Research on Path Planning of Fully Automatic Planter for Small Cultivated Area Based on Improved Genetic Algorithm

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Abstract. In the development of modern agriculture, automated machinery is widely used in agricultural cultivation, which is of great significance in innovating the mode of agricultural and rural business and promoting the modernisation of agriculture and rural areas. Nowadays, due to the complex terrain of small-scale farming areas, the existing large-scale agricultural machinery is restricted, and mainly, seeding relies on the workforce, resulting in the intensification of farmland abandonment in the hilly and mountainous areas in the south. Therefore, it is imperative to design an automated planter that can be applied to small-scale farming areas, and path planning is an important part of the automated planter. In this paper, an improved genetic algorithm is proposed to focus on the path planning research for small agricultural seeders. The algorithm improves the drawbacks of the traditional genetic algorithm through multi-objective optimisation, the intrinsic correlation between the number of turns and the difficulty of passage and the weight allocation, constructs a comprehensive, objective function, and realises the optimal decision of path planning. Through coding, fitness function, and other aspects of the improvement, this paper break through the limitations of the traditional genetic algorithm to a greater extent to improve the efficiency and quality of seeding for the realisation of agricultural automation to inject a strong impetus.

Keywords: Genetic Algorithm, Path Planning, Multi-objective Optimization, Differential Evolution.

1. Introduction

At this stage, the use of mechanical devices in small farming areas accounted for a small proportion of the overall farming, mainly because the small farming areas than large-scale cultivation of complex terrain is not suitable for large-scale agricultural machinery, agricultural production stage of the sowing link still mainly relies on manual work. Such as the South[1]is dominated by paddy fields, and most farmers are family-based smallholder management and small-scale production, so the situation of farmland abandonment in the hilly and mountainous areas of the South is becoming increasingly severe. In order to effectively solve the problem, the use of agricultural machinery to replace manual liberation of productivity is an inevitable trend of development. However, South China is unsuitable for large-scale operation of the seeding machine, so the design of a small-scale cultivation area for the fully automated seeding machine is significant. For automated planting machinery, the planning path is the most important. The geography of North China and Northeast China plains are different cultivated fields in South China is more complex; how to Different from the geographical situation of North China and Northeast China plains, the cultivated fields in South China are more complicated, and how to make reasonable route planning is a great challenge.

In order to solve the above problems, this paper proposes a fully automatic planter path planning method based on an improved genetic algorithm for small cultivated areas. The terrain is modeled in detail for the complex geographic environment, and the farmland terrain is subdivided, such as flat land, gentle slopes, steep slopes, terraces, etc. Multi-objective optimization[2]is performed to improve the limitations of the traditional genetic algorithms in path planning (obstacles, road breaks, etc.) [3], and different weights are assigned to different types of terrains, e.g., it is easier to travel on flat land, and more challenging to travel on steep slopes; For a large region of farmland, it can be divided into a grid, and a large area can be divided into a grid so that it will be easy to travel on flat land. The grid can be divided for large areas of farmland, and after individual path planning for small areas, all the paths can be integrated and connected[4]to better cope with the planting needs of southern farmland.

The research content of this paper mainly includes modeling the terrain of small farming areas, subdividing the terrain types, and developing a multi-objective optimization method for path planning based on these terrains; improving the genetic algorithm to improve its global search ability in complex environments, and solving the limitations of the traditional algorithms; and finally, verifying that the improved algorithm outperforms the A-algorithm for path planning in complex terrains by comparing it with the A-algorithm. These studies help to improve the seeding efficiency and reduce the dependence on manual operation.

2. Design and Implementation of Improved Genetic Algorithm

2.1. Terrain modeling

The terrain needs to be modeled in order to efficiently plan the path of a fully automated planter in a small cultivated area. This study uses a simplified but effective method to represent and categorize the terrain.

2.1.1 Data acquisition

At the beginning of the use of automatic seeding machine for data acquisition, small areas need to be sown; each small area is divided into a 5m x 5m small grid (default in $25m^2$ within the regional geography will not change significantly), the car needs to be equipped with GPS receiver, inclination sensors, soil moisture sensors, etc. to record the specific information of the grid nodes of the division of the cultivation area: coordinates, altitude, slope, Soil moisture, etc.

