

THREE-DIMENSIONAL PATH PLANNING OF APPLE HARVESTING ROBOT BASED ON IMPROVED GENETIC ALGORITHM

基于改进遗传算法的苹果收获机器人三维路径规划

Zeyuan YAN¹⁾ *, Ming SUN¹⁾

¹⁾ Xinxiang Vocational and Technical College, 453006, Xinxiang, Henan, China

*E-mail: yanzeyuan@xxvtc.edu.cn

Corresponding author: Dr. Zeyuan Yan

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ABSTRACT

In recent years, the problem of “rural labor shortage” in China has become increasingly serious, with a large number of young laborers going out to work, leading to an increasing amount of idle rural land. With the intensification of population aging and the reduction of agricultural labor force in China, resulting in an urgent demand for agricultural robots. With the rapid development of agricultural machinery and automation technology, agricultural robots have been continuously developing. They can better adapt to the development of biotechnology in agriculture, and traditional harvesting methods may undergo significant changes, with an increased focus on the cultivation of crops. Therefore, this paper introduces a new encoding scheme on the basis of traditional genetic algorithm (GA) and proposes an improved double encoding GA. This new encoding scheme is used on the crossover link, whereas the path node sequence encoding scheme is still used on the mutation link. The selection operation is placed after the mutation, and the merging sorting and elitist selection are performed on the parent population, crossover population, and mutation population before selection, thereby accelerating the convergence speed. On the basis of the improved GA, the three-dimensional path of the apple harvesting robot is designed and planned, with the addition of adaptive adjustment function during the progress. The experimental simulation results show that the three-dimensional path planning of the apple harvesting mobile robot based on the improved GA can minimize the number of paths and loops and well meet the operational requirements of the harvesting robot.

摘要

近年来,我国“农村劳动力短缺”问题日益严重,大量年轻劳动力外出务工,导致农村闲置土地数量不断增加。随着中国人口老龄化的加剧和农业劳动力的减少,对农业机器人的需求迫切。随着农业机械及其自动化技术的快速发展,农业机器人也在不断发展。它们可以更好地适应农业生物技术的发展,传统的收获方法可能会发生重大变化,越来越注重作物的种植。因此,本文在传统遗传算法(GA)的基础上引入了一种新的编码方案,并提出了一种改进的双编码GA。这种新的编码方案用于交叉链路,而路径节点序列编码方案仍用于变异链路。变异后进行选择操作,选择前对亲本种群、交叉种群和变异种群进行合并排序和精英选择,从而加快收敛速度。在改进遗传算法的基础上,设计并规划了苹果收获机器人的三维路径,并在过程中加入了自适应调整功能。实验仿真结果表明,基于改进遗传算法的苹果收获移动机器人三维路径规划可以使路径和回路的数量最小化,很好地满足收获机器人的操作要求。

INTRODUCTION

China is the world's largest producer of apples. With the accelerated pace of urbanization in China, a large number of young people have migrated to cities for work, resulting in a shortage of labor in rural areas. This phenomenon has led to a lack of labor for apple harvesting, and manual apple harvesting is faced with challenges, such as large workload and low efficiency. The transformation of agricultural production towards automation and intelligence is becoming urgent (Alavi A. et al., 2011). With the rapid development of information technology, microelectronics, and agricultural mechanization, research on agricultural robots has achieved significant breakthroughs and been applied in various production fields, thereby promoting the development of agricultural production towards automation and intelligent integration. Harvesting is one of the most important processes in fruit and vegetable cultivation.

Fruits and vegetables generally have a short harvest period, large harvesting tasks, and high requirements, which all result in significant physical exhaustion for harvesters (Chen M. et al., 2020). Currently, manual labor is mainly relied upon for fruit and vegetable harvesting in China, thus leading to high economic costs and low harvesting quality and directly affecting the economic income of fruit farmers (Cheng X. Y. et al., 2019). With the gradual maturity of robot technology, China has begun to increase investment in the research of agricultural robots to achieve automation in the harvesting process. This action is of great significance for liberating rural labor and improving harvesting efficiency and quality (Erhui L. et al., 2017). Path planning is the most important part of the operation of harvesting robots. The intelligence and automation of harvesting robots are mainly reflected in the planning of their motion range and workspace (Geng X. et al., 2021). Apple orchards generally have complex terrains, and harvesting robots require good path planning techniques to navigate through them to save time and optimize the three-dimensional path calculation during the operation. By utilizing environmental models, collision simulations can be performed to successfully avoid obstacles and achieve optimal motion paths for fruit and vegetable harvesting robots.

