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A Fast Path Planning Method of Seedling Tray Replanting Based on Improved Particle Swarm Optimization

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Abstract: In the factory nursery, qualified seedlings can be used to replant unqualified seedlings or missing seedlings in the seedling tray through automatic transplanters. Due to the random positions of unqualified and missing seedlings, the end effector of the automatic replanting machine spends substantial time shuttling between the supply tray and the target tray to complete the replanting task. Therefore, we proposed a fast path planning method based on improved particle swarm optimization and compared it with the fixed sequence method and genetic algorithm in experiments with different replanting numbers in different tray types. The experiment shows that the improved particle swarm optimization algorithm and genetic algorithm can shorten the length of the replantation path by about 20% compared with the fixed sequence method, and the running time of the improved particle swarm optimization algorithm is 57.63% less than the genetic algorithm on average. The replanting path optimization method based on improved particle swarm optimization designed in this research can significantly optimize the length and time of the replanting path of the seedling tray, improve the efficiency of the replanting operation, and meet the real-time requirements.

Keywords: plug seedling replanting; fixed sequence method; genetic algorithm; particle swarm optimization; path planning

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1. Introduction

Traditional seedlings are mainly raised by the bed-and-soil method, which has the disadvantages of large floor space, unguaranteed seedling and emergence rates, large number of seeds used, and scattered seedlings. Factory nursery refers to the use of a seedling tray, in the production of seedlings with modern machinery and advanced nursery facilities, fertilization and irrigation technology, link control technology and information management technology, and other advanced technical means throughout the entire process of seedling production, in a modernized model of seedling production, management, and operation, to achieve the large-scale production of seedlings [1]. Compared with traditional seedling production methods, factory seedling production can effectively shorten the seedling time, improve seedling efficiency, enhance seedling quality, and reduce production costs through efficient and uniform management [2]. Since the 1980s, based on the digestion and absorption of mature foreign seedling technology, China has gradually carried out research on factory seedling production technology, which has been established in China for more than 40 years [3]. The development plan for the vegetable industry of the Ministry of Agriculture points out that in 2020, the sown area of vegetables in China will reach 15.66 million hectares, the annual output will exceed 580 million tons, and the annual per capita possession will reach 400 kg [4]. The current national intensive seedling supply is about 100 billion seedlings, much lower than the national demand for the seedling-replanted vegetable seedlings of 680 billion seedlings [5]. Thus, it can be observed that the current market for vegetable seedling nurseries in China is huge, the traditional nursery method has been unable to meet the market demand, and the factory seedling tray nursery has a broad development prospect [6–11].

The low productivity, high labor intensity, and difficulty in realizing large area operation by manual work method have hindered the development of factory nursery technology to some extent; therefore, it is inappropriate to use the manual method for replanting tasks in factory nurseries. In recent years, with the development of computer technology, machine learning algorithms have been more and more widely used in different fields [12,13], while increasingly more scholars are applying them to automatic replanting machines [14–17]. In 1987, Kutz et al. of Auburn University, USA [18] designed a method to replant potted seedlings by attaching a seedling grabber to a Puma 560 robot, which could replant 36 seedlings in 3.3 min by combining L-shaped replanting path control from a 392-hole seedling tray to an adjacent 36-hole seedling tray. In 2001, K.H. Ryu et al. [19] designed and developed a replanting robot based on a Cartesian coordinate system for cucumber and tomato seedlings. In 2009, Xiaopeng Wang et al. [20,21] designed a transplanter for replanting seedlings in various sizes of seedling trays at Nanjing Agricultural University and used trajectory planning to determine the velocity, position, and acceleration parameters of the end effector. In 2013, Xiu Wang et al. [22], from the Beijing Agricultural Intelligent Equipment Technology Research Center, designed a new sorting transplanter with a failure rate of less than 10% for the identification of high-quality pepper seedlings on five different seedling trays and a measurement error of about 5 mm for seedling height, and a replanting success rate of 90.0% at a speed of 700 cycles per hour on a 6 × 12-hole seedling tray. In 2016, Hanping Mao and others [23] from Jiangsu University developed a light and simple automatic replanting machine with replanting efficiency of 1025 and 1221 plants/hour for 72- and 128-hole seedling trays seedlings, respectively, with an average replanting success rate of 90.70% and seedling bowl clamping fragmentation rate of less than 5%, achieving better automatic seedling picking and replanting. In 2017, based on a three-degree-of-freedom Delta parallel mechanism and pneumatic seedling picking claw, Jianping Hu and others [24] designed a high-speed pot seedling replanting robot, and the qualification rate of pot seedling replanting was 95.5% and the qualification rate of replenishment seedling was 92% when the maximum acceleration was equal to 30 m/s^2. In 2018, Luhua Han et al. [25] developed a greenhouse seedling multi-tasking robot replanting workbench, and when the working efficiency was set to 960 plants/hour/hand claw, the replanting success rate was up to 90%.

Automatic transplanters can efficiently replace unqualified seedlings with qualified seedlings, replenish missing seedling trays, and can also perform pre-processing for most farm tasks. During the work of the transplanter, the efficiency of the work can be enhanced without increasing the cost by planning the movement path of the gripper. To achieve this goal, it is necessary to carry out reasonable planning for replanting operations. In 2013, Junhua Tong et al. [26] proposed a model algorithm based on a genetic algorithm suitable for solving the replanting path optimization problem; when replanting a total of 50 potted seedlings, the optimization magnitude was greater than 8.5%, the path length was shortened by at least 3.7 m, and the average computation time of this algorithm was 0.65 s. In 2015, Zhuohua Jiang et al. [27] proposed a replanting path planning method based on an ant colony algorithm (ACA), when using 200 hole-size seedling trays, the average length of ACA was reduced by 6000.9 mm compared with GA, and the average running time of GA and ACA in MATLAB was 0.32 s and 0.94 s, respectively. In 2016, Junhua Tong et al. [28] proposed a method for optimizing the thinning replanting path of greenhouse potted seedlings based on the greedy algorithm. In the thinning path planning of dense seedling trays, the optimal scheme (GAS3) was optimized by 106% compared with the fixed-order scheme, and the average computation time of the algorithm was 0.84 s. The greedy algorithm scheme can optimize the thinning replanting path length and meet the real-time requirements of replanting operations, thus improving the replanting efficiency. In 2017, Leiying He et al. [29] proposed a greedy genetic algorithm by fusing the characteristics of greedy algorithm and genetic algorithm, and the greedy genetic algorithm optimized the planning path length by 33.8%~41.3% compared with the fixed order method, and the optimized length lengthened with the increase of the number of cavities; the operation time of greedy genetic algorithm was 1.81 s and the operation time of genetic algorithm was 5.59 s, respectively. In 2018, Shoujiang Xu et al. [30] designed a model algorithm based on the hybrid frog-hopping algorithm for the automatic bowl-shifting problem during replanting operations. The path of the end effector in the replanting operation was optimized. In 2019, Ronghua Ji et al. [31] integrated the advantages of the ant colony algorithm and the greedy algorithm to address the problem that the convergence speed of the ant colony algorithm is slow and it is difficult to reach the global optimum due to the increase in the number of holes in the seedling tray, and proposed a greedy and colony-based automatic replanting path segmentation-seeking algorithm (GACS algorithm) for potted seedlings. The experimental results show that the running time of the GACS algorithm is reduced to within 20% of that of ACO, and the path optimization length and convergence speed of the algorithm are better than those of ACO for 50-, 72-, and 128-hole-size seedling trays.

Current researchers mainly use the greedy algorithm [32], ant colony algorithm [33], genetic algorithm [34], and other intelligent algorithms for path planning on the length of the replanting path of the seedling tray; compared with the traditional fixed-order method, replanting path length has been substantially optimized to shorten the replanting time and improve the replanting efficiency. However, the intelligent algorithms require a certain amount of computational time cost, and the replanting path of the next target tray needs to be replanted after the current target tray replanting, so shortening the computational time of the path planning algorithm can improve the overall efficiency of seeding replanting to a certain extent.

The purpose of this study is to design a path planning method for an automatic replanting machine that shortens the computation time of the path planning algorithm, expecting to shorten the algorithm running time while ensuring the algorithm's path length optimization capability to meet the requirements of high accuracy and speed of the automatic replanting machine.

2. Materials and Methods

To carry out the subsequent work in an orderly manner and verify the effectiveness of the improved particle swarm algorithm, an overall planning of the whole work is carried out in this paper, and the subsequent work will be carried out in an orderly manner according to the planning; the flow diagram is shown in Figure 1.