2.1.2 Universal judgment

Based on the collected data, this paper classifies the terrain into the following categories: flat: slope < 5°; gentle slopes: 5° ≤ slope < 15°; steep slopes: slope ≥ 15°; wetlands: soil humidity > 40%, through Matlab to create arrays[5]to encompass the above information, in the specific data mentioned above as a support, it is necessary to prepare for the specific path planning, and therefore need to determine the model established to ensure the realization of the function of automatic seeding machine. Whether it can guarantee the realization of the function of automatic seeder when judging whether a terrain can be seeded or not due to the lack of uniform standards for the difficulty coefficient of farmland access, this study proposes an evaluation method based on multiple factors. Four main factors, namely slope, soil moisture, surface roughness, and obstacle density, were considered, and the comprehensive difficulty coefficient was obtained by weighted summation:

$$d_i = 0.4f(slope) + 0.3g(moisture) + 0.2h(roughness) + 0.1i(obstacle) \qquad (1)$$

Where each function takes the range of (0,1), the weights and functional forms of the factors were adjusted through small-scale field tests. This approach provides a flexible framework that can be adapted to specific farmland situations. In future studies, a machine learning approach can be introduced to optimize the model further with a large amount of field data.

2.2. Multi-objective optimization design

Several conflicting objectives need to be considered in designing the path planning of a fully automatic planter for small cultivated areas. To balance these objectives, a multi-objective optimization method is used. In this paper, the following objectives are considered: maximize the coverage (C), minimize the path length (L), minimize the number of turns (T), and minimize the passage difficulty (D). These objectives are combined into a composite objective function by means of a weighted sum.

$$F = w_1C - w_2L - w_3T - w_4D \tag{2}$$

Where w_1, w_2, w_3, w_4 are the weight coefficients, which can be adjusted according to the actual demand. Each objective function is explained in detail.

(1) Coverage (C):

$$C = A_c \,/\, A_t \tag{3}$$

where A_c is the arable area covered and A_t is the total arable area. The objective is to make C as close to 1 as possible.

(2) Path length (L):

$$L = \sum_{ij} d(p_i - p_j) \tag{4}$$

Where, $d(p_i - p_j)$ is the distance between two neighboring points p_i and p_j on the path. The objective is to minimize L.

(3) Number of turns (T):

$$T = \sum_i I(\theta_i > \theta_{th}) \tag{5}$$

where, θ_i is the angle of the ith turn on the path, θ_{th} is a preset turn threshold (e.g., 30°), and I is an indicator function that is 1 when the condition is satisfied and 0 otherwise. The goal is to minimize T.

(4) Accessibility (D):

$$D = \frac{\sum_i d_i}{n} \tag{6}$$

where, d_i is the passage difficulty factor of the ith point on the path (range 0-1), n is the total number of points on the path. The objective is to minimize D.

Based on the above, the integrated objective function can be expressed as follows.

$$F = w_1(A_c \,/\, A_t) - w_2(\sum_{ij} d(p_i - p_j)) - w_3(\sum_i I(\theta_i > \theta_{th})) - w_4\left(\frac{\sum_i d_i}{n}\right) \tag{7}$$

In order to make the different objectives comparable with each other, each objective was normalized[6] by.

$$F\_y = w_1 {}^{C}/_{C_{max}} - w_2 {}^{L}/_{L_{max}} - w_3 {}^{T}/_{T_{max}} - w_4 {}^{D}/_{D_{max}} \tag{8}$$

C_{max}, L_{max}, T_{max} and D_{max} are the maximum values of each target in the current population.

The choice of weights has a significant impact on the final results. The weights can be adjusted according to different application scenarios, and the following are the weight coefficients that can be selected for some simulated application scenarios:

(1) Flat: w_1= 0.4, w_2= 0.3, w_3= 0.2, w_4= 0.1.

(2) High efficiency: w_1= 0.3, w_2= 0.4, w_3= 0.2, w_4= 0.1.

(3) Energy saving: w_1= 0.3, w_2= 0.2, w_3= 0.3, w_4= 0.2.