The use of robots to harvest fruit was first proposed by Schertz and Brown in the 1960s. Since then, harvesting robots have undergone over 50 years of development, from the earliest robots that took dozens of seconds to harvest fruit to those that can do it within 10 seconds today. Research on fruit-picking robots in China has mainly focused on three aspects: apple image processing, robotic action control, and harvesting path planning.

First, two studies on apple image processing have been conducted. Satyam et al. (2021) applied dynamic threshold segmentation based on OTSU to the apple fruit image, used the information correlation between images to reduce the target fruit processing area, and finally employed a fast and mean-free correlation algorithm to track and recognize the target fruit (Satyam P. et al., 2021). Haiying et al. (2018) used the red-green color difference method to segment out apples and extract their centers and radii and then established a matching strategy on the basis of area features combined with polar geometry to achieve fruit matching and positioning by using binocular vision. In the two studies, ordinary RGB images were only processed, and they had high complexity (Haiying B. et al., 2018). Luo et al. (2017) transformed the problem of apple harvesting path planning into that of 3D apple harvesting robot control. They combined binocular camera images with the apple's position information to propose an improved genetic algorithm (GA) that solved local convergence issues and increased harvesting efficiency. However, this algorithm did not consider obstacles in the actual harvesting situation, making it less suitable for complex environments, in which fruit trees grow in real-world situations (Luo L. F. et al., 2017). Wang et al. (2017) used a Kinect camera to provide color and 3D shape information and employed an efficient point cloud-based algorithm to achieve high apple recognition rates with a positioning accuracy of less than 10 mm. This approach can simultaneously recognize and process images of 20 apples in less than 1 second. Although this approach employed a depth camera for fast recognition and positioning, it did not consider path planning to improve apple harvesting efficiency (Hu Z. et al., 2022).

Second, control issues related to robotic action have become a hot research topic in the field of intelligent control (Jiang C. et al., 2021) (Kangkang M. et al., 2023) (Lee Y. et al., 2020) (Mahi Ö. K. M. et al., 2015) (Mas A. et al., 2020). Research on apple-picking robots based on deep reinforcement learning (DRL) architecture has emerged as a topic among scholars, but no mature theoretical framework for controlling apple-picking robots based on DRL architecture has appeared yet. Therefore, DRL-based apple-picking robots remain at an exploratory stage domestically and internationally. Li et al. (2019) proposed a trajectory planning method for apple-picking robots on the basis of stepwise transfer strategies. This method utilized the idea of transfer learning to transfer optimal strategies for trajectory planning from obstacle-free scenarios to scenarios with single obstacles, and then to scenarios with mixed obstacles, thereby improving the training efficiency and network performance of DRL algorithms (Li S. Y. et al., 2019). Although relatively few direct achievements related to DRL apple-picking robots were gained since the advent of DRL algorithms, some theoretical explorations have been conducted on DRL fruit-picking robots with similar content. For example, Tang et al. (2020) proposed a path planning method for orchard robotics with fast collision-free path generation on the basis of DRL for watermelon harvesting (Tang Y. et al., 2020). Cao et al. (2019) proposed a path planning method for virtual orchard robotics on the basis of DRL with obstacle avoidance capabilities. This method can achieve fast trajectory planning for a large number of harvesting tasks, and it is suitable for tasks where the positions of obstacles are unknown or change over time. The approach achieved an average success rate of over 96.7% in virtual orchard scenarios with variously placed obstacles (Cao X. et al., 2019).

Third, research on path optimization for fruit-picking robots has mainly focused on methods, such as topological methods (Paull M. L. et al., 2018), visibility graphs (Perveen K. et al., 2023), grid-based methods (Mohanasundaram S. et al. 2021), and potential fields methods (Ratta Q. et al., 2021). Progress has been made in research on path planning for mobile robots in terms of algorithms for global path planning and obstacle avoidance techniques (Swetha K. et al., 2021). However, path optimization is a key factor in determining harvesting efficiency (Mousavi S. M. et al., 2017), and it remains an understudied area. GAs have been widely used to solve optimization problems, such as two-dimensional path planning (Sarangapani C. et al., 2016).