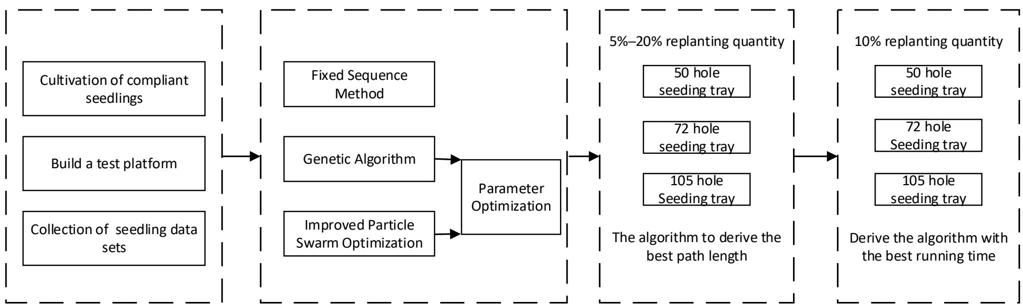

Figure 1. Flow diagram of the experiment.

2.1. Materials and Equipment

Capsicum is an annual or limited perennial herb belonging to the genus *Capsicum* in the family Solanaceae. The initial stage of growth and development of pepper seedlings is the germination period, and the seeds emerge in about 5–8 days after germination and sowing in general, and the first true leaves grow in about 15 days until the flower buds are revealed called the seedling stage. In this study, the seedlings of pepper were cultivated in a greenhouse, the name of the variety is Chinese big pepper, cultivated and provided by Beijing Zhongnong Futong Horticulture Co., Ltd., Beijing, China, in March 2019, the image collection site is shown in Figure 2, and the original images collected are shown in Figure 3.

Figure 2. Image acquisition site map of seedlings.

Figure 3. Acquired raw images.

In this research, the seedling tray replanting test platform was made according to the actual 1:1, as shown in Figure 4. The left side is the target tray, and the right side is the seedling supply tray. The replanting manipulator is driven by the XYZ three-axis linear module to replant. Before replanting, the grade information of the seedlings in the seedling tray has been obtained from the target tray and supply tray after image recognition, and the substrate of unqualified seedlings or missing seedlings in the target tray has been removed. During replanting, the end effector grabs the qualified seedlings from the supply tray and moves them to the corresponding position in the target tray for replanting.

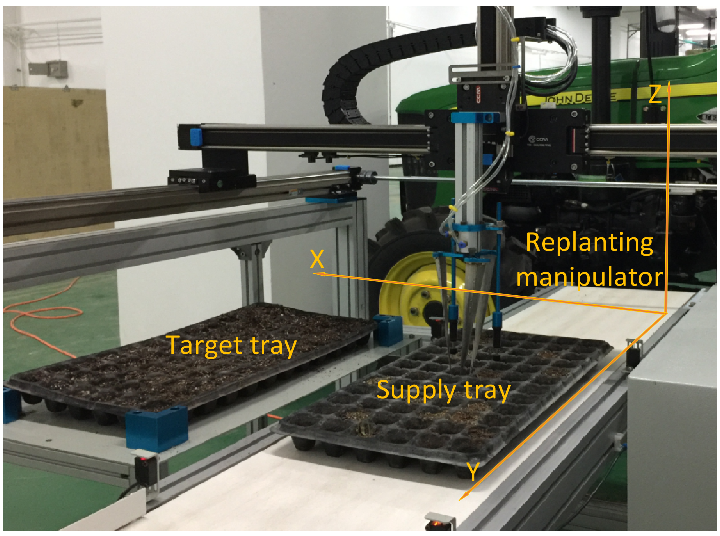

Figure 4. Experimental platform for replanting seedling tray.

The sequence of actions of the end effector for the complete replanting of a target tray is as follows: The initial position of the end effector is at the upper right corner of the supply tray. According to the replanting planning path, the end effector first moves above the first qualified seedling to be captured in the supply tray, and then the end effector moves down to capture the seedlings and up to a fixed height, and then moves above the first replanting position in the target tray, and then the end effector releases the seedlings and moves up to a fixed height. Then, the end effector moves to the second qualified seedling position in the supply tray, and repeats the previous action until all the holes to be replanted in the target tray are replanted, then the end effector returns to the initial position, and the replanting operation is finished.

Using the 50-hole plate replanting as an example, a planar model for replanting paths was established based on the distribution of seedling supply and target trays in the replanting test platform, as shown in Figure 5. The seedling legend represents qualified seedlings, the hollow circle legend represents unqualified seedlings, and the black square represents the missing seedlings. Both the supply and target trays are 50-hole seedling trays (5×10) with dimensions of 540 mm in length and 280 mm in width, and the initial position of the end effector movement is at the bottom left O of the supply tray. The numbering rules of the seedling trays are as follows: in this study, the seedling trays with 50 holes were numbered from 1 to 50, from left to right, from top to bottom, and the target trays with 50 holes were numbered from 51 to 100, from left to right, from top to bottom, in that order. The rules for setting cell numbers in 72-hole and 105-hole seedling trays are the same as those for 50-hole seedling trays.

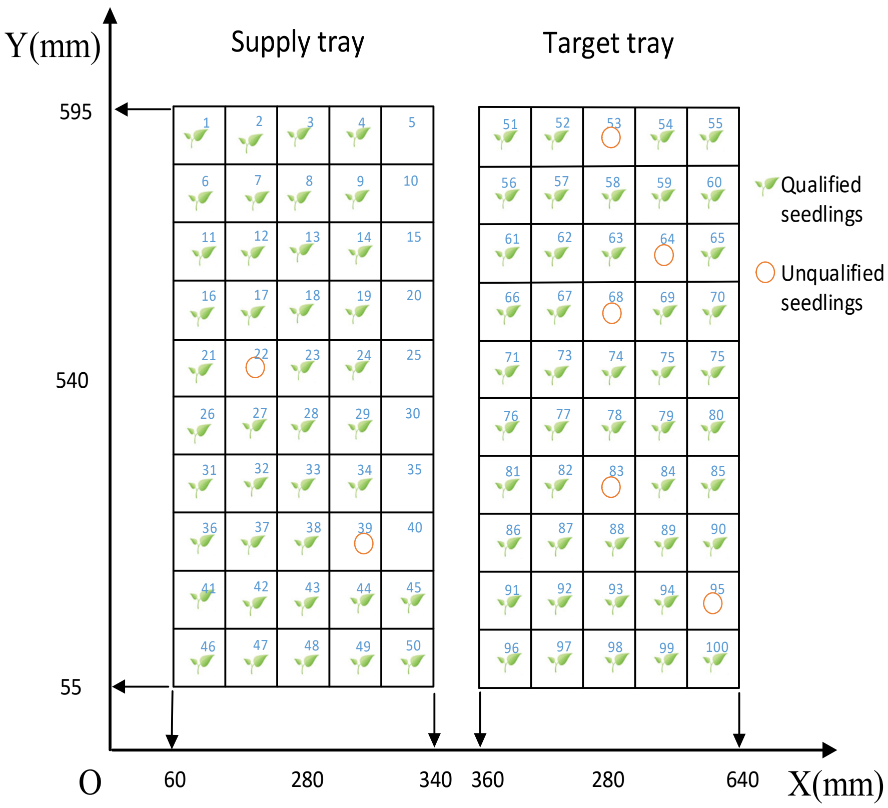

Figure 5. Planar model of seedling tray replanting path planning.

2.2. Path Planning Algorithm

The algorithm implementation environment: Intel(R) Core(TM) i7-8750H CPU @2.20 GHz 2.21 GHz, 16 GB memory (Intel, Santa Clara, CA, USA), Nvidia GTX1060 graphics card (Nvidia, Santa Clara, CA, USA); software environment: Matlab2018b (The MathWorks, Natick, MA, USA), Windows 10 64 bit operating systems (Microsoft, Redmond, WA, USA). In this paper, based on the detection results of the machine vision system and seeding replanting path planning model, three algorithms are used, namely the fixed-order method, genetic algorithm, and improved particle swarm optimization, to optimize the design of the seeding replanting path.