(4) Steep slopes: w_1= 0.3, w_2= 0.2, w_3= 0.2, w_4= 0.3.

In the optimization process, the following constraints are also introduced: lower limit of coverage: $C \geq C_{min}$ (e.g., C_{min}= 0.95); maximal path length: $L \leq L_{max}$; maximal number of turns: $T \leq T_{max}$; and maximal average access difficulty: $D \leq D_{max}$.

These constraints are introduced into the objective function through the penalty function method:

$$F\_f = F\_y - \lambda_1 max(0, C_{min} - C) - \lambda_2 max(0, L - L_{max}) - \lambda_3 max(0, T - T_{max}) - \lambda_4 max(0, D - D_{max}) \tag{9}$$

Among them, $\lambda_1, \lambda_2, \lambda_3$ and λ_4 are penalty factors, which are used to control the strictness of the constraints.

By means of the above Multi-objective optimization design can balance coverage, path length, number of turns, and passage difficulty, thus obtaining an efficient and practical path planning scheme. Each parameter can be flexibly adjusted according to specific terrain characteristics and operational requirements to obtain the best seeding path.

2.3. Genetic Algorithm Improvement

The algorithm was improved to overcome the limitations of traditional genetic algorithms in complex terrains in agriculture[7].

(1) Coding method: integer coding represents paths, and each gene represents a moving direction (up, down, left, right). The traditional encoding method must be optimized for practical problems (e.g.,path planning in complex terrain).When performing genetic operations (e.g., crossover, mutation), complex transformations are required to correlate with actual path decisions, which increases the computational overhead. The improved genetic algorithm uses integer encoding to represent paths, which reduces the time of encoding conversion and thus improves the running efficiency of the algorithm and fits better with the path planning problem.

(2) Initialization population: When generating the initial population, the terrain constraints are considered to avoid generating invalid paths.

(3) Adaptation function: use the multi-objective function defined in 2.2 as the adaptability function, which is significantly improved for complex terrain, making it more suitable for this kind of path planning problems with unique constraints and improving the applicability of the algorithm for path planning in the field of agriculture. The careful consideration of path length, path smoothness, path security, and other factors in the genetic algorithm when dealing with different path planning problems can help find the optimal path more in line with the actual needs.

(4) Selection strategy: Adopt the elite retention strategy to ensure that the optimal individual is not lost in the evolutionary process. Allow the algorithm to continue to evolve based on the existing excellent solutions, avoiding repeated searches, thus improving its convergence speed and efficiency.

(5) Differential evolution[8]: compared with the traditional genetic algorithm, the introduction of differential evolution algorithm to improve the traditional selection, crossover, and mutation process so that it has a more robust global search capability and higher convergence speed when solving global optimization problems in continuous space. For example, in the mutation process of differential evolution, three individuals in the population are selected, their differences are calculated, and this difference is added to another individual to generate a new mutated individual. This mutation method can better maintain the diversity of the population, thus improving the algorithm's global search ability. At the same time, terrain constraints are considered when mutating, allowing mutation only to feasible directions. This ensures that the mutated individuals are more likely to be valid solutions, reduces the generation of invalid mutated individuals, and improves the efficiency of the mutation operation.

(6) Local search: After each generation of evolution, a local search is performed on the optimal individual to optimize the path further. This helps the algorithm find a better solution faster, reduces the number of iterations required to reach a satisfactory solution, and improves its overall efficiency.

3. Comparison of the improved genetic algorithm with the A* algorithm

3.1. A* algorithm

A* (A-Star) algorithm[9]is a heuristic search algorithm widely used in path planning problems. Combining the advantages of Dijkstra's algorithm[9]of breadth-first search and greedy best-first search, it can find the optimal path from the starting point to the endpoint in a shorter time, and it is one of the most commonly used algorithms in path planning problems. Therefore, in this paper, we compare the improved genetic algorithm with the A* algorithm to determine whether the improved genetic algorithm can realize path planning in complex terrain.

3.2. Simulation experiments and result analysis of the improved genetic algorithm

To verify the effectiveness of the improved genetic algorithm (PGA) described in this paper, the improved genetic algorithm and the A* algorithm are used to conduct path planning simulation experiments in simple and relatively complex terrains, respectively.

