and scene analysis, and manipulator control with desired angle [2].

Based on the research background of the new intelligent cotton picker project, in order to improve the picking efficiency and optimize the picking path, this paper puts forward the exploration and Research on the path planning technology of the picking head of the cotton picker, and verifies the proposed planning algorithm through experiments and simulation. In order to compare the searching ability of other path planning algorithms, the searching efficiency and searching ability of hybrid particle swarm optimization algorithm in the field of path planning are studied. Hybrid particle swarm optimization (HPSO) is an improved particle swarm optimization (PSO) algorithm, which is based on the evolutionary method of particle swarm optimization (PSO). The simulation results show that the optimization rate and ability of the algorithm are different from those of the improved multi group genetic algorithm.

2. Proposed Method

2.1. Path Planning Method of Cotton Picking Robot

2.1.1. Global Path Planning

Global path planning, also known as static or offline path planning, does not require high real-time, so it is a kind of pre planning. Although the planning results are global and better, there is a problem of poor robustness [3]. Its main methods are: visual graph method, free space method, optimal control method, grid method, topology method, neural network method and so on [4].

1) Visual graph method

The visual graph method is a planning method for solving the shortest path problem [5]. In order to ensure the shortest path, the problem of path planning is to find the shortest connection segment among moving objects, obstacles and target points. But when the moving object is a particle whose size can be ignored, such path search will not only prolong the search time, but also increase the probability of collision with obstacles [6].

2) Free space law

The free space method uses some convex polygons, generalized cones and other geometric shapes to construct the space environment, and uses the connected graph to represent the planned space, and searches the connected graph of the planned object in the process of motion to complete the task of path planning. There are two steps to complete path planning with free space method: planning space problem and searching path problem [7-8].

3) Optimal control method

In order to solve the optimal control problem, it is necessary to establish a motion equation describing the controlled motion process, give the allowable value range of control variables, specify the initial state and target state of the motion process, and specify a performance index to evaluate the quality of the motion process [9-10]. The initial motion state of the problem can be described as follows:

$$x(t)|_{t=t_0} = x_0 \quad (1)$$

4) Grid method

In this algorithm, the grid density will have a great impact on the path planning of planning objects [11]. The smaller the grid density, the smaller the storage capacity, the shorter the path planning time, but the lower the resolution, the lower the accuracy of the path planning [12]; the larger the grid density, the larger the storage space, although the resolution is improved, the planning time will be very long, resulting in the algorithm search difficulty sharply increased, and the accuracy of the obstacles will also become higher [13-14]. Therefore, the grid density in the planning should be selected according to the needs.

5) Neural network method

Artificial neural network is a research hotspot in the field of artificial intelligence [15-16]. Its essence is to use the neural network algorithm to model the spatial environment to form the network operation nodes required by the algorithm, and then constrain the path points through the collision function and distance function, and obtain the function extremum to determine the planning path equation of the planning object, so as to make the planning object close to the optimal path [17]. The process can be expressed as follows:

2.1.2. Local Path Planning

Local path planning, also known as dynamic or online path planning, is generally based on sensors to obtain working environment information [18-19]. This kind of planning needs to collect environmental data online, and requires the system of planning object to have high-speed information processing ability and calculation ability, high robustness to environmental error and noise, and real-time feedback and correction of planning results. However, due to the lack of global environment information, the planning results may not be optimal, or even the correct path or complete path may not be found [20-21]. The algorithm mainly includes artificial potential field method, particle swarm optimization algorithm, neural network method, genetic algorithm, ant colony algorithm, fuzzy logic algorithm, etc [22].

1) Artificial potential field method

The basic principle of artificial potential field method is to put the planning object, obstacle and target point as a particle in the same working environment, and then define the gravitational field and repulsive field between them. In the path finding process, because the planning object is affected by the gravitational field of the target point and the repulsive field of the obstacle point, it will advance under the action of the resultant force, and the optimal path is planned by this way [23-24].

2) Particle swarm optimization algorithm

Particle swarm optimization (PSO) is an evolutionary computing technology based on swarm intelligence theory, which is derived from the foraging behavior of birds. Its basic idea is to find the optimal solution through cooperation and information sharing among individuals in the Group [25]. The algorithm starts from randomly scattering particles and evolves according to the fitness of each particle. Its basic evolution algorithm is shown in the formula.

$$v_{id}(t+1) = \omega * v_{id}(t) + \alpha * r_1(p_{id} - x_{id}(t) + \beta * r_2 * (p_{gd} - x_{id}(t))$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (2)$$

3) Genetic algorithm

Body algorithm is a kind of simulation intelligent search method based on natural selection evolution theory. It starts from randomly generating a certain number of initial population after coding, and repeats the operation steps like artificial selection evolution, and finally obtains the desired optimal solution. Genetic algorithm has many advantages. The parallel search method overcomes the local optimal problem caused by single line search method, and has good search ability. Moreover, the path search and calculation of genetic algorithm can complete the planning task independently without relying on other redundant information. However, the algorithm has many rules and elements, and has the disadvantage of low operation speed [26-27].