2.2.1. Fixed-Order Path Planning Method

The fixed sequence method (FS) is where the replanting robot transfers seedlings from the supply tray to the target tray in a fixed sequence each time. Since both the supply tray and the target tray can be combined from left to right, from right to left, from top to bottom, and from bottom to top, the fixed sequence method for replanting also has many combination schemes. In the literature [28], it is known that the path length is shortest in the fixed-order method by retrieving seedlings in the order of right to left and top to bottom in the hole cells in the supply tray and placing seedlings in the order of left to right and top to bottom in the target tray at intervals, so the above scheme was used in this study. The complete replanting path of the fixed-order method is shown by the arrow in Figure 5, and the plan is as follows: the replanting robot starts from the origin O position and reaches the first position of the top-to-bottom and right-to-left seedling pickup in the supply tray, i.e., the hole cell in the 9th row and 6th column of the supply tray for seedling pickup. Then, the 1st position of the target tray is moved from left to right, and from top to bottom, i.e., the 3rd cell in the 1st row of the target tray for seedling release. In the process of obtaining seedlings, the position of unqualified seedlings is skipped, and so on, until the target tray has finished replanting all five holes to be replanted, then it returns to the origin O. The sequence number of obtaining five qualified seedlings in the supply tray and the sequence number of putting five seedlings in the target tray are shown in Figure 6.

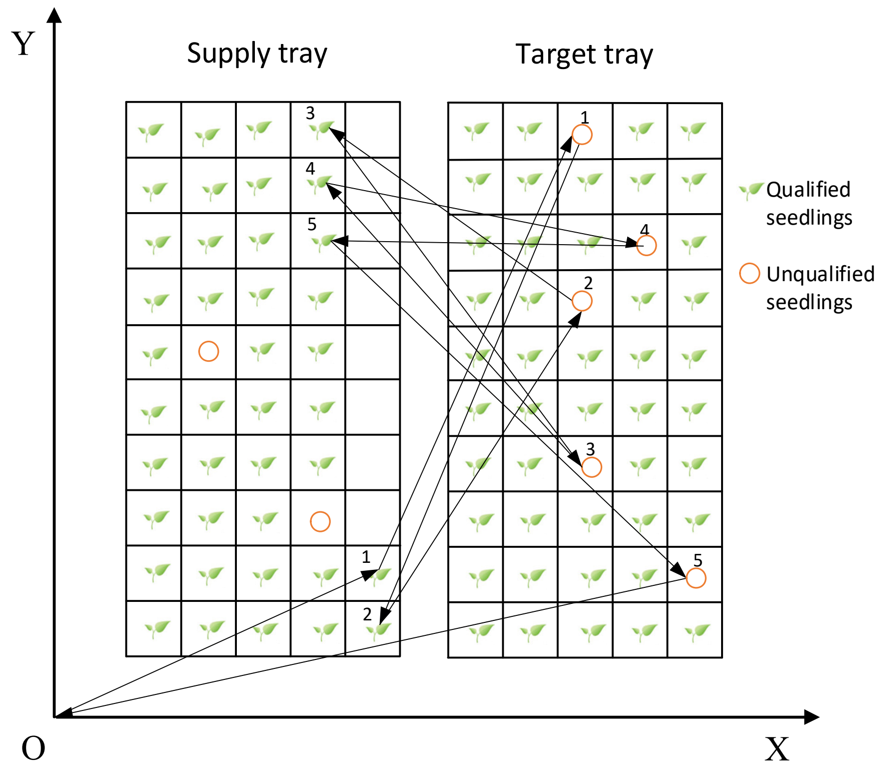

Figure 6. Fixed sequence method path planning (50 holes as an example, 5 holes to be replanted).

2.2.2. Genetic Algorithm-Based Path Planning Method

Genetic Algorithm (GA) is a class of randomized search methods that evolved from the evolutionary laws of the biological world. In other words, at each generation, the next generation population is selected according to the fitness of the individuals in the problem domain, and the population representing the new set of solutions is generated through combinatorial crossover and subjective and objective variation with the help of genetic operators, gradually achieving "survival of the fittest and elimination of the fittest" and evolving to produce better solutions until the optimization criterion is satisfied [35]. The standard genetic algorithm flow diagram is shown in Figure 7.

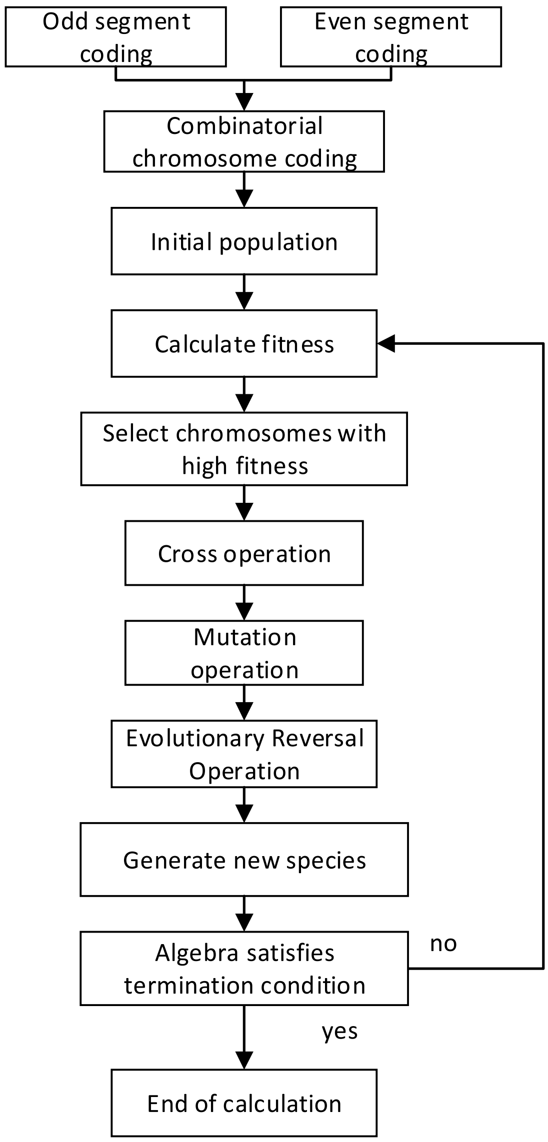

Figure 7. Flow diagram of standard genetic algorithm.

Genetic algorithm-based replanting robot path planning. This study uses an integer alignment coding method to separately code odd and even terms. Suppose a 50-hole seedling tray is replanted to a 50-hole seedling tray. The number of replants to be replanted in the target tray is 5, and the replanting location is known. A set of valid codes is as follows: X = [3 53 11 58 18 61 20 72 32 77], and the probabilities of selection, crossover, and variation in the genetic operator are set to 0.9, 0.6–0.9 and 0.02–0.05, respectively, with a population size of 100 and several iterations of 100. By replanting path sequence after the operations of selection, crossover, and mutation, multiple new population sequences can be generated, and the shortest replanting total path length will be obtained after a certain number of iterations.

2.2.3. Path Planning Method Based on Improved Particle Swarm Optimization

Particle swarm optimization (PSO) is a population-intelligent optimization algorithm. The principle of the PSO algorithm [36] is as follows: first, a group of particles is initialized in the feasible solution space, and each particle can be represented as a potential optimal solution of the extreme value optimization problem with three characteristic indicators: velocity, position, and fitness value. The goodness of the particle fitness value represents the degree of superiority or inferiority of the particle, which is calculated by the fitness function.

The particle moves in the solution space by tracking the individual and population extremes to update the position of the individual and adjust the flight speed of the particle. The individual extreme value and population extreme value refer to the optimal position of fitness value searched by an individual particle and the optimal position of fitness searched by all particles in the population, respectively. The fitness value is recalculated after each particle updates its position, and the positions of the individual and population extremes are updated by comparing the fitness value of the newly generated particles with the fitness value of the individual and population extremes, and finally, the optimal position of the particles is searched. The flow diagram of the standard particle swarm optimization is shown in Figure 8a.