In the present paper, GAs were applied to optimize three-dimensional paths for apple picking. An improved GA that updates information based on limited domain information and adaptive updating rules were present to enhance convergence speed and solve issues, such as premature convergence and local optima solutions. A code for the path optimization algorithm was written, and its performance in three-dimensional path planning for apple picking was validated using both basic GAs and the improved GA approach (Castro. et al., 2020).

MATERIALS AND METHODS

In general, the three-dimensional path optimization problem for apple picking robots can be described as follows: An apple picking robot needs to pick n apples, and the distance between the picked apples is known. If the apple picking robot only picks each picking object once, the shortest path for the apple picking robot starts from a certain picking point and ultimately returns to the starting point. The sequence numbers of n picking objects is recorded to form a set, and the circuit that the apple picking robot passes through after picking n picking points is recorded.

$$P = \{p_1 \rightarrow p_2 \rightarrow \dots \rightarrow p_n \rightarrow p_1\} \quad (1)$$

where $p_i \in N$, $p_i \neq p_j (i \neq j)$, $i = 1, 2, 3, \dots, n$, if the distance matrix between picking points is $D = (d_{ij})_{n \times n}$, then the mathematical model of the three-dimensional path optimization problem of the apple picking robot can be expressed as follows:

$$\min f(P) = \sum_{i=1}^{n-1} d_{p_i, p_{i+1}} + d_{p_n, p_1} \quad (2)$$

Among them $f(P)$, represents the total path length of the apple picking robot's walking path.

Genetic algorithm

GA was proposed by Professor J. Holland in the 1970s, and it is commonly referred to as traditional GA or standard GA (Xiaoming Y. et al., 2017). It simulates and draws inspiration from the phenomena of gene inheritance, crossover, and mutation in the process of natural biological evolution and designs the three main stages of individual selection, crossover, and mutation in the population from an algorithmic perspective. The retained and inherited individuals are those that have been evaluated as optimal through adaptability, reflecting the mechanism of "survival of the fittest, survival of the fittest" in the biological world. They continue to iterate and evolve in accordance with this until a certain convergence condition is met (Xiaoqiang S. et al., 2019). GA is a probability search algorithm with global optimization capabilities, high universality, parallelism, and robustness. It has been successfully applied to solve path optimization problems, and its basic steps are as follows:

(1) The gene encoding scheme and set algorithm parameters are determined. The gene encoding scheme is designed on the basis of the feasible solution characteristics of the optimization problem, and its encoding structure and values are usually used for the path optimization problem of apple picking robots, which is based on nonrepeating sequence encoding of path nodes. The algorithm parameters mainly include population size, number of iterations, crossover probability, and mutation probability.

(2) The population is initialized, that is, a group of individuals is generated in accordance with the requirements of the genetic encoding scheme and the size of the population.

(3) The quality of individual populations is evaluated using fitness functions. Among them, the fitness function is usually constructed on the basis of the objective function of the optimization problem.

(4) Selection operation refers to selecting a sufficient number of individuals in accordance with a certain strategy on the basis of their fitness to form an offspring population. The better the individual's fitness, the greater the probability of being selected. The commonly used selection strategies include roulette wheel strategy, elite strategy, and ranking optimization strategy.

(5) Cross operation refers to the random pairing of individuals in the offspring population, where genes are randomly exchanged on the basis of crossover probability. This step gives individuals the opportunity to obtain more excellent genes, thereby enhancing the diversity of the offspring population and maintaining strong search and optimization abilities.

(6) Mutation operation refers to randomly selecting some offspring individuals, changing certain gene loci of the individual based on the probability of mutation, and causing them to mutate into new individuals, thereby expanding the search and optimization scope.

(7) Steps (3)–(6) are repeated until the genetic evolution operation reaches the termination condition of the iteration. Traditional GAs have a universal algorithm framework with clear steps, and they allow for self-designed processes. However, they also have drawbacks, such as slow convergence speed or premature convergence, leading to local optima. Therefore, improving the above steps has always been the main direction for improving algorithm performance.