4) Ant colony algorithm

Ant colony algorithm is also a bionic intelligent search algorithm [28]. Ant colony algorithm is a model-based structured optimization search algorithm. It has strong robustness, excellent distributed computing, and can easily deal with constraints. It is very suitable to solve the optimization search problem of 3D space path planning.

2.2. Image Segmentation

2.2.1. RGB Color Space

RGB color space is the most common model in life. It relies on the three primary color model, with red, green and blue as the basic colors. Through the superposition of three colors, you can get any visible color [29].

At the same time, it is also the most convenient color model to express color information. In RGB color space, any visible color f can be mixed by three basic colors: red, green and blue, as follows:

$$F = r[R] + g[G] + b[B] \quad (3)$$

RGB color space can also be represented by an intuitive three-dimensional model. When the components of the three colors are all 0, they are black light. Otherwise, when the components of the three colors are all the strongest, their colors are white light.

The physical meaning of the feature components in RGB color space is clear, but the difference between the two colors is not clear. The visual difference between the two colors cannot be directly expressed by the distance in the stereo model. As a basic color model, RGB color space can derive the feature values of other color spaces.

2.2.2. Image Adaptive Threshold Segmentation Based on Otsu Algorithm

Cotton segmentation algorithm is essentially to solve the problem of image point classification, that is, to judge whether each pixel in the image belongs to cotton or background. To solve the classification problem, the most common method is the threshold based segmentation method. The common threshold segmentation method is easy to be affected by the light, and it is difficult to determine the appropriate threshold. Therefore, this paper proposes an image adaptive threshold segmentation strategy based on Otsu algorithm.

Otsu algorithm uses the clustering idea. It divides all pixels in the image into two categories: target and background according to the gray-scale characteristics of the image. The larger the variance between the background and the target, the greater the difference between the two types of pixels in the image. Therefore, the maximum variance between the categories means that the difference between the segmented target and the background information is the largest.

Assuming that the size of image I (x, y) is pixels, the segmentation threshold of background and target is t, the number of pixels whose gray value is greater than the threshold is N1, and the number of pixels whose gray value is less than the threshold T is N_2, the following relationship holds:

$$N_1 + N_2 = M \times N \quad (4)$$

If the average gray level in the target area is recorded as μ_1, the average gray level of the whole image is recorded as μ_2, and the variance between classes is recorded as μ, then:

$$\mu = \omega_1 \times \mu_1 + \omega_2 \times \mu_2 \quad (5)$$

$$g = \omega_1 \times (\mu_1 - \mu)^2 + \omega_2 \times (\mu_2 - \mu)^2 \quad (6)$$

There are:

$$g = \omega_1 \mu_1^2 + \omega_2 \mu_2^2 - (\omega_1 \mu_1 + \omega_2 \mu_2) = \omega_1 \omega_2 (\mu_1 - \mu_2)^2 \quad (7)$$

2.2.3. Image Segmentation Algorithm Based on Machine Learning

BP neural network is a multilayer feedforward network trained by error back propagation algorithm, which is one of the most widely used neural network models at present. BP network can learn and store a large number of input-output mapping relationships without revealing the mathematical equations describing the mapping relationship in advance. Its learning rule is to use the steepest descent method to adjust the weight and bias of the network through back propagation, so as to minimize the square sum of the network error.

Training a BP neural network, in fact, is to adjust the weight and bias of the network. The training process of BP neural network is divided into two parts: 1) forward transmission, layer by layer wave type transmission of output value; 2) reverse feedback, reverse layer by layer adjustment of weight and bias.

Momentum BP method introduces momentum factor $\alpha(0 < \alpha < 1)$ in the weight updating stage of standard BP algorithm, so that the weight correction value has certain inertia:

$$\Delta\omega(n) = -\mu(1 - \alpha)\nabla e(n) + \alpha\Delta\omega(n - 1) \quad (8)$$

Where, μ is the learning rate, n is the current training times, and α is the momentum factor. The update direction and amplitude of the weight are not only related to the gradient calculated this time, but also to the direction and amplitude of the last update, so that the update of the weight has a certain ability of anti-vibration and accelerating convergence.