In order to simulate the possible environment of the planter, a small area of agricultural land is simulated by using Matlab in a 20×20 grid; the red point in the lower left corner is the starting point of the planter, the red point in the lower right corner is the termination point of the planter, the white grid represents the feasible area, and the lilac grid represents the obstacles in the environment, and green lines on the map represent the paths planned by the improved genetic algorithm. Green lines represent the paths planned by the A* algorithm. In the map, the path planned by the improved genetic algorithm is represented by a green line, and a blue line represents the route planned by the A* algorithm, and the value of the heuristic function used by the A* algorithm in this paper is set to the weight of 1.5 in the reference[10]. The two algorithms plan the routes in the environment by themselves, and the difference between them is compared, as shown in the following Figure 1, Figure 2, Figure 3 and Figure 4.

Figure 1 Path planning map (simple)

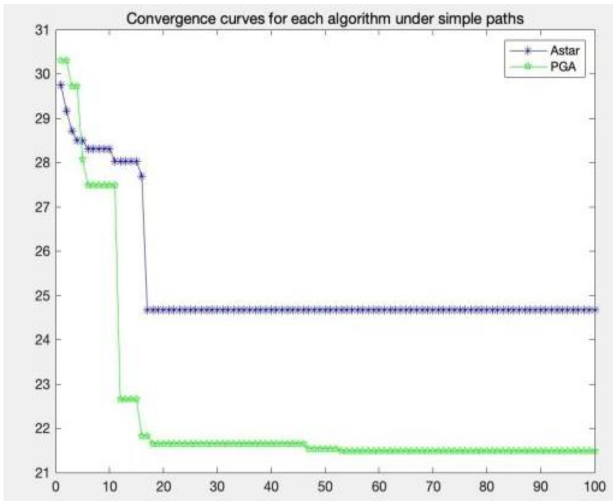

Figure 2 Convergence plot (simple)

Figure 3 Path planning map (complex)

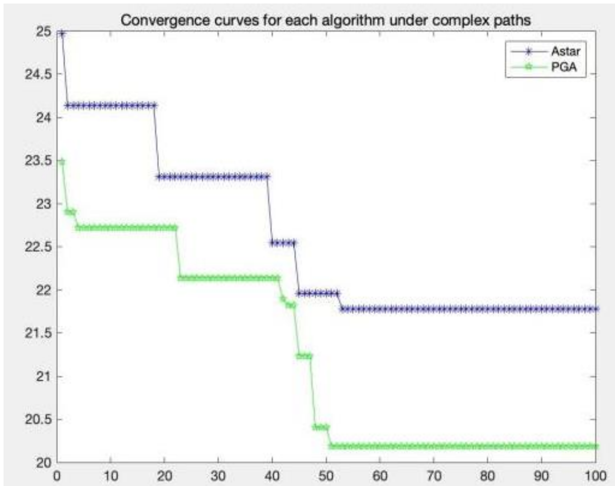

Figure 4 Convergence plot (complex)

To verify the effectiveness of the optimized genetic algorithm, the parameters of the two algorithms for path planning are compared in the following Table.1.

Table.1. Summary of parameters of different path planning algorithms

Arithmetic	PGA	A*
Path length (simple)	21.4853	24.6766
Number of turns (simple)	9	16
Path length (complex)	20.1876	23.7793
Number of turns (complex)	9	17

From the above table and the picture of the information reflected in the results of the analysis of easy-to-get, for simple terrain path planning, improved genetic algorithm and A* algorithm have a strong adaptive capacity, the above Figure 1 represents the two algorithms were planned for simple terrain path, the length of the path planning by the Table 1 can be seen in the improved genetic algorithm path length is slightly shorter than the same as the A* algorithm, and the number of turns is similar, slightly better; but for complex terrain, the improved genetic algorithm is stronger than the A* algorithm, as shown in Figure 3. The length of path planning is similar to that of the A* algorithm, and the number of turns is about the same; the improved genetic algorithm is slightly better; however, for the complex terrain, the adaptive ability of the improved genetic algorithm is more vital than that of A* algorithm, as shown in Figure 3, the improved genetic algorithm is smoother than A* algorithm, and the path is shorter than A* algorithm as shown in Figure 3, it proves that the improved genetic algorithm can plan more reasonable routes in a more complex environment, and the length and the number of turns are also significantly better than the A* algorithm. The path length and the number of turns of the improved genetic algorithm are also significantly better than the traditional A* algorithm; from the convergence curves in Figure 2 and Figure 4, it can be seen that the improved genetic algorithm converges faster and better, so the above conclusions make the improved genetic algorithm valid.