Dual Encoding Improved GA

When GA is used to solve the path optimization problem of apple picking robots, the most commonly used genetic encoding scheme is the sequence encoding of path nodes composed of each picking point. Its advantages are intuitiveness, strong correspondence, and easy-to-calculate individual fitness. The disadvantage is that if individuals directly cross operate, it can easily lead to duplicate genes or gene deletions between two individuals, thereby becoming illegal individuals. This article proposes a reproducible natural number encoding with a one-to-one mapping relationship with the sequence encoding of path nodes. Therefore, in this paper, this new encoding scheme is introduced on the basis of traditional Gas, and a dual encoding improved GA is proposed. This new encoding scheme is adopted in the crossover stage, whereas the path node sequence encoding scheme is still used in the mutation stage. The selection operation is placed after the mutation, and the parent population, the crossover population, and the mutated population are merged, sorted, and selected by elites before selection to accelerate the convergence speed. The following are specific instructions for each step of the algorithm in this article.

The sequence encoding of path nodes is the encoding corresponding to equation (1), which is usually represented by non-repeating natural number encoding. In actual coding, the starting point picking point number at the end of equation (1) can be removed. For example, when $n=6$, both sequences are valid encodings:

$$P_1=\{2,5,3,1,4,6\}, P_2=\{3,2,5,6,4,1\}$$

The basic idea of repeatable natural number encoding is to uniquely map the sequence encoding of path nodes to repeatable natural number encoding, as follows:

$$f : P \rightarrow Q$$

$$P = \{p_n, p_{n-1}, \dots, p_2, p_1\}$$

$$Q = \{q_n, q_{n-1}, \dots, q_2, q_1\}$$

The mapping rule is: equal to the number of codes on the left side of the code with a value of i in P (denoted as) that are smaller than that value. To facilitate code generation and conversion

$$t_j = \begin{cases} 1, & p_j < p_k, j = n, n-1, \dots, k+1 \\ 0, & \text{else} \end{cases} \tag{3}$$

The calculation formula for then is

$$q_i = \sum_{j=k+1}^n t_j, i = 1, 2, \dots, n. \tag{4}$$

For example, mapping the above encoding results in: because in the encoding, the number of codes on the left side of code 6 that are smaller than it is 5, and the other numbers are also similar. Similarly, encoded mapping codes. Analyzing the mapping code q , it can be found that it has the following characteristics:

$$q_1 \equiv 0, 0 \leq q_i < i \tag{5}$$

Therefore, the mapping code q can also remove bits and be represented as:

$$q = \{q_{n-1}, \dots, q_2, q_1, 0 \leq q_i \leq i\} \tag{6}$$

In summary, the encoding q can be obtained from the mapping of encoding p in accordance with Equations (5) and (6), or it can be directly randomly generated according to equation (6).

Therefore, the second encoding scheme has the characteristics of simple mapping rules, flexible generation methods, and repeatable codes. It can be highly utilized in solving the problem of apple picking robots by using GAs. For the convenience of GA calls, the following is an algorithm for converting these two codes to each other.

According to the design concept of improving GA with dual encoding, genetic evolution will be completed in the order of “crossover mutation selection”. During this period, only reproducible natural number encoding is used in the crossover stage, whereas path node sequence encoding is still used in the remaining stages, so that individual fitness calculation and mutation operation are not affected. Due to the lower complexity of encoding conversion than crossover operation, using two encoding conversions to complete one round of crossover operation is worthwhile for genetic evolution operations. Therefore, the initial population of the algorithm in this article is initialized on the basis of the sequence encoding of path nodes (excluding the return starting point at the end). For example, when the number of picking points $n = 6$, the gene encoding of each individual in the population is a sequence encoded by natural numbers. The task of constructing fitness functions with random nonrepeating permutations of 1–6 is to evaluate the quality of individual populations. For the path optimization problem of apple picking robots, the shorter the circuit of the apple picking robot is, the better the individual. Therefore, this algorithm takes the objective function as the fitness function of the algorithm, that is, for any individual P in the population, its fitness is:

$$fit(P) = \sum_{i=1}^{n-1} d_{p_i, p_{i+1}} + d_{p_n, p_1} \quad (7)$$

The crossover operator of GAs attempts to retain more excellent genes and improve individual fitness. Usually, the crossover operator needs to consider the sequence of genes and the content of genes themselves. In this regard, the crossover strategy designed by the algorithm in this article is based on the second encoding method, which selects the following three operators, in turn, to perform crossover operations on individual populations:

(1) Two-point crossing refers to randomly generating two gene points and exchanging the genes at the corresponding positions of two individuals.