2.3. Positioning Technology of Cotton Peach

2.3.1. Basic Principle of Visual Servo

For the agricultural harvesting robot which relies on the machine vision technology to carry on the picking operation, having the excellent vision system is the most basic guarantee that it can complete the fruit and vegetable picking. The motion control based on visual servo is to make the moving executive part of the picking robot realize the movement of any angle accurately and quickly, and finish the picking of fruits and vegetables.

Visual servo technology is to let the picking robot imitate human to obtain external visual information, and control the human body's moving organs to complete corresponding actions after brain processing and judgment. Specifically for the robot, the computer obtains the image information through the external visual sensor, uses the image processing program to identify and locate the target object, and then sends the analysis and calculation of the motion control amount to the robot motion control unit, so as to guide the robot to complete the corresponding motion and task.

According to the number of cameras in the robot vision system, only one camera is called monocular vision servo system, two cameras are called binaural vision servo system, and three or more cameras are called multi vision servo system.

According to the types of feedback error control signals, robot visual servo system can be divided into image-based and position-based visual servo control systems. The position based visual servo system needs to express the three-dimensional coordinates of the target object and the manipulator in the world coordinate system, and complete the guidance of the manipulator according to the relative coordinates in the same coordinate system. The image-based visual servo system simplifies the control process of the robot. The image features defined in the two-dimensional plane are directly used in the control of the manipulator, and the control parameters are calculated according to the image feature information, which has become a common visual servo method.

According to the position of the vision sensor installed in the robot system, it can be divided into end closed-loop and end open-loop vision servo systems. In the camera field of view, the control system that can get the image information of the end actuator and the target object at the same time is called the end closed-loop visual servo control system. In the camera field of view, only the target object can be obtained, but not the end actuator system is called the end open-loop visual servo control system.

Image-based visual servo system does not need three-dimensional position coordinates. The camera transforms the target in the space into a two-dimensional image plane through perspective imaging transformation, extracts image features that can reflect the target information, compares them with the desired image features, and sends the errors of the two to the robot joint controller, so that the robot can make corresponding adjustments.

2.3.2. Machine Vision Positioning System

Machine vision is a subject and technology that implant human vision function into intelligent robot. The purpose of its positioning system is to perceive the three-dimensional position information of the target, which is mainly divided into passive vision and active vision. Active vision refers to the use of the light source provided by the sensor itself to obtain the three-dimensional position information of the target, mainly represented by time of flight ranging

(TOF) and structured light method. Under the condition of natural light, the passive vision uses the camera to collect the object image, and then calculates the three-dimensional information of the object according to the vision algorithm, which is mainly divided into monocular vision and binocular vision.

Each of the above schemes has its own advantages and disadvantages. The basic principle of the time of flight ranging method is to get the time when the sensor receives the light returned from the object by continuously sending light pulses to the target object, so as to calculate the distance between the object and the sensor. The image resolution of this method is low, which can be used for some simple obstacle avoidance and visual navigation, It is not suitable for the occasion with high measurement accuracy requirements.

The basic principle of structured light ranging is that the sensor radiates a large number of laser speckle. These laser speckle will show different characteristics according to the distance from the sensor. Finally, these speckle with different characteristics will return to the sensor, and the distance of the target object can be calculated. Its positioning accuracy is very high, but it is easy to be affected by the light in strong light, resulting in positioning errors.

As one of the most active branches in the field of computer vision, binocular vision system simulates the method of human eyes to perceive the depth information of the world. It uses two cameras to obtain the image of the same object from different positions, and finally recovers the three-dimensional position information of the object through the parallax of two images to the same point. This method has high image resolution and good positioning accuracy, but it has high requirements for the algorithm, and it is easy to be affected by the image quality, and the effect is not good in the dark environment.

In conclusion, binocular stereo vision system does not need special light source and is not easy to be affected by strong light. On the contrary, under strong light, image quality is better and positioning accuracy is higher. Its structure is simple and its price is cheap, so it is very suitable for positioning system of cotton.

2.3.3. Target Cotton Positioning Method

In the field of view of the camera, there are many cotton with different shapes. The structure of the picking arm determines that only one cotton can be picked at a time, and the cotton target of priority picking can be selected. Therefore, determining the picking order is the necessary condition for the success of picking. In order to determine the target cotton more quickly and eliminate the target that is obviously not suitable for picking now, we set some exclusion conditions.

When the parallel picking mechanism picks cotton, it always makes the picking mouth close to the cotton position as much as possible, and the camera is installed on the front picking mouth, so that the observed cotton image range is limited, so the cotton beyond the visible range of the image need not be considered temporarily.

After the above cotton is excluded, the remaining visible cotton can be picked. Since the camera is installed at the front of the picking mouth, the picking mouth is close to the cotton when picking. Generally, the diameter of the cotton to be harvested in full bloom usually has little difference, and the outline is almost circular. With such conditions, it can be said that the cotton corresponding to the largest area outline is closest to the picking mouth, The posture adjustment of the picking mechanism is the smallest and the picking is the easiest. We can pick the target cotton first and improve the picking efficiency.