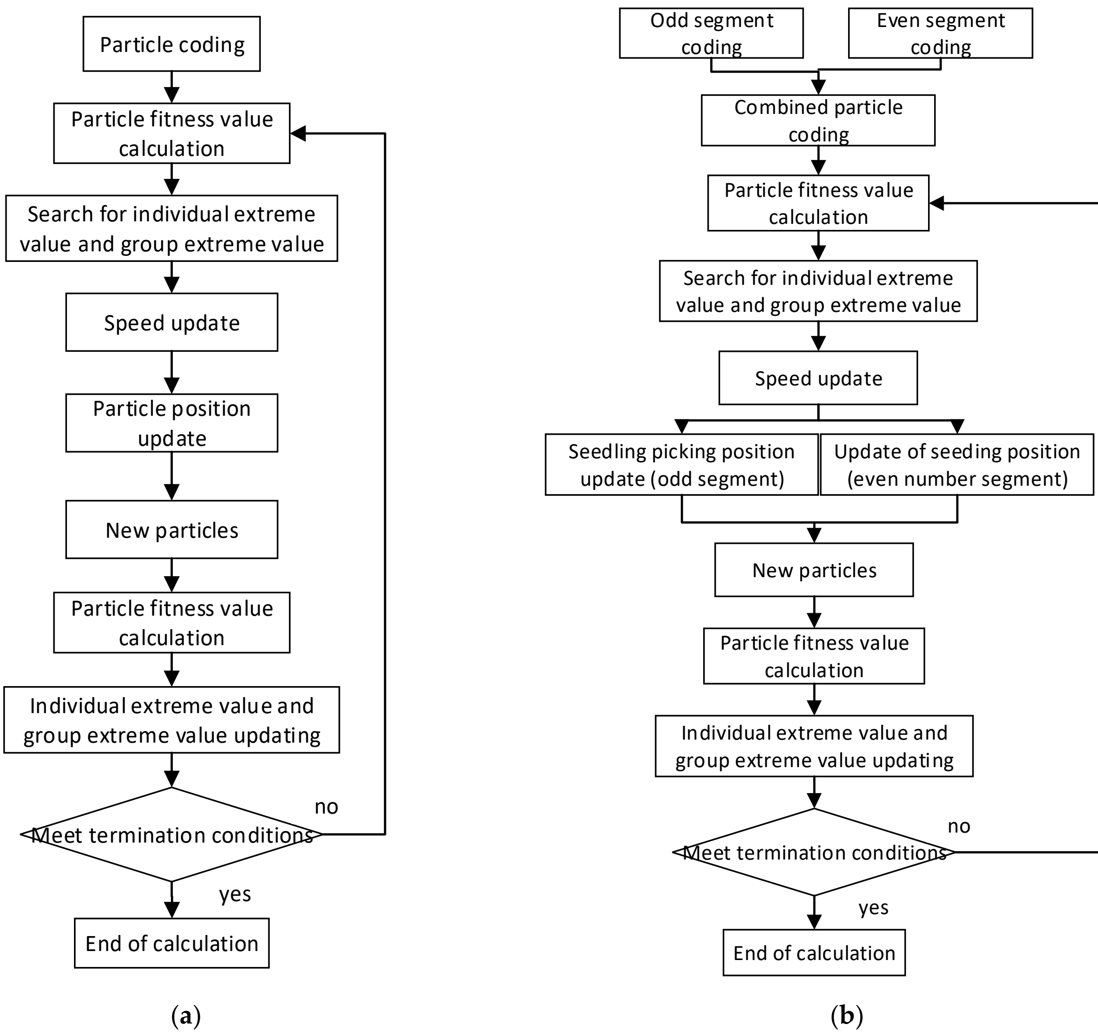

Figure 8. Flow diagram of particle swarm optimization. (**a**) standard particle swarm optimization; (**b**) improved particle swarm optimization.

In this paper, we propose a replanting path planning method based on the improved particle swarm optimization according to the replanting path planning model of seedling tray seedlings, and the flow diagram of the algorithm is shown in Figure 8b. The main improvement is to propose a combined particle coding method and to propose the seedling picking location update operator and seedling release location update operator according to the replanting path planning criterion, and the specific implementation process and improvement of the algorithm are as follows:

(1) Combined particle coding

According to the greenhouse replanting method, the replanting robot needs to select a qualified seedling from the supply tray, move it to the replanting location in the seedling tray to be replanted, and then move it to the next supply location after completing the replanting, and so on, until the unqualified or missing holes in the seedling tray to be replanted are completed. Since replanting is a discrete problem, this study uses integer coding for the particles and determines the length of the particle coding according to the number of missing or unqualified seedlings. Assuming that the number of seedlings to be replanted in the target tray is 5, and the numbers of the seedlings are known to be 55, 65, 76, 77, and 89, a set of codes B = [55 65 89 76 77] is obtained by arranging them in random order. Therefore, the position numbers of the qualified seedlings were selected randomly from the seedling supply tray of 5 and put in random order to obtain a set of codes: A = [3 22 9 34 45], then the total length of the particles is 10 and the code of this article is X = [3 55 22 65 9 89 34 76 45 77].

(2) Particle fitness calculation

The particle fitness function is the total replanting path length of the robot, and the total length is the particle code plus the start and end position. Let the start position be O (X_0, Y_0), then the total length of the replanting path is calculated as shown in Equation (1).

$$L = \sqrt{(x_0 - x_1)^2 + (y_0 - y_1)^2} + \sum_{i=1}^{n-1} \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2} + \sqrt{(x_n - x_0)^2 + (y_n - y_0)^2} \tag{1}$$

(3) Velocity update calculation

Suppose a particle population is $X = (X_1, X_2, \ldots, X_n)$ consisting of n particles in a D-dimensional space of feasible solutions. The ith particle can be represented as a D-dimensional vector $X_i = (X_{i1}, X_{i2}, \ldots, X_{id})^{\mathrm{T}}$, which represents the position of the i th particle in the D-dimensional feasible solution space, i.e., represents a potential solution of the extreme value problem. The fitness value corresponding to each particle position X_i is calculated according to the objective function. The velocity of the ith particle is $V_i = (V_{i1}, V_{i2}, \ldots, V_{id})^{\mathrm{T}}$, its extremum is denoted as $P_i = (P_{i1}, P_{i2}, \ldots, P_{id})^{\mathrm{T}}$, and the population extremum of the population is denoted as $P_g = (P_{i1}, P_{i2}, \ldots, P_{id})^{\mathrm{T}}$. The velocity update and position update equations are as follows:

$$V_{id}^{k+1} = \omega V_{id}^{k} + c_1 r_1 (P_{id}^{k} - X_{id}^{k}) + c_2 r_2 (P_{gd}^{k} - X_{id}^{k}) \tag{2}$$

$$X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k+1} \tag{3}$$

where d represents the particle dimension; i represents the particle number; k is the current iteration number; V is the particle velocity; c_1 and c_2 are the acceleration factors; r_1 and r_2 are random numbers distributed in the interval [0, 1].

(4) Seedling position update operator (odd segment)

The odd-numbered items in the coding sequence are the seedling positions in the seedling supply tray, and the position update is adjusted according to the particle velocity change. The position update rule for the odd segment is as follows:

(1) Equation (3) is used for the position of update of the odd segment code in which the particle velocity value is rounded after the particle velocity update to ensure that the position value in the particle code is an integer.

For example, assuming that the particle velocity is obtained after the calculation by the velocity update Formula (2), the odd segment of the velocity is extracted as V_a, and the value of the odd segment of the velocity is integrated by using the rounding method as shown in V_1.

Va = [2.1994 12.3921 3.2433 0.2997 7.0217]

V_1 = [2 12 3 0 7]

The above article's odd segment position code is A. The new position code A_1 is obtained after calculation by Equation (3).

A = [3 22 9 34 45]

A_1 = [5 34 12 34 52]

(2) Repeat position processing in odd segment encoding. Cycle scan all positions of the particle, starting with the second bit of the particle encoding; if there is a duplicate position in the particle encoding, the value of the latter bit is added 1. For example, if there is a duplicate at position 34 in A_1, add 1 to the second 34 position and change it to 35.

A_1 = [5 34 12 34 52]

A_2 = [5 34 12 35 52]

(3) When the odd-numbered segment code contains the unqualified or missing seedling position in the seedling supply tray, it is replaced by the remaining qualified seedling position in the seedling supply tray. For example, if position 12 in the supply tray is not qualified or missing and cannot be used as the supply position, a position is generated randomly from the remaining qualified positions of the positions in the outgoing code and replaced with that position.

A_2 = [5 34 12 35 52]

A_3 = [5 34 7 35 52]

(4) Replacement of out-of-range positions. The value range of the particle code is checked, the values that are out of the boundary are deleted, and the corresponding positions are replaced randomly using the unselected position sequence number. For example, A is an odd segment sequence after the position update, where the value of the fifth position [28] is out of the range of positions of the 50-hole-size seedling supply tray, so a random position is generated from the remaining qualified seedling positions of the seedling tray for replacement, and the result is shown in A1.

A_3 = [5 34 7 35 52]

A_4 = [5 34 7 35 29]

(5) Seedling placement position update operator (even numbered segment)

The even number in the coding sequence is the position to be replanted in the target tray, and its position update is position-adjusted according to the velocity change. The position update rule is described as follows: the above particle even segment position is B, the velocity even segment is V_b, and the position is updated to B_1. Record the size of each value in the original position and the bit where it is located, and swap each of them from B to B_2 according to the size order of the new position, e.g.,

B = [55 65 89 76 77], where the order of the magnitude of each value is [5 4 1 3 2].

V_b = [2.4353 −9.6542 5.3342 18.7654 −1.3298]

B_1 = [57.4353 55.3458 83.6658 94.7654 75.6702],

where the order of the magnitude of each value is [4 5 2 1 3]. Then the values in B are arranged in the order in B_1, with the largest value in B placed in the 4th position, the second largest value in the 3rd position, and so on.