(2) Fragment crossing refers to the random generation of two gene points, where the gene fragments between two individuals are exchanged as a whole.

(3) Consistent crossover refers to the exchange of each corresponding gene point between two individuals based on the probability of crossover.

The above three crossover operators gradually increase the degree of modification of individual excellent genes, and their effect on the fitness of new individuals after crossover increases in turn. By taking turns using them, the degree of evolution of population genes can be reasonably controlled, making the crossover effect of the algorithm more significant. Before the above crossover operator is executed, the “ p to q ” algorithm of encoding conversion must be called first to convert the path node sequence encoding p into a repeatable natural number encoding q . After the crossover operation is completed, the “ q to p ” algorithm is called to convert the encoding q into encoding p .

In genetic algorithm, mutation operator is mainly used to maintain population diversity and ensure the local optimization ability of the algorithm, especially in the late stage of genetic evolution. Because the designed crossover operator has significant crossover effect on individual populations and plays a part in evolution. Therefore, the mutation strategy of the algorithm can avoid damaging the cross effect. That is, one of the following four mutation operators is directly selected to make the parental population mutate a single population:

(1) Gene transposition refers to the direct exchange of genes at two random locations in an individual to be mutated.

(2) In gene reverse order, a random gene fragment is placed in reverse order from the individual to be mutated.

(3) In gene right shift, a random gene segment in the mutated individual is rotated to the right once.

(4) In gene left shift, a random gene segment in the mutated individual is rotated to the left once.

The above four mutation operators can have a significant effect on individual genes, causing changes in the path of apple picking robots and thereby increasing population diversity. Therefore, their comprehensive application could improve the mutation effect of the algorithm.

By selecting operators, GAs can evolve towards ideal solutions. Traditional selection operators, such as roulette strategy and tournament strategy, fully embody the “survival of the fittest” mechanism of GAs.

However, in situations where individual evolution efficiency is not high, the convergence speed is slow, and even premature convergence occurs. Considering the above factors, the crossover and mutation operators of the algorithm in this paper operate directly on the parent population, which can enable individuals to fully evolve. Therefore, the design of the selection operator mainly draws on the idea of elite individual selection. The specific approach is to merge the offspring population of the parent population and the mutated offspring population, calculate the individual fitness values of the merged population in ascending order, and select the top N (population size) individuals as the next-generation population directly. The above selection operator is executed after mutation operation. Compared with traditional selection operators, this selection operator combines the population of parents and children for selection, thus allowing individuals with sufficient evolution in various stages of inheritance to be selected and inherited into the next generation. Therefore, the convergence speed of inheritance is faster.

RESULTS

Experimental simulation and analysis were conducted from three aspects to test the performance and effectiveness of dual encoding improved GA. First, the population quality and diversity of the dual encoding improved GA and the traditional single encoding GA was compared. Then, the dual encoding improved GA, other GAs, and other intelligent heuristic algorithms were compared in terms of solution performance.

Experimental Environment and Parameter Settings

The experimental hardware environment is Intel Core i7-7200U CPU/8GB, the operating system is Windows 10, and the programming environment is Matlab2018a. The population size and iteration times of GA were set to $N = 30$ and $G = 400$, and those of the double coding improved GA were set to $N = 50$ and $G = 800$, respectively. The required crossover probability and mutation probability for the algorithm were set to $P_c = 0.8$ and $P_m = 0.1$, respectively. The node of the apple picking robot's operation area was set as 0, and its coordinate value is (0,0,0). The orchard has 29 picking points, represented by corresponding coordinates X, Y, and Z values. The number of each picking point is known (Table 1). The three-dimensional distribution of apple picking points is shown in Figure 1.