3. Experiments

3.1. Robot Controller and Body

The robot controller used is the second generation of IRC5C compact controller. The electronic limit switch and Safe Move TM of this generation of controller create excellent conditions for both flexibility and safety of the robot, greatly improve the high-speed accuracy of the robot control, and have strong adaptability to various working environments and I/O, combined with the highly plastic advanced programming preamble RAPID, It has flexible program control function. Its overall dimension is. 310x449x442mm, weight is 30kg, input voltage is single-phase 220 / 230V, frequency is 50-60Hz.

The robot body is a joint manipulator with six degrees of freedom. The repetitive positioning accuracy of irb1200-5 / 0.9 robot can reach 0.025mm, the working range can reach 901mm, the normal working load of the end manipulator can reach 5kg, and the weight of the manipulator body is 52kg. The robot body has three installation modes, i.e. wall type, ground type and ceiling type.

Combined with the comprehensive consideration of the project, the installation mode of the manipulator is ceiling installation, i.e. inverted installation. In the experiment, cotton target points are randomly distributed in a certain height range to simulate the random distribution of cotton in the actual picking environment as much as possible, and verify the path planning under the random distribution of target points in the three-dimensional space.

3.2. Experimental Setup

Also in the actual experiment, comparing the operation results of the four algorithms, each algorithm runs 10 times, through iterative optimization algorithm, the optimal path is finally output, and the control robot runs according to the optimal path. In the robot program, the running speed is set to 200 mm / s, and the turning radius of the arrival point is "fine", that is to say, it reaches the target point in the way of accurate point arrival, Stop at each target point for 0.5s and start to move to the next target point. The running time and path length of the robot in 10 times of running are counted.

Since there are 16 target points, the number of evolutionary algebra or individuals can be appropriately reduced. In the hybrid particle swarm optimization algorithm, the number of particles is set to 500, and the evolution algebra is still set to the maximum of 200 generations; in the basic genetic algorithm, the maximum evolution algebra is set to 100 generations; in the multi population genetic algorithm, the optimal individual algebra of the elite population remains the same, and the evolution ending condition is to keep 10 generations; in the improved multi population genetic algorithm, the initial temperature t_0 = 50 and the ending temperature tend = 1 are set; Then the evolution algebra is 38 generations.

3.3. Data Acquisition

The main influencing factors of stereo matching error are matching algorithm and target scene information. In order to ensure the accuracy of training results, the measurement data of cotton in natural environment should be selected in theory. However, in natural environment, it is very difficult to get the real location of cotton. Therefore, we select the experimental scene indoors to simulate the natural environment of cotton, Select the picking point of cotton as the experimental object.

Select the parallel binocular vision measurement system as the measurement tool, calculate the three-dimensional coordinates of the cotton picking point in the image, and obtain the real position of the picking point through the accurate ABB Robot, take the three-dimensional coordinates under the measurement system as the input of the prediction model, and the error between the measurement results and the real position of the picking point as the model output. In order to ensure the reliability of the results, the experiment collected a number of groups of pictures under different conditions, and finally established 200 groups of sample data, 120 groups as training samples, 80 groups as test samples.

4. Discussion

4.1. Path Planning

4.1.1. Hybrid Particle Swarm Optimization

Table 1. Experiment data of hybrid PSO

Serial number	1	2	3	4	5	6	7	8	9	10
Time (s)	6.33	6.29	6.30	6.31	6.27	6.29	6.37	6.30	6.29	6.32
Real machine operation (s)	23.29	23.29	23.29	23.29	23.80	23.98	23.98	23.48	23.98	23.29
Length (mm)	2687	2687	2687	2687	2781	2819	2819	2722	2819	2687

It can be seen from the statistical data of the 10 operations that in the 10 experiments, the number of times of finding the global optimal path is 5, and the probability of getting the global optimal solution is 50%; however, based on the later experimental data, it can be seen that the length of the local optimal solution path is 2819mm, compared with other local optimal solutions, the local optimal solution appears to be larger; therefore, it can be seen that there is a large fluctuation in the optimization results.