B_2 = [65 55 77 89 76]

(6) Particle code combination

Combine the updated position code A_4 of the odd segment and the updated position code B_2 of the seven segments into a new particle code X_1, e.g.,

A_4 = [5 34 7 35 29]

B_2 = [65 55 77 89 76]

X_1 = [5 65 34 55 7 77 35 89 29 76]

(7) Repeat steps 2 to step 6 until the number of iterations is completed and the calculation is finished.

2.3. Optimization of Algorithm Parameters

To achieve the optimal performance of the two algorithms, the parameters of the particle swarm optimization and the genetic algorithm are optimized in this paper.

2.3.1. Particle Swarm Optimization Is Parameter Setting

The particle swarm optimization parameters mainly contain inertia weight W, acceleration factor C_1, acceleration factor C_2, random number R_1, and random number R_2, where R_1 and R_2 are random numbers from 0 to 1. Therefore, the parameters to be determined are W, C_1, and C_2. Inertia weight W: the higher the value, the stronger the global search ability, and the lower the weight, the stronger the local search ability. Commonly used inertia weight-obtaining methods are the fixed inertia-obtaining method and the inertia weight linear decreasing method, and so on. In this paper, we use the linear decreasing weight method. The linear decreasing inertia weight algorithm uses larger inertia weights at the beginning of the calculation to ensure the global search ability of the algorithm and uses smaller inertia weights at the end of the calculation to ensure the local search ability of the algorithm. The specific formula is as follows:

$$w = (w_1 - w_2) \times \frac{MaxIter - CurIter}{MaxIter} + w_2 \tag{4}$$

Acceleration factor C_1. C_2: the acceleration factor is a set of important parameters to adjust the particle's own experience and group experience to influence the particle motion trajectory. If the value of C_1 is small and the value of C_2 is large, the particles mainly rely on the group experience to influence the motion of the particles, and the convergence speed is accelerated, but some complex problems may lead to local convergence. If the value of C_1 is small and the value of C_2 is small, the particles mainly rely on their own experience to influence the motion of the particles, and the interaction ability among the particles in the population is weakened, which causes too much wandering in the local range and the optimal solution cannot be found. In general, the acceleration factor uses values between 0 and 4. In this paper, we set 8 different levels, distributed between 0.1 and 2, and the criteria for using values are shown in Table 1.

Table 1. Particle swarm optimization parameter.

Parameter	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
C_1	0.1	0.3	0.6	0.9	1.2	1.5	1.8	2
C_2	0.1	0.3	0.6	0.9	1.2	1.5	1.8	2

In this paper, 5 seedlings were replanted with a 50-hole seedling tray as the test sample, and the replanting path lengths of two parameters, C_1 and C_2, were calculated under different combinations of levels based on the inertia weight linear decreasing method, and each combination was calculated 10 times to take the average of the path lengths, and the three-dimensional plot (C_1, C_2, path lengths in three dimensions) was drawn using origin software, as shown in Figure 9.

As can be seen in Figure 9, optimal performance is achieved when the population size of 100, C_1 of 0.3, and C_2 of 0.3 is chosen when the particle swarm optimization is used.

2.3.2. Genetic Algorithm Parameter Setting

In this study, the selection probability Ps is set to 0.9 and the number of iterations is set to 100. Crossover probability Pc: the crossover probability determines the frequency of the crossover operation, and the higher the frequency, the faster the convergence to the most probable optimal solution region, therefore, a larger crossover probability is usually chosen, generally using the value of 0.6~0.9, but not set to 1, because a crossover probability that is too high will lead to premature convergence. Variation probability P_m: variation probability generally uses a small value of 0.02~0.05, if set to 1, it degenerates into random search, so the algorithm is extremely unstable and easy to falls into the local optimal point and leads to premature maturity. The genetic algorithm parameters are selected as shown in Table 2.

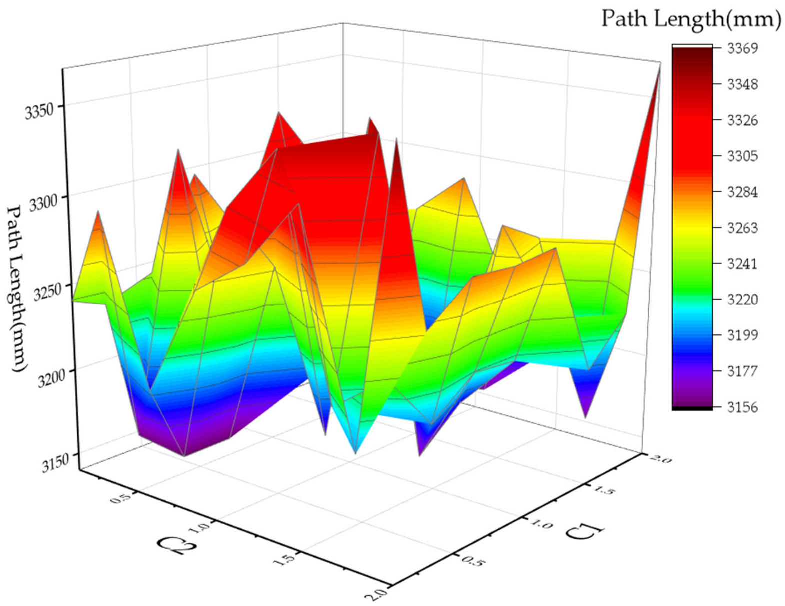

Figure 9. Three-dimensional diagram of the path calculation for acceleration factors C_1 and C_2 with different values of parameters.

Table 2. Genetic algorithm parameters.

Parameter	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7
P_c	0.6	0.7	0.8	0.9			
P_m	0.02	0.025	0.03	0.035	0.04	0.045	0.05

In this paper, 5 seedlings were replanted with a 50-hole seedling tray as the test sample, and the replanting path lengths of P_c and P_m were calculated for two parameters at different combinations of levels, and the average of the path lengths was obtained as 10 times for each combination, and the three-dimensional plots (P_c, P_m, and path lengths in three dimensions) were drawn using origin software, as shown in Figure 10.

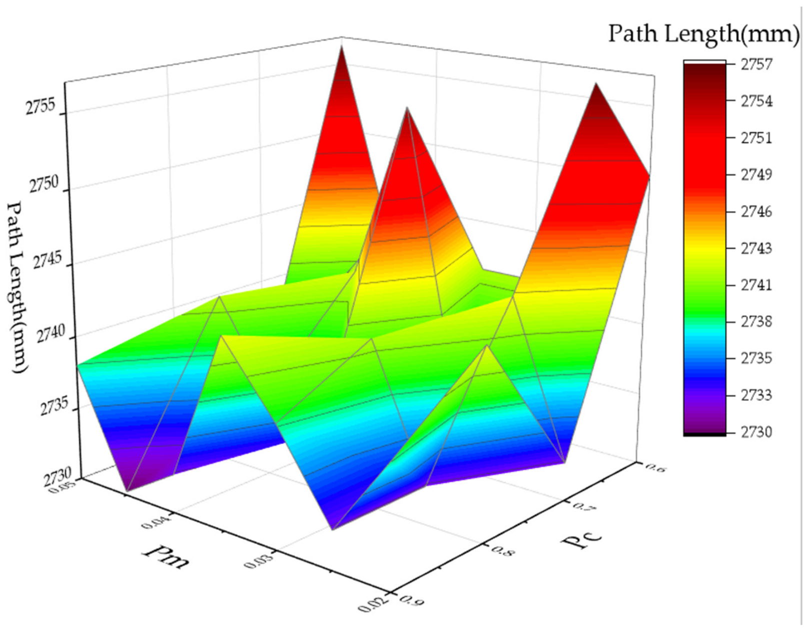

Figure 10. Three-dimensional diagram of the path calculation for Pc and Pm with different values of parameters.

It can be seen from Figure 10 that optimal performance can be achieved when the population size of 100, P_c of 0.9, and P_m of 0.045 are chosen when the genetic algorithm is used.

3. Results and Discussion

From the literature [11], it is known that the percentage of missing and substandard seedlings in seedling trays is around 5% to 20%. In this study, simulation experiments were conducted based on 50-, 72-, and 105-hole seedling tray replanting models with the fixed-order method, genetic algorithm, and improved particle swarm optimization.