Table 1

Apple Picking Point Information Table

| Picking point number | Coordinate X | Coordinate Y | Coordinate Z | Picking volume | Picking point number | Coordinate X | Coordinate Y | Outbound quantity | Picking volume |
|----------------------|--------------|--------------|--------------|----------------|----------------------|--------------|--------------|-------------------|----------------|
| 0 | 0 | 0 | 0 | 0 | 15 | 40 | 40 | 1.7 | 1 |
| 1 | 13 | 29 | 1.2 | 1 | 16 | 20 | 49 | 1.6 | 1 |
| 2 | 32 | 44 | 2.3 | 1 | 17 | 32 | 55 | 1.5 | 1 |
| 3 | 8 | 23 | 1.1 | 1 | 18 | 17 | 17 | 1.9 | 1 |
| 4 | 5 | 57 | 1.8 | 1 | 19 | 24 | 9 | 2.9 | 1 |
| 5 | 47 | 58 | 2.2 | 1 | 20 | 31 | 98 | 1 | 1 |
| 6 | 44 | 78 | 2.3 | 1 | 21 | 4 | 35 | 2.2 | 1 |
| 7 | 23 | 7 | 1.8 | 1 | 22 | 11 | 51 | 2 | 1 |
| 8 | 14 | 16 | 2.2 | 1 | 23 | 25 | 43 | 2.1 | 1 |
| 9 | 30 | 92 | 1.8 | 1 | 24 | 50 | 14 | 1.1 | 1 |
| 10 | 15 | 14 | 2.5 | 1 | 25 | 36 | 96 | 1.3 | 1 |
| 11 | 5 | 91 | 2.8 | 1 | 26 | 49 | 79 | 2.3 | 1 |
| 12 | 9 | 0 | 1.1 | 1 | 27 | 38 | 71 | 2.7 | 1 |
| 13 | 50 | 36 | 1.3 | 1 | 28 | 42 | 31 | 2.4 | 1 |
| 14 | 33 | 64 | 3 | 1 | 29 | 28 | 98 | 1.5 | 1 |

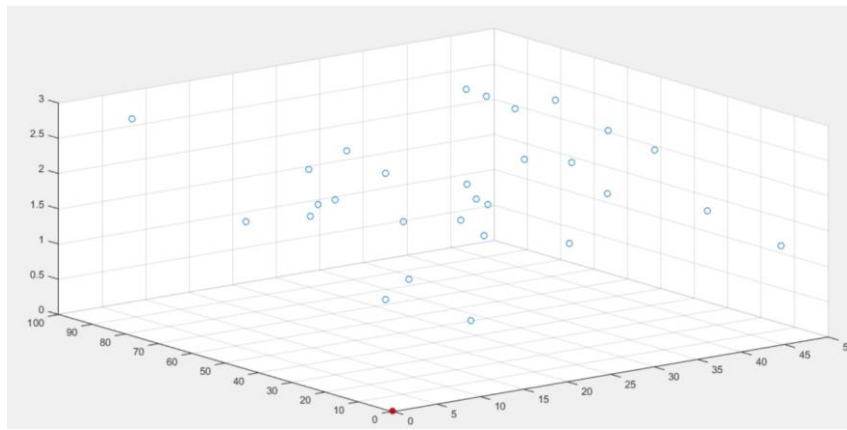


Fig. 1 - 3D Distribution of apple picking points

Experiment and Comparative Analysis

A dual coding improved GA was used to solve the three-dimensional path optimization model of apple picking and agricultural transportation robots, with a maximum iteration number of 2500 and a total travel distance as the objective function. A satisfactory solution can be obtained by solving the model, with a total travel distance of 1901.54 m for the robot. This algorithm took 61.62 seconds. The path map of the dual coding improved GA is shown in Figure 2, the convergence curve of the dual coding improved GA is shown in Figure 3, and the output result of the dual coding improved GA is shown in Figure 2.