4.1.2. Basic Genetic Algorithm

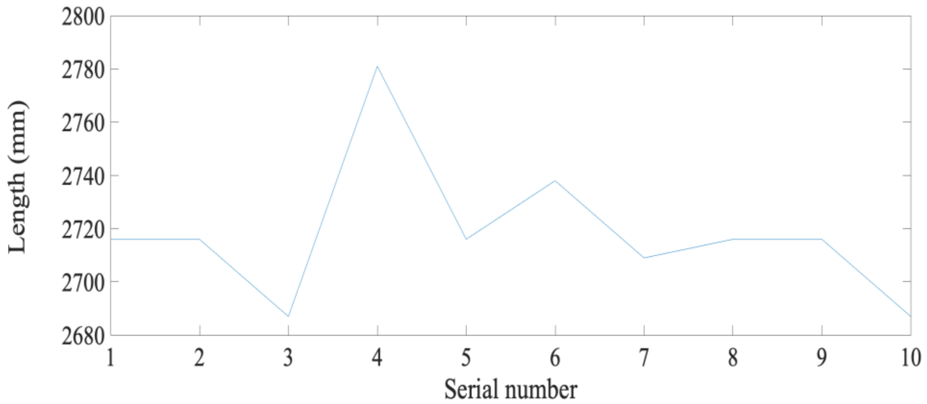

Figure 1. Experiment data of GA

In the basic genetic algorithm, in this 10 experiments, the number of global optimal solution 2687mm is twice, and the probability of global optimal solution is 20%; it is easy to fall into the local optimal solution path with path length of 2716mm, and the number of times to fall into the local optimal solution is five, as shown in Figure 1; therefore, it can be seen that the basic genetic algorithm has shortcomings in the global optimization rate.

4.1.3. Multi Population Genetic Algorithm

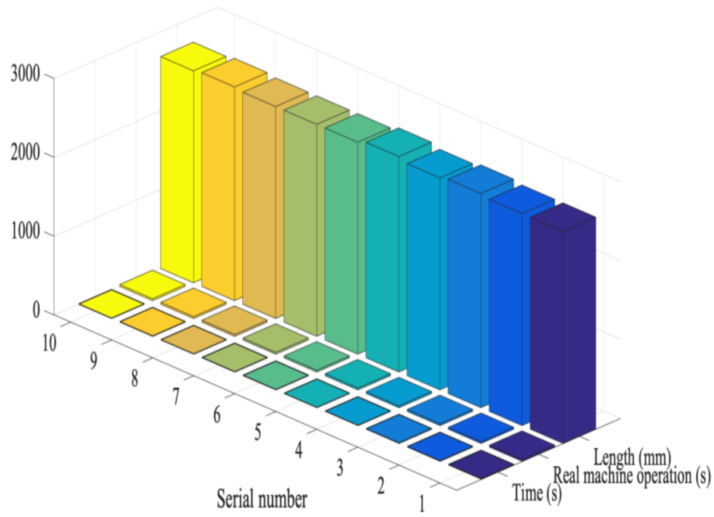

Figure 2. Experiment data of MPGA

In the multi population genetic algorithm, due to the idea of multi population co evolution, its evolution efficiency and global most worry are higher than that of the basic genetic algorithm. In the physical experiment part, the number of global optimal solutions is 7 times, the global optimal rate is 70%, which is significantly higher than 20% of the basic genetic algorithm, as shown in Figure 2; and the fluctuation amplitude of the local optimal solution is smaller than that of the basic genetic algorithm, and there is no 2781mm local optimal path.

4.1.4. Improved Multi Population Genetic Algorithm

Table 2. Experiment data of improved MPGA

Serial number	1	2	3	4	5	6	7	8	9	10
Time (s)	10.49	10.55	10.61	10.51	10.76	10.71	10.77	10.69	10.90	10.77
Real machine operation (s)	23.29	23.29	23.29	23.45	23.29	23.29	23.29	23.29	23.29	23.29
Length (mm)	2687	2687	2687	2716	2687	2687	2687	2687	2687	2687

In the 10 practical operations, the global optimal solution times are 9, the global optimal rate reaches 90%, the only local optimal path is 2716mm, which is the closest to the global optimal solution. It can be seen that the global optimization rate of the improved multi population genetic algorithm is significantly higher than other algorithms in this experiment. Finally, the comprehensive operation data of the four algorithms are shown in Figure 3:

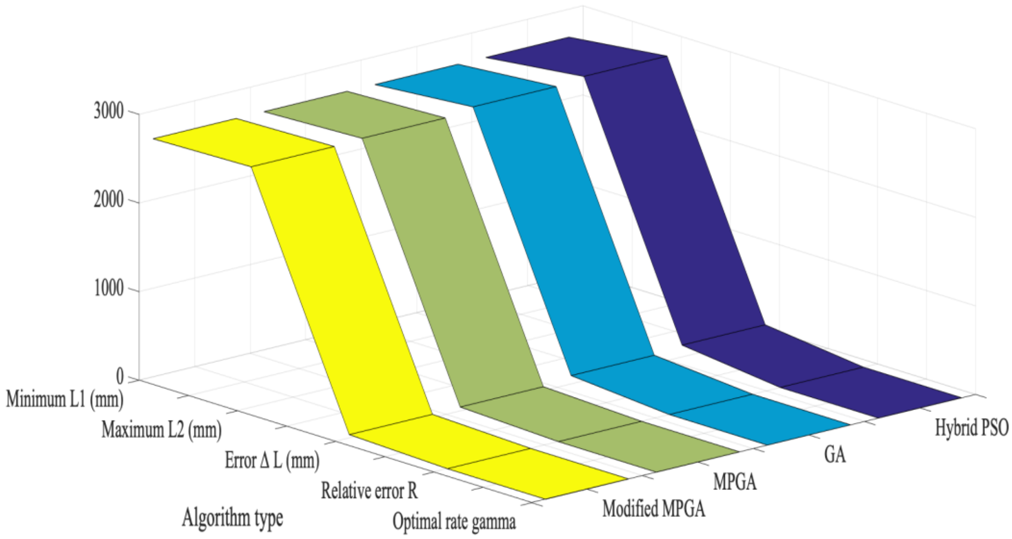

Figure 3. Data analysis results

It can be seen from the actual experimental data of the above three algorithms that the global optimization rate of hybrid particle swarm optimization algorithm is 50%, but the optimization result is the most unstable; the global optimization rate of basic genetic algorithm is 20%, the global optimization rate of multi population genetic algorithm is 70%, and the global optimization rate of improved multi population genetic algorithm is 90%. Therefore, the improvement of the global optimization rate of improved MPGA is verified by real experiments, The improvement of the performance of the proposed algorithm is proved by experiments.

Therefore, through the comparison of the real experiment, it is concluded that the improved multi group genetic algorithm is the best of the several algorithms studied in this paper in terms of the global optimization rate and speed, so this algorithm is used in the actual application of path optimization.

4.2. Positioning Error Analysis of Cotton Peach

The improved BP neural network algorithm is used to train the learning samples. The realization process of the prediction model is as follows: input the data of the learning samples into the network after normalization, set the excitation functions of the hidden layer and the output layer of the network as Tansig functions, the maximum number of iterations is 5000, the expected error is 0.001, the learning rate is 0.01, and the momentum coefficient is 0.9. In this paper, after 4259 times of training, a neural network model is established to predict the measurement error of cotton picking point in the measurement system, and the measurement result is compensated. A new measurement data is obtained as the final measurement value. The comparison between the original data in the learning sample and the error of the measurement result after compensation is shown in Figure 4.

In the X and Z direction, the measurement error of the original data has obvious deviation, including system error and random error. In the Y direction, the measurement error is mainly random error. After error compensation, the measurement error in the X and Z direction is within 5mm, and the measurement error in the Y direction is also within 8mm. This shows that the measurement of the visual system The prediction model of measurement error well expresses the nonlinear model between the original measurement value and measurement error.

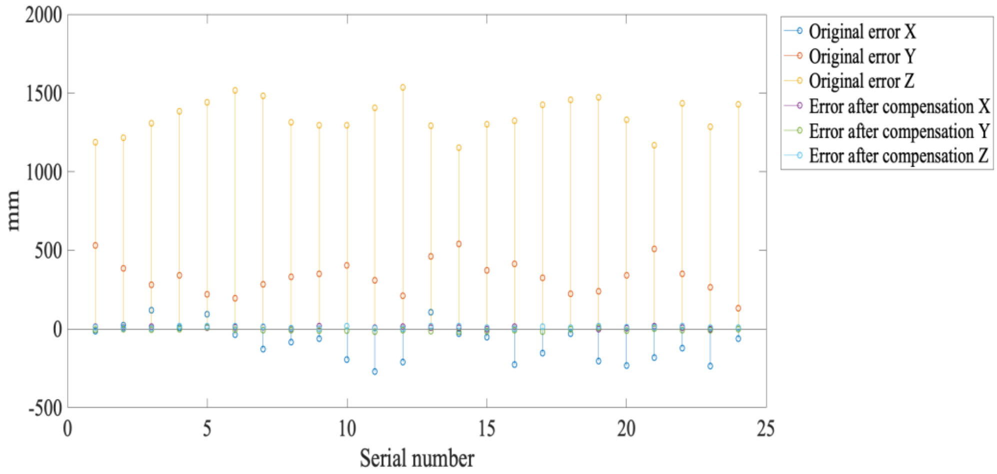

Figure 4. Comparison of measurement error between original data and compensated data

5. Conclusion

With the wide application of various types of robots, the research on robots has reached a more in-depth level. Due to the wide range of robotics, according to the needs of different applications, many research fields have been developed, among which path planning is a hot research direction. This paper first summarizes the application of robot, then through the research of common path planning technology proposed by domestic and foreign scholars, according to the known degree of the target to the environment, the common path planning algorithms are roughly divided into two categories: global and local planning, and its characteristics, advantages and disadvantages in application are briefly analyzed. At the same time, combined with the views of other scholars, this chapter puts forward some forward-looking views on the follow-up development of path planning technology.