3.1. Replanting Path Planning Test for 50-Hole Seedling Trays

3.1.1. Replanting Path Planning Test for 50-Hole Seedling Trays with 5–20% Replanting Quantity

The fixed-order method, genetic algorithm, and improved particle swarm optimization were used to test the path planning for 50-hole target seedling trays with replanting numbers of 5–20%. The replanting path lengths of the three different algorithms were calculated for the cases of 3, 4, 5, 6, 7, 8, 9, and 10 randomly missing seedlings in the target trays, as shown in Table 3.

Table 3. Data for replanting path planning of 50-hole-size seedling trays with 5% to 20% replanting.

Number of Replanting	FS (mm)	GA (mm)	PSO (mm)	e (mm)	r1 (%)	r2 (%)
3	2991.60	2665.46	2472.62	192.84	10.90	17.35
4	3778.80	3217.96	2979.74	238.22	14.84	21.15
5	4444.94	3675.56	3362.29	313.27	17.31	24.36
6	5221.43	4201.96	4132.41	69.55	19.52	20.86
7	5914.42	4673.76	4692.54	−18.78	20.98	20.66
8	6772.81	5279.33	5378.80	−99.47	22.05	20.58
9	7251.32	5521.23	5787.34	−266.11	23.86	20.19
10	8080.09	5989.18	6219.95	−230.77	25.88	23.02
Average	/	/	/	/	19.41	21.02

Note: fixed sequence method (FS); genetic algorithm (GA); particle swarm optimization (PSO); the number of populations in the GA and PSO algorithms is 100 and the number of iterations is 100. $e = GA - PSO$, $r1 = (FS - GA)/FS \times 100\%$, $r2 = (FS - PSO)/FS \times 100\%$.

From Table 3 of the test data and Figure 11 of the comparison of replanting path lengths of the three algorithms for different replanting numbers in 50-hole seedling trays, it can be seen that in the replanting range from 5% to 20% (3 to 10 seedlings), GA and PSO optimized the replanting path lengths substantially compared to FS at 19.41%, and 21.02%, respectively. PSO outperformed GA in the replanting range from 3 to 6 seedlings and GA outperformed PSO in the replanting range from 7 to 10 seedlings, but the difference in the optimized path length between the two was not significant.

3.1.2. Replanting Path Planning Test for 50-Hole Seedling Trays with 10% Replanting

The fixed-order method, genetic algorithm, and improved particle swarm optimization were used to test the path planning of a 50-hole target tray with 10% replanting. Target trays were randomly generated for 10 different scenarios (5 seedlings to be replanted, different locations for each replanting), each with different locations and numbers of qualified seedlings in the supply tray. In each case, the fixed-order method was operated once, the genetic algorithm and the improved particle swarm optimization were operated 10 times, and the average value of the planned path length was recorded. The running time of the genetic algorithm and the improved particle swarm optimization was calculated for the same population size and number of iterations.

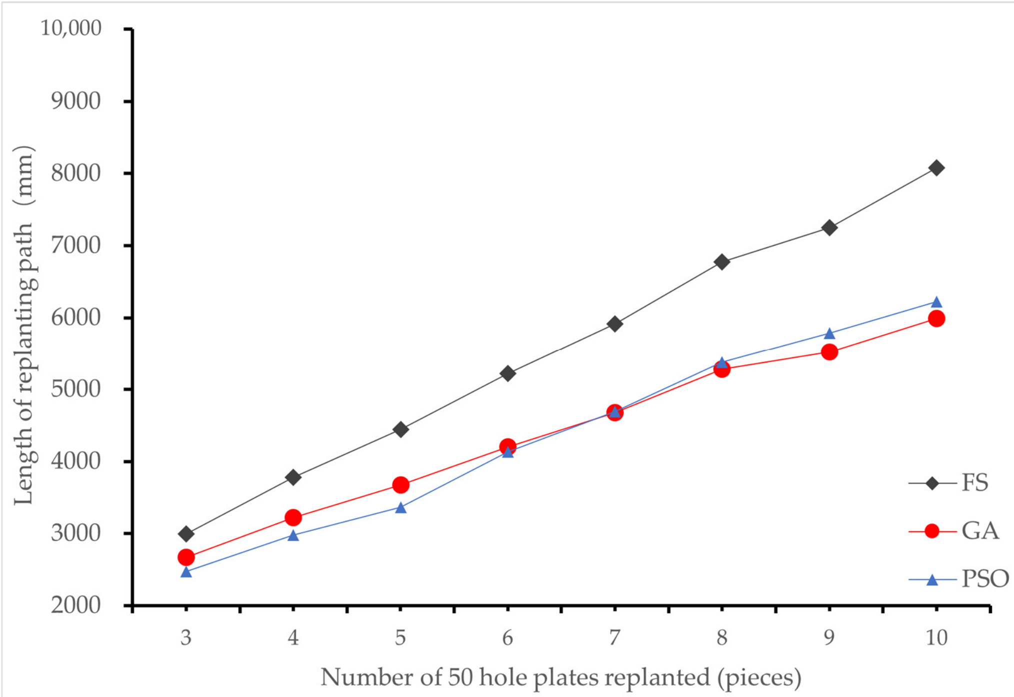

Figure 11. Comparison of path lengths planned by three algorithms for 50-hole seedling trays with different replanting numbers.

From the data in Table 4, it can be seen that the PSO algorithm and GA algorithm compared to FS in the path optimization were reduced by 10.59% and 11.50%; the PSO algorithm and GA algorithm optimization effect is similar, the GA algorithm compared to the PSO algorithm path shortened by 28.47 mm on average. From the running time, the PSO algorithm compared to the GA algorithm reduced by 58.05%.

Table 4. Replanting path planning data for replanting 10% of 50-hole-size seedling trays.

Serial No	FS (mm)	GA (mm)	PSO (mm)	e (mm)	r1 (%)	r2 (%)	Time (GA)	Time (PSO)	r3 (%)
1	2248.78	1971.69	1981.01	−9.32	12.32	11.91	2.2666	0.9732	57.06
2	3524.64	3127.93	3159.80	−31.87	11.26	10.35	2.3633	0.9747	58.76
3	3138.54	2848.13	2887.64	−39.51	9.25	7.99	2.2891	0.9542	58.32
4	2786.05	2619.12	2666.41	−47.29	5.99	4.29	2.3567	0.9714	58.78
5	3151.32	2801.87	2857.01	−55.14	11.09	9.34	2.2274	0.9587	56.96
6	3378.62	2997.29	2993.13	4.16	11.29	11.41	2.2796	0.9924	56.47
7	3382.79	2869.45	2896.22	−26.77	15.18	14.38	2.2969	0.9717	57.70
8	3337.79	3122.95	3164.44	−41.49	6.44	5.19	2.3604	0.9790	58.52
9	3395.63	2748.84	2761.31	−12.47	19.05	18.68	2.3619	0.9619	59.27
10	3367.58	2925.95	2950.97	−25.02	13.11	12.37	2.3800	0.9849	58.62
Average	3171.17	2803.32	2831.79	−28.47	11.50	10.59	2.3182	0.9722	58.05

Note: the number of populations in the GA and PSO algorithms is 100 and the number of iterations is 100. e = GA − PSO, r1 = (FS − GA)/FS × 100%, r2 = (FS − PSO)/FS × 100%, r3 = (TGA − TPSO)/TGA × 100%.

3.2. Replanting Path Planning Test with 72-Hole Seedling Trays

3.2.1. Replanting Path Planning Test for 72-Hole Seedling Trays with 5–20% Replanting Quantity

The fixed-order method, genetic algorithm, and improved particle swarm optimization were used to test the path planning for 72-hole target seedling trays with replanting numbers from 5 to 20%. The replanting path lengths of the three different algorithms were calculated for the cases of 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, and 14 randomly missing seedlings in the target trays, as shown in Table 5.

Table 5. Replanting path planning data for replanting from 5% to 20% of 72-hole-size seedling trays.

Number of Replanting	FS (mm)	GA (mm)	PSO (mm)	e (mm)	r1 (%)	r2 (%)
4	2994.56	3001.71	2801.03	200.68	−0.24	6.46
5	3806.63	3474.84	3361.52	113.32	8.72	11.69
6	4544.81	4183.64	3938.27	245.37	7.95	13.35
7	5473.38	4520.61	4596.34	−75.73	17.40	16.02
8	5986.81	5104.67	5023.12	81.55	14.73	16.10
9	6558.08	5407.68	5605.23	−197.55	17.54	14.53
10	7019.04	5574.34	5807.53	−233.19	20.58	17.26
11	7400.95	6235.31	6609.03	−373.72	15.75	10.70
12	8194.72	6645.94	6963.80	−317.86	18.90	15.02
13	8645.39	7377.96	7649.34	−271.38	14.66	11.52
14	9437.74	7669.57	7976.82	−307.25	18.74	15.48
Average	/	/	/	/	14.07	13.47

Note: the number of populations in the GA and PSO algorithms is 100 and the number of iterations is 100. e = GA − PSO, r1 = (FS − GA)/FS × 100%, r2 = (FS − PSO)/FS × 100%, r3 = (TGA − TPSO)/TGA × 100%.