4. Conclusions

In this paper, we study the path-planning problem of a fully automatic seeder in a small, cultivated area and propose a path-planning model based on an improved genetic algorithm. The model simulates the collection and classification of terrain data, multi-objective optimal design, genetic algorithm improvement, and grid division and path integration to simulate the effect of path planning in experimentally cultivated areas, aiming to improve the planter's path planning efficiency in complex farmland. The experimental results show that the improved genetic algorithm proposed in this paper has significant advantages over the traditional algorithm in terms of path length, number of turns, difficulty of passage, and convergence effect of the algorithm, which can effectively help to improve the operational efficiency of the planter and the quality of seeding from the aspect of path planning.

Although specific results have been achieved, this study still has certain limitations. In the process of terrain data acquisition and classification, the data's accuracy may affect the overall model's accuracy. In addition, although the genetic algorithm is improved in this paper, the defect that it is easy to fall into local optimization still exists, which may affect the global optimality of path planning. The experiments in this study mainly focus on the simulation of path planning during seeding, and the effects of weather conditions and seed characteristics on the seeding process in the actual seeding situation have yet to be studied in this paper, which may bring certain limitations in practical applications.

In the future, the existing algorithms can be further optimized. New hybrid algorithms can be explored, such as combining genetic algorithms with particle swarm algorithms and ant colony algorithms, to improve the global search capability and overcome the limitation of local optimum. In addition, future research needs to consider various factors affecting seeding more comprehensively, construct more complex path-planning models, and integrate them into the actual seeding work to provide more adapted seeding solutions for small-scale cultivation areas.

References

[1] FU Congying, GUO Xi, HAN Yi, JIANG Ye Feng, LAI Zhaohao. A study on the coupling of natural quality of arable land and farming conditions in hilly areas in the south of China - A case study of Fengxin County, Jiangxi Province[J]. Southwest Journal of Agriculture,2020, Vol.33(3): 599-606.

[2] LIN Du. Path planning based on genetic algorithm in complex environment[D]. Shanghai:Donghua University, 2017.

[3] R. Sun, H. Huang, H. Chao, X. T. Huo, J. Y. Chen. Multi-objective optimization-improved genetic algorithm path planning model[J]. Journal of Guizhou University (Natural Science Edition),2023, Vol. 40 (1): 95-100, 124

[4] Qin Xueshuai. Research on intelligent vehicle path planning and tracking control based on multi-segment curve splicing and fitting [D]. Chongqing University of Commerce and Industry, 2023.

[5] BAO Qinyue, SHI Hai, GUO Hui. Underwater measurement and terrain modeling based on unmanned ship data[J]. Green Technology,2024,26(6):275-278.

[6] Liu Y. Research on several evolutionary algorithms for solving high-dimensional multi-objective optimization problems[D]. Shaanxi:Xi'an University of Electronic Science and Technology,2020.

[7] Xue WK. Application of genetic algorithm in agricultural mobile robot path planning - based on matrix binary coding[J]. Research on Agricultural Mechanization,2019, Vol.41(12): 69-73.

[8] P. Zhao, X. Ding, T. Cheng, S. Yan Mo. Improved genetic algorithm based on differential evolutionary algorithm for UUV path planning[J]. Automation Application,2024,65(5): 25-28

[9] Zhang H. Research on path planning algorithm of logistics robot[D]. Jilin:Changchun University of Technology,2023.

[10] Xing Mengyang, Du Jiahao, Wu Jingqi, et al. Complex parking lot path planning based on improved A~* algorithm[J]. Intelligent Computer and Applications, 2022, 12(04): 126-129.