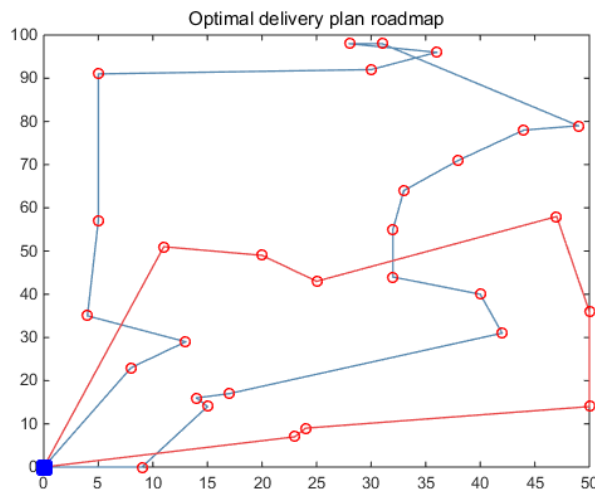


Fig. 2 - Path map of dual encoding improved genetic algorithm

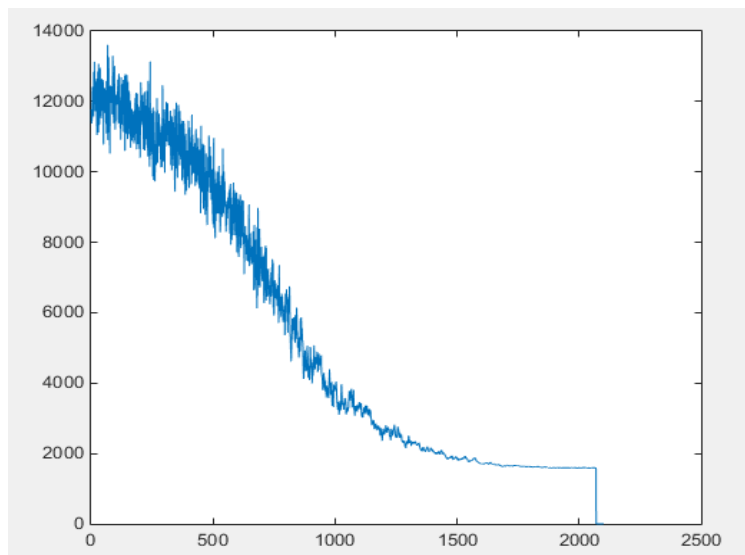


Fig. 3 - Convergence curve of dual encoding improved genetic algorithm

Table 2

Output results of double encoding improved genetic algorithm

| Picking path | Total Distance | Algorithm convergence time |
|---|----------------|----------------------------|
| 0→12→10→8→18→28→15→2→17→14→27→6→26→2 0→29→25→9→11→4→21→1→3→0 | 1901.54m | 61.62s |
| 0→7→19→24→13→5→23→16→22→0 | | |

Table 2 shows the output results of the dual coding improved genetic algorithm. A traditional GA solution model was designed to further verify the effectiveness of the dual encoding improved G. With the initial cost and parameters unchanged, the total travel of the harvesting robot is 2226.61 m. The algorithm took 88.85 seconds. The path diagram of the traditional GA is shown in Figure 4, the convergence curve of the traditional GA is shown in Figure 5, and the output results of the traditional GA are shown in Table 3.