In the complex cotton field environment, there are many gray information of the background area similar to cotton, but because of occlusion, the brightness information of some cotton areas is low, so it is difficult to completely segment cotton from the background area by threshold segmentation. This paper mainly analyzes the key vision technology of intelligent cotton picker, including cotton image segmentation algorithm, binocular vision positioning system. Based on the application of irb1200-5 / 0.9 industrial manipulator end effector cotton picking head in path planning, combined with the spatial target points randomly distributed in the field, three kinds of genetic algorithms are tested in the aspect of index performance in path optimization, which verifies the improvement of the proposed algorithm in optimization rate and other indexes.

The efficiency and ability of hybrid particle swarm optimization in the field of path planning are studied. Based on the basic particle swarm optimization (PSO) algorithm, the evolutionary method of exchanging information with individual extreme value and global extreme value is adopted for particle evolution. Combined with the crossover and mutation operations of genetic algorithm, the hybrid PSO algorithm can jump out of the local optimal solution as much as possible and search for the global optimal solution. After that, the gap between the improved GA and the improved GA is verified by experiments. Finally, it is still decided to use the improved multi population genetic algorithm in the real experiment.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1] *Luo, Lufeng, Zou, Xiangjun, Xiong, Juntao. Automatic positioning for picking point of grape picking robot in natural environment. Nongye Gongcheng Xuebao/transactions of the Chinese Society of Agricultural Engineering, 2015, 31(2):14-21(8).*

[2] *D. Wang, H. Song, D. He. Research advance on vision system of apple picking robot. Transactions of the Chinese Society of Agricultural Engineering, 2017, 33(10):59-69.*

[3] *Jie C , Zhen-Jie G . An Improved Ant Colony Algorithm and Application in Picking Robot Multi-objective Path Planning. Journal of Chinese Computer Systems, 2015, 4(4):160-169.*

[4] *C. Zhang, L. Li, Q. Dong. Recognition for machine picking seed cotton impurities based on GA-SVM model. Nongye Gongcheng Xuebao/transactions of the Chinese Society of Agricultural Engineering, 2016, 32(24):189-196.*

[5] *Krug R , Stoyanov T , Tincani V , et al. The Next Step in Robot Commissioning: Autonomous Picking and Palletizing. IEEE Robotics & Automation Letters, 2017, 1(1):546-553. https://doi.org/10.1109/LRA.2016.2519944.*

[6] *Giovanni Boschetti. A Picking Strategy for Circular Conveyor Tracking. Journal of Intelligent & Robotic Systems, 2015, 81(2):1-15. https://doi.org/10.1007/s10846-015-0242-y.*

[7] *Fakoor, Mahdi, Kosari, Amirreza, Jafarzadeh, Mohsen. Humanoid Robot Path Planning with Fuzzy Markov Decision Processes. Journal of Applied Research & Technology, 2016, 14(5):300-310. https://doi.org/10.1016/j.jart.2016.06.006.*

[8] *J. Liu, J. Yang, H. Liu. Robot global path planning based on ant colony optimization with artificial potential field. Transactions of the Chinese Society for Agricultural Machinery, 2015, 46(9):18-27.*

[9] *H. Qu, L.-W. Huang, X. Ke. Research of improved ant colony based robot path planning under dynamic environment. Dianzi Keji Daxue Xuebao/journal of the University of Electronic Science & Technology of China, 2015, 44(2):260-265.*

[10] *Tiffany Hwu, Alexander Y. Wang, Nicolas Oros. Adaptive Robot Path Planning Using a Spiking Neuron Algorithm With Axonal Delays. IEEE Transactions on Cognitive & Developmental Systems, 2018, 10(2):126-137. https://doi.org/10.1109/TCDS.2017.2655539.*

[11] *Cheng Zhang. Path Planning for Robot based on Chaotic Artificial Potential Field Method. Science Technology & Engineering, 2018, 317(1):012056. https://doi.org/10.1088/1757-899X/317/1/012056.*

[12] *Gang Wang，Jun Zhou. Dynamic robot path planning system using neural network, Journal of Intelligent & Fuzzy Systems, 2021, 40(2):3055-3063. https://doi.org/10.3233/JIFS-189344.*

[13] *WAN Xiaofeng, HU Wei, ZHENG Bojia. Robot path planning method based on improved ant colony algorithm and Morphin algorithm. Science & Technology Review, 2015, 33(3):84-89.*