From Table 5 of the test data and Figure 12 of the comparison of the replanting path lengths for the three algorithms for different replanting numbers in the 72-hole seedling trays, it can be seen that in the replanting range from 5% to 20% (4 to 14 seedlings), GA and PSO optimized the replanting path lengths substantially compared to FS, 14.07% and 13.47%, respectively. In the replanting range of 4–6 and 8 seedlings, PSO outperformed GA, and in the replanting range of 7 and 9–14 seedlings, GA outperformed the PSO, but the difference in the optimized path length between the two was not significant.

3.2.2. Replanting Path Planning Test for a 72-Hole Seedling Tray with 10% Replanting

The fixed-order method, genetic algorithm, and improved particle swarm optimization were used to test the path planning of 72-hole target trays with 10% replanting. Target trays were randomly generated for 10 different scenarios (seven seedlings to be replanted, different locations for each replanting), each with different locations and numbers of eligible seedlings in the supply tray. In each case, the fixed-order method was operated once, the genetic algorithm and the improved particle swarm optimization were operated 10 times, and the average value of the planned path length was recorded. The running time of the genetic algorithm and the improved particle swarm optimization was calculated for the same population size and number of iterations.

From the data in Table 6, it can be seen that the PSO algorithm and GA algorithm reduce by 28.81% and 28.08%, respectively. Compared to FS in the path optimization, PSO algorithm and GA algorithm have similar optimization effect; the PSO algorithm reduces the path by 44.31 mm on average compared to the GA algorithm. From the running time, the PSO algorithm reduces by 59.79% on average compared to the GA algorithm.

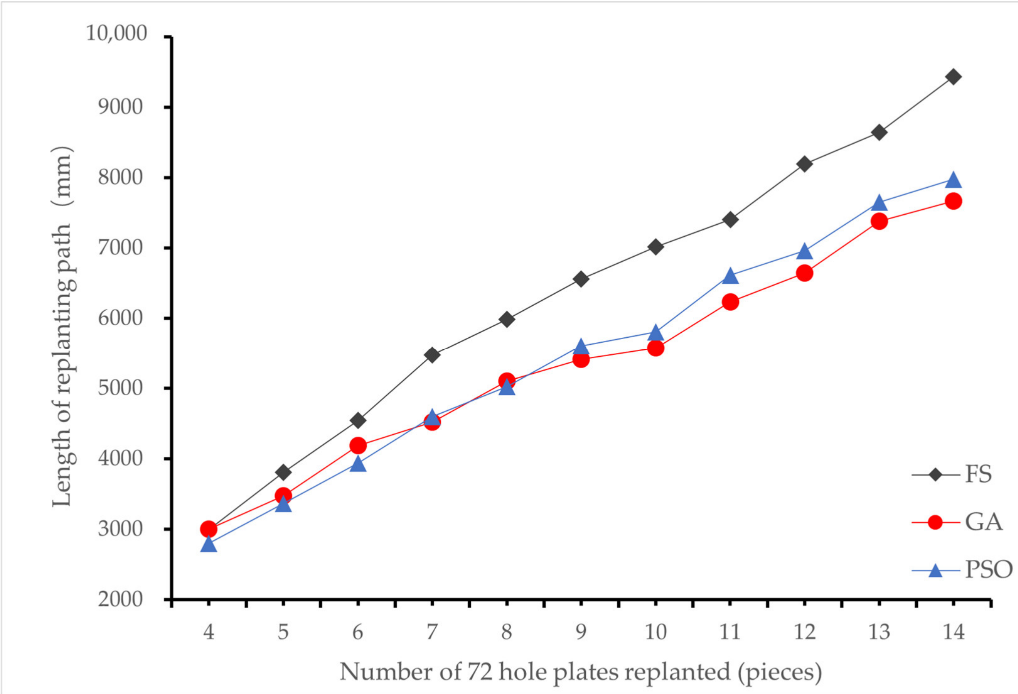

Figure 12. Comparison of path lengths planned by three algorithms for 72-hole seedling trays with different replanting numbers.

Table 6. Replanting path planning data for 10% replanting of 72-hole-size seedling trays.

Serial No	FS (mm)	GA (mm)	PSO (mm)	e (mm)	r1 (%)	r2 (%)	Time (GA)	Time (PSO)	r3 (%)
1	5471.16	3603.59	3500.36	103.23	34.13	36.02	2.5199	1.0086	59.97
2	5819.32	4469.41	4375.92	93.49	23.19	24.80	2.5299	1.0132	59.95
3	4553.5	3514.09	3640.5	−126.41	22.82	20.05	2.5255	1.0565	58.16
4	4962.23	3315.24	3360.4	−45.16	33.19	32.28	2.5199	1.0078	60.01
5	5871.38	4655.48	4554.62	100.86	20.70	22.42	2.6034	0.9972	61.69
6	5555.82	3914.09	3725.73	188.36	29.54	32.94	2.5133	1.0157	59.58
7	4753.39	3390.91	3398.12	−7.21	28.66	28.51	2.5260	1.0091	60.05
8	5497.17	3971.93	4148.8	−176.87	27.74	24.52	2.5355	1.1002	56.60
9	5699.25	3884.64	3750.24	134.4	31.83	34.19	2.6302	0.9933	62.23
10	5251.65	3728.98	3550.61	178.37	28.99	32.39	2.4866	1.0018	59.71
Average	5343.48	3844.83	3800.53	44.31	28.08	28.81	2.5390	1.0203	59.79

Note: the number of populations in GA and PSO algorithms is 100 and the number of iterations is 100. e = GA − PSO, r1 = (FS − GA)/FS × 100%, r2 = (FS − PSO)/FS × 100%, r3 = (TGA − TPSO)/TGA × 100%.

3.3. Replanting Path Planning Test for 105-Hole Seedling Trays

3.3.1. Path Planning Test for Replanting 105-Hole Seedling Trays 5–20% Replanting

The fixed-order method, genetic algorithm, and improved particle swarm optimization were used to test the path planning of 105-hole target trays with 5–20% replanting. Replanting path lengths of the three algorithms were calculated for the cases of 5, 7, 9, 11, 13, 15, 17, 19, and 21 randomly missing seedlings in the target trays, as shown in Table 7.

Table 7. Replanting path planning data for replanting from 5% to 20% of 105-hole-size seedling trays.

Number of Replanting	FS (mm)	GA (mm)	PSO (mm)	e (mm)	r1 (%)	r2 (%)
5	4626.83	3045.83	2801.28	244.55	34.17	39.46
7	5700.16	4031.08	3846.21	184.87	29.28	32.52
9	6521.69	4963.72	4872.71	91.01	23.89	25.28
11	7530.11	5991.30	5845.45	145.85	20.44	22.37
13	8506.13	7024.97	7317.80	−292.83	17.41	13.97
15	9159.77	7730.32	7917.21	−186.89	15.61	13.57
17	10,398.79	9078.10	9130.27	−52.17	12.70	12.20
19	11,736.63	10,463.17	11,326.85	−863.68	10.85	3.49
21	13,404.15	11,259.28	11,817.37	−558.09	16.00	11.84
Average	/	/	/	/	14.07	13.47

Note: the number of populations in the GA and PSO algorithms is 100 and the number of iterations is 100. e = GA − PSO, r1 = (FS − GA)/FS × 100%, r2 = (FS − PSO)/FS × 100%.

From Table 7 of the test data and Figure 13 of the comparison of replanting path lengths for the three algorithms for different replanting numbers in 105-hole seedling trays, it can be seen that in the replanting range from 5% to 20% (5 to 21 seedlings), GA and PSO optimized the replanting path lengths substantially compared to FS, at 20.04% and 19.41%, respectively. PSO outperformed GA in the replanting amounts of 5, 7, 9, and 11 seedlings, and GA outperformed PSO in the replanting amounts of 13, 15, 17, 19, and 21 seedlings, but the difference in the optimized path length between the two was not significant.