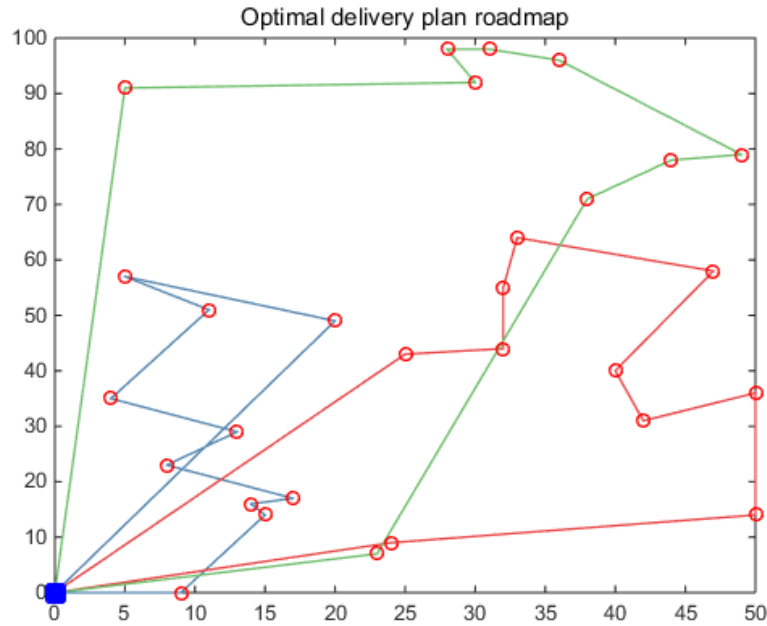


Fig. 4 - Traditional genetic algorithm path map

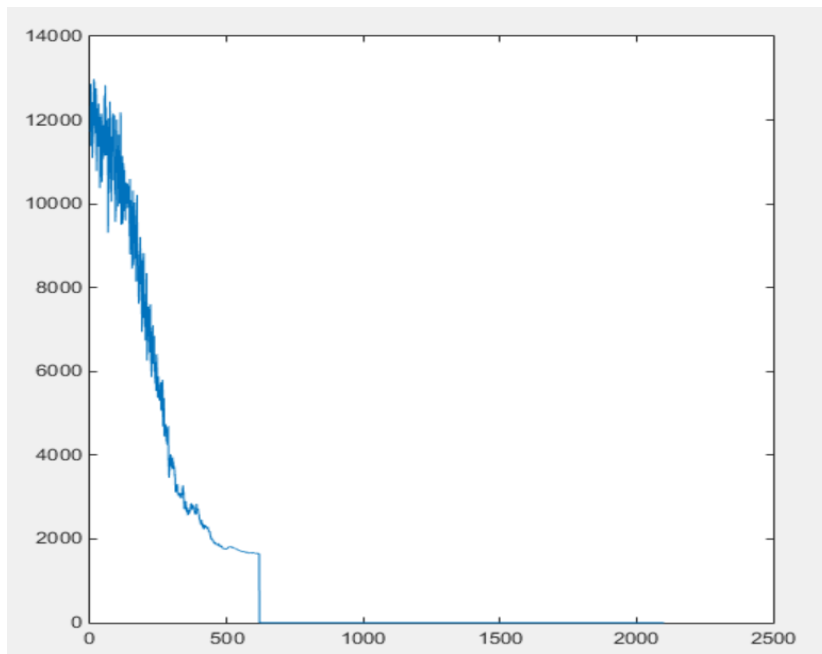


Fig. 5 - Convergence curve of traditional genetic algorithm

Table 3

| Optimal Service Path | | |
|---------------------------------|----------------|----------------------------|
| Picking path | Total Distance | Algorithm convergence time |
| 0→12→10→8→18→3→1→21→22→4→16→0 | 2226.61m | 88.85s |
| 0→23→2→17→14→5→15→28→13→24→19→0 | | |
| 0→7→27→6→26→25→20→29→9→11→0 | | |

As shown in Table 3, the double coding improved GA has strong exploratory and convergent properties, and the value of the objective function is better than that in traditional GAs. The dual coding improved GA outperformed traditional GAs in terms of robot quantity, travel distance, and algorithm time. The traditional GA requires three paths to complete the apple picking task, whereas the dual coding improved GA only requires one path to complete the same task, thereby increasing the efficiency by 50%. In terms of the travel distance of the harvesting robot, the traditional GA has a total travel distance of 2226.61 m, whereas the double coding improved GA has a total travel distance of 1901.54 m to complete the same task. In terms of algorithm time, the traditional GA has a convergence time of 88.85 seconds, whereas the double coding improved GA has a convergence time of 61.62 seconds, which improves the algorithm efficiency by 30.64%.

CONCLUSIONS

In response to the problem of long walking paths and low efficiency of picking robots during the picking process, a three-dimensional optimal path planning for apple picking robots based on a dual coding improved GA was designed. The optimization problem of apple picking paths was transformed into a Travel Salesman Problem, local planning adjustments were made in real-time on the basis of the actual problems, and the optimal path was determined based on the number of robot turns. During the research process, MatLab was used for simulation experiments and analysis, and improvement plans were proposed to significantly improve the efficiency of robot operation. It enhances the stability during the operation process, saves considerable time and costs for fruit farmers, and confirms the reliability of the path planning scheme. Through algorithm research, software development and debugging, and simulation experiments, the following conclusions were drawn:

Under the general framework of GA, the optimization problem of apple picking path is transformed into a Travel Salesman Problem. A gene repeatable coding scheme is introduced for the optimization problem of apple picking path, making the design of crossover operators more flexible and convenient. This outcome not only avoids the generation of illegally encoded individuals but also greatly enhances the quality and diversity of the population. Compared with the time required for encoding conversion added in the algorithm, the experiments showed that this approach is worthwhile.

Selecting multiple crossover and mutation operators, in turn, and applying them to different individuals enhance the algorithm's local optimization ability, especially in the later stages of iteration, which helps the algorithm avoid premature convergence and jump out of local optima. These improvement ideas have positive significance in promoting the application and development of GAs. Combined with other strategies of GAs, they can even further effectively solve the optimization problem of large-scale apple picking paths, thereby providing more decision-making basis for production practice in the future.

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