[14] *Kaplan A , Kingry N , Uhing P , et al. Time-Optimal Path Planning With Power Schedules for a Solar-Powered Ground Robot. Automation Science and Engineering, IEEE Transactions on, 2017, 14(2):1235-1244. https://doi.org/10.1109/TASE.2016.2533418.*

[15] *.Khan, A. N., Cao, X., & Pitafi, A. H. Personality Traits as Predictor of M-Payment Systems: A*

SEM-Neural Networks Approach. Journal of Organizational and End User Computing (JOEUC), 2019, 31(4), 89-110. http://doi.org/10.4018/JOEUC.2019100105.
[16] *Z. Wang, Z. Feng, G. Ye. Analysis of dual-robot path planning based on artificial bee colony algorithm. Hanjie Xuebao/transactions of the China Welding Institution, 2015, 36(2):97-100.*
[17] *Wei-Jen Chen, Bing-Gang Jhong, Mei-Yung Chen. Design of Path Planning and Obstacle Avoidance for a Wheeled Mobile Robot. International Journal of Fuzzy Systems, 2016, 18(6):1-12. https://doi.org/10.1007/s40815-016-0224-7.*
[18] *F. Zhang, N. Li, R. Yuan. Robot path planning algorithm based on reinforcement learning. Huazhong Keji Daxue Xuebao (Ziran Kexue Ban)/Journal of Huazhong University of Science and Technology (Natural Science Edition), 2018, 46(12):65-70.*
[19] *Chi-Lun Lo, Chi-Hua Chen*, Jin-Li Hu, Kuen-Rong Lo, Hsun-Jung Cho, "A Fuel-Efficient Route Plan Method Based on Game Theory," Journal of Internet Technology, 2019, 20(3):925-932.*
[20] *Rayssa Almeida Garcia, Leonardo Lima Pepino Macedo, Danila Cabral do Nascimento. Nucleases as a barrier to gene silencing in the cotton boll weevil, Anthonomus grandis. Plos One, 2017, 12(12):e0189600. https://doi.org/10.1371/journal.pone.0189600.*
[21] *I. Ali, A. Shakeel, A. Saeed. Combining ability analysis and heterotic studies for within-boll yield components and fibre quality in cotton. Journal of Animal & Plant Sciences, 2016, 26(1):156-162.*
[22] *Khan, A. N., Cao, X., & Pitafi, A. H. Personality Traits as Predictor of M-Payment Systems: A SEM-Neural Networks Approach. Journal of Organizational and End User Computing (JOEUC), 2019, 31(4), 89-110. http://doi.org/10.4018/JOEUC.2019100105.*
[23] *Enrique Gino Medrano, Alois A. Bell, Sara E. Duke. Cotton (Gossypium hirsutum L.) boll rotting bacteria vectored by the brown stink bug, Euschistus servus (Say) (Hemiptera: Pentatomidae). Journal of Applied Microbiology, 2016, 121(3):757-766. https://doi.org/10.1111/jam.13197.*
[24] *Muhammad Farrukh Saleem, Muhammad Shahid, Abdul Shakoor. Removal of early fruit branches triggered regulations in senescence, boll attributes and yield of Bt cotton genotypes. Annals of Applied Biology, 2018, 172(2):224-235. https://doi.org/10.1111/aab.12415.*
[25] *Spurgeon D W . Captures of Boll Weevils (Coleoptera: Curculionidae) in Relation to Trap Distance From Cotton Fields. Journal of Economic Entomology, 2016, 109(2):676-683. https://doi.org/10.1093/jee/tov392.*
[26] *Meiling Zhang, Xianliang Song, Hong Ji. Carbon partitioning in the boll plays an important role in fiber quality in colored cotton. Cellulose, 2016, 24(2):1-11. https://doi.org/10.1007/s10570-016-1139-z.*
[27] *WU You, ZHAO Wen-qing, MENG Ya-li. Relationships between temperature-light meteorological factors and seedcotton biomass per boll at different boll positions. Journal of Integrative Agriculture, 2018, 17(6):1315-1326. https://doi.org/10.1016/S2095-3119(17)61820-3.*
[28] *Dominic D. Reisig, F. P. F. Reay-Jones, A. D. Meijer. Aggregation and Association of NDVI, Boll Injury, and Stink Bugs in North Carolina Cotton. Journal of Insect Science, 2015, 15(1):134. https://doi.org/10.1093/jisesa/iev119.*
[29] *M. Huang, L. Shi, Y. Zhang. Revised design and experiments on brush-rolling cotton harvester. Transactions of the Chinese Society of Agricultural Engineering, 2017, 33(20):41-47.*