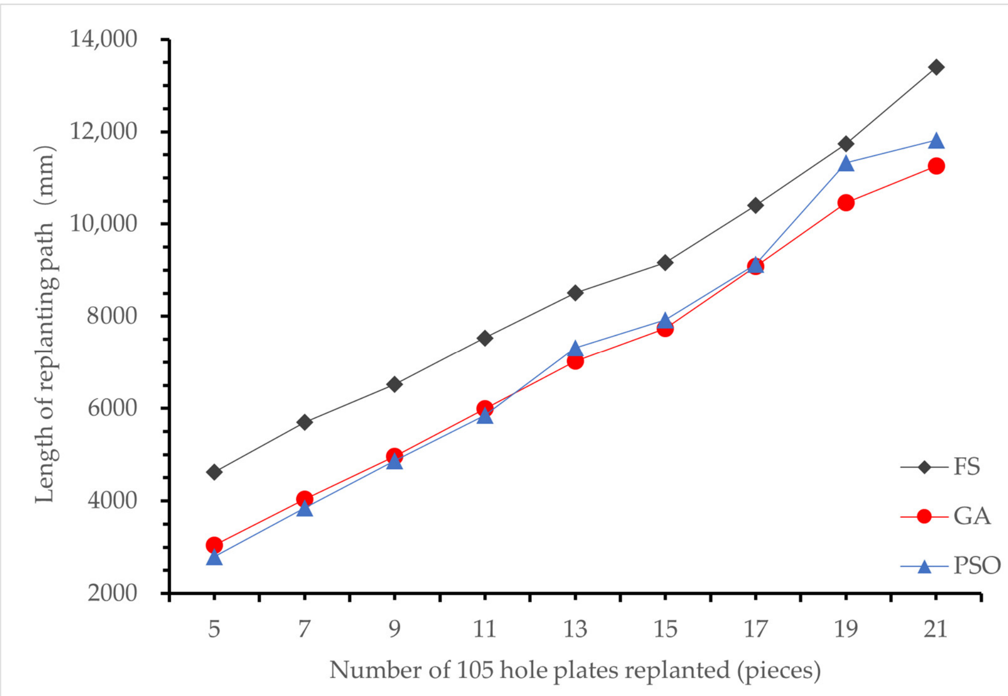

Figure 13. Comparison of path lengths planned by three algorithms for 105-hole seedling trays with different replanting numbers.

3.3.2. Replanting Path Planning Test for 105-Hole Seedling Trays with 10% Replanting Number

The fixed-order method, genetic algorithm, and improved particle swarm optimization were used to test the path planning for 105-hole target trays with a 10% replanting number. Target trays were randomly generated for 10 different scenarios (11 seedlings to be replanted, each with a different distribution of locations to be replanted), each with different locations and numbers of qualified seedlings in the supply tray. In each case, the fixed-order method was operated once, the genetic algorithm and the improved particle swarm optimization were operated 10 times, and the average value of the planned path length was recorded. The running time of the genetic algorithm and the improved particle swarm optimization was calculated for the same population size and number of iterations.

From the data in Table 8, it can be seen that the PSO algorithm and the GA algorithm reduce by 29.36% and 31.09% respectively compared to FS in the path optimization; the PSO algorithm and the GA algorithm have similar optimization effects, and the GA algorithm reduces the path by 142.46 mm on average compared to the PSO algorithm. In terms of running time, the PSO algorithm reduces by 55.06% compared to the GA algorithm.

Table 8. Replanting path planning data for replanting 10% of 105-hole-size seedling trays.

Serial No	FS (mm)	GA (mm)	PSO (mm)	e (mm)	r1 (%)	r2 (%)	Time (GA)	Time (PSO)	r3 (%)
1	8160.27	5550.51	5704.15	−153.64	31.98	30.10	3.5157	1.4819	57.85
2	8786.58	5844.80	6420.66	−575.86	33.48	26.93	3.2936	1.4771	55.15
3	8112.86	5533.13	5784.15	−251.02	31.80	28.70	3.5098	1.5160	56.81
4	8522.22	5792.78	5739.12	53.66	32.03	32.66	3.3608	1.5012	55.33
5	8281.36	5905.31	5712.46	192.85	28.69	31.02	3.3197	1.5317	53.86
6	7968.31	5199.72	5287.27	−87.55	34.75	33.65	3.3598	1.4911	55.62
7	7732.35	5587.81	5562.36	25.45	27.73	28.06	3.2863	1.5124	53.98
8	7754.31	5246.52	5398.02	−151.5	32.34	30.39	3.3029	1.5276	53.75
9	7761.83	5243.84	5600.69	−356.85	32.44	27.84	3.3093	1.5400	53.46
10	8058.54	5987.40	6107.55	−120.15	25.70	24.21	3.3113	1.4964	54.81
Average	8113.86	5589.18	5731.64	−142.46	31.09	29.36	3.35692	1.50754	55.06

Note: the number of populations in the GA and PSO algorithms is 100 and the number of iterations is 150. e = GA − PSO, r1 = (FS − GA)/FS × 100%, r2 = (FS − PSO)/FS × 100%, r3 = (TGA − TPSO)/TGA × 100%.

3.4. Discussion

In this paper, a fast path planning method based on improved particle swarm optimization is proposed, and a comparison test with a fixed sequence method and genetic algorithm is conducted on three sizes of seedling trays with 50, 72, and 105 holes for a replanting quantity in the range from 5% to 20% to obtain the degree of optimization of the three path planning methods on replanting path length. Then, 10% replanting was performed on three sizes of seedling trays to obtain the difference in algorithm running time between the three path planning methods.

(1) When replanting tests were conducted for target trays with replanting numbers from 5 to 20%, the results from the data in Table 3, Table 5, and Table 7 showed the following:

For the 50-hole seedling trays, PSO and GA reduced the replanting path length by 21.02% and 19.41% compared to FS respectively. For 72-hole seedling trays, PSO and GA reduced the replanting path length by 13.47% and 14.07% compared to FS, respectively. For 105-hole seedling trays, PSO and GA reduced the replanting path length by 19.41% and 20.04% compared to FS, respectively. PSO reduced the replanting path length by an average of 17.97% compared to FS, and GA reduced the replanting path length by an average of 17.84% compared to FS.

(2) When replanting tests were conducted on target trays with 10% replant quantity, the results from the data in Table 4, Table 6, and Table 8 showed the following:

In terms of the degree of replanting path optimization, for the 50-hole seedling trays, PSO and GA reduced the replanting path length by 10.59% and 11.50% compared to FS, respectively. For the 72-hole seedling trays, PSO and GA reduced the replanting path length by 28.81% and 28.08% compared to FS, respectively. For the 105-hole seedling trays, PSO and GA reduced the replanting path length by 29.36% and 31.09% compared to FS, respectively. Both PSO and GA significantly reduced the path length compared to FS in the replanting path planning, and the degree of optimization was similar between them, with a difference of about 1%. However, in terms of running time, it is noteworthy that PSO reduced by 58.05%, 59.79%, and 55.06%, compared with GA for three different sizes of seedling trays with 50, 72, and 105 holes, with an average reduction of 57.63%, and PSO greatly improved the algorithm running time.

Overall, PSO and GA have similar optimization abilities in replanting path length, with an average optimization of about 20% compared to FS in replanting path length. However, PSO has a great improvement in algorithm running time, and PSO running time is shortened by 57.63% on average compared with GA, which can effectively improve the efficiency of automatic replanting machines.

Compared with the ability of the genetic algorithm [26], greedy algorithm [28], and ant colony algorithm [37] to optimize the path length by 7.65–10.6%, the improved particle swarm optimization algorithm in this research has better performance in the path optimization ability and has made great progress in shortening the algorithm calculation time.

4. Conclusions

In our study, we proposed a fast path planning method based on improved particle swarm optimization, and the combined particle coding was used to design a two-stage position update operator for picking and placing seedlings, which realized the optimization of the replanting path. The parameters of the improved particle swarm optimization designed in this paper were optimized through simulation tests, and the optimal performance was achieved when the population size f = 100, C_1 = 0.3, and C_2 = 0.3. To verify the optimization performance of the proposed path planning method, a comparative test of the fixed sequence method, genetic algorithm, and improved particle swarm optimization algorithm was carried out for the 50-, 72-, and 105-hole seedling tray replanting models. The experimental results show that the improved particle swarm optimization method can greatly shorten the running time of the algorithm, optimize the replanting path, improve the efficiency of replanting, and meet the real-time requirements.

Although the performance of the improved particle swarm optimization algorithm in this research has greatly improved the computation time and path length, it only optimized the moving path of the XY horizontal plane, while the time of the Z-axis up and down movement and end effector action was fixed, so there was still room for the optimization of algorithm calculation time in the future. Moreover, it is not comprehensive to improve the efficiency of automatic replanting machines only from the aspect of path planning, but also to take into account the recognition system of seedlings and the grasping mechanism of the end effector. In the future, we will comprehensively consider the cooperation between the three aspects to further improve the efficiency of replanting.

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