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IMPROVED PARTICLE SWARM PATH PLANNING FOR UNMANNED VEHICLES BASED ON SPACE PARTITION

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Abstract. *Path planning is the core problem that determines the operation accuracy of the unmanned vehicles. The application of particle swarm optimization algorithm in path planning has achieved good results. However, there are still some problems such as slow convergence and local optimal solutions. To address these problems, an improved fractional-order particle swarm gravitational search algorithm based on space partition is proposed in this paper. According to the particle swarm algorithm, we obtain some initial feasible paths. Combined with the characteristics of obstacles in the environmental map and the number of intersection points between the initial path and the circle center line, the environmental map is decomposed into several sub-regions to narrow the feasible path search space by the space partition method, which can reduce the complexity of the search region, avoid the problem of local optimal solutions generated in the global search, and improve the efficiency of the refinement search in the next stage. In the refinement search stage, combining with the fractional order calculus and the gravitational search in the particle swarm, the algorithm can enhance the global convergence, and take the energy consumption constraint and dynamic parameters. Through simulation experiments, the feasibility of the algorithm is verified. It shows that the improved algorithm can improve the convergence performance during path search and can plan a feasible path with lower energy consumption while ensuring the path accuracy.*

Keywords: Space partition, Particle swarm optimization, Gravitational search, Fractional calculus, Dynamic parameter

1. **Introduction.** The path planning problem can be described as an optimization problem subject to several constraints and performance criteria (such as shortest path, barrierless route, and energy loss) [1]. It is also the core problem for the accurate operation of unmanned vehicles [2]. The feasible path with high precision can improve the operating efficiency of unmanned vehicles, and the working cost with low energy consumption is also an important factor of unmanned vehicles.

The traditional particle swarm optimization (PSO) algorithm has fewer parameters and is relatively convenient to implement. However, the convergence rate is slow and it is easy to produce local optimal solutions. The current research on PSO mainly focuses on the update and improvement of the parameters, such as adjusting the inertia weight value [3-5] and the acceleration factor [6]. The algorithm in [7] changes the population topology structure to improve the optimization performance, as well as hybrid genetic algorithm [8,9], ant colony algorithm [10], simulated annealing [11,12] and other related optimization methods. These methods have good optimization performance to a certain

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extent, but there are still problems such as premature convergence. [13] adopts a method combining hierarchical clustering with particle swarm optimization to locate and track multiple peaks in the dynamic environment. It can achieve extreme value solution. [14] uses fitness variance to measure particle diversity by improving inertia weight and localization, and increases particle diversity to overcome the problem of precocity of particle swarm. However, it may increase the overall search time.

The gravity search algorithm (GSA) has good convergence performance and high search ability. However, it may also fall into the local optimal solution [15]. [16] applies gravity search algorithm to fuel management optimization problem, which plays a good effect on multi-objective optimization. It can also be extended to other optimization problems in the field of nuclear engineering.

[17] proposes a full-coverage path algorithm, which divides the spatial region according to the different environmental conditions for the first time. In the existing sub-regions, the secondary mesh processing is carried out through the principle of cellular automata to obtain the final space partition result, so as to reduce the search probability of the repeated region during the coverage search and effectively optimize the number of turns of the UAV. [18] mainly uses the separator line and UAV to divide the space in parallel, and selects convex decomposition at the concave point in the area, which can quickly generate effective UAV search area and path. However, it may increase the length of non-working path. Moreover, in the practical application, it is also necessary to consider the influence of obstacles in the actual environment on the regional partition. In [19], the gravitational search algorithm is combined with a traditional particle swarm algorithm to optimize the power system dispatch scheme. The constraints of the network loss conditions are considered, resulting in lower generation costs and better dispatch results. [20] wants to optimize the path planning and positioning error of the manipulator. Firstly, the multi-colony ant colony optimization algorithm was used to determine the shortest trajectory of obstacle avoidance. Secondly, quantum mechanics was introduced into the particle swarm optimization algorithm, which can optimize the optimal error of each moving point in the trajectory. The optimized manipulator realized less joint movement. In [21], the path planning obstacle avoidance strategy of two-link manipulator was studied by means of cyclic heuristic search and A* algorithm. The effectiveness and performance of the two algorithms were compared through experiments.

In view of the above analysis content, some of the existing researches only consider the influence of the algorithm itself on the local optimal solution. It does not consider the influence of the environment map (search space). This paper considers this problem and conduct research to solve it. The combination of particle swarm gravitational search algorithm in [19] can improve the efficiency of particle search, but cannot guarantee the global convergence. The historical memory of fractional order can help improve the convergence performance of the algorithm.

This paper proposes a fractional particle swarm optimization gravitational search algorithm (FPSOGSA) based on space partition. According to the characteristics of the adopted environmental map, some feasible paths are obtained through the PSO. Combined with the space partition method, the environmental map is decomposed into multiple sub-regions to reduce the search range of particles, so as to improve the search efficiency. With the combination of PSO with fractional calculus and gravity search algorithm, the convergence performance of the algorithm is improved. Considering the energy consumption constraint in the speed update term, dynamic parameters are introduced to adjust the search update step. The main contributions of this paper are as follows.

1) By space partitioning, a number of sub-regions are obtained. The path search in the sub-regions can avoid the interference caused by the local optimum, reduce the search

complexity, and help to solve the problem of low global search efficiency and improve the search efficiency of feasible paths.

2) The combination of PSO and gravity search algorithm is helpful to improve the particle search ability. At the same time, the fractional calculus in the velocity update term can improve the global convergence of the algorithm.

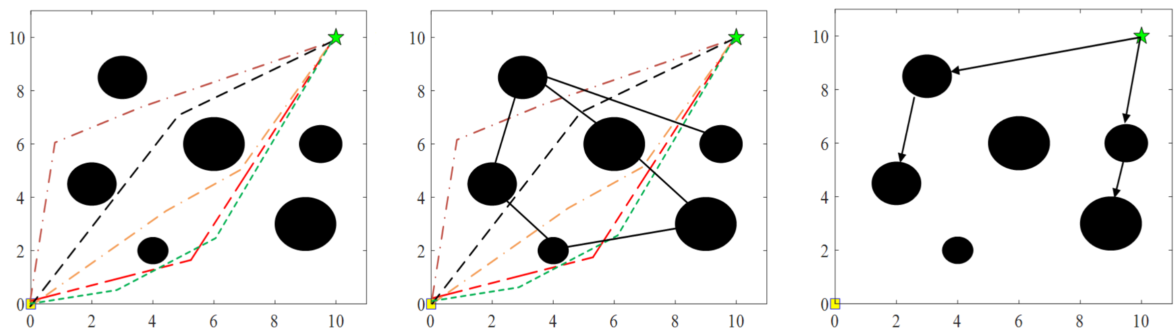
3) In the position update term, with the energy consumption factor, the particle search step size is adjusted by dynamic parameters, and a feasible path with low energy consumption can be obtained.

The remainder of this paper is organized as follows. Section 2 mainly introduces the method of region division. In Section 3, the particle swarm gravitational search algorithm based on fractional order is introduced. Section 4 discusses the simulation and practical results. Finally, the conclusion has been presented in Section 5.

2. Region Optimization Partition.

2.1. Space partition. For the space partition, the partition method will be different according to the actual needs. When dividing the space, the geometric vertex or a point on the edge of the obstacle can be selected for some common regional spatial connection points. According to the characteristics of the spatial obstacles in the environmental map, the geometric center of the obstacles is regarded as the connection nodes of the region boundary. Starting from the initial node, it extends to next node. The spatial region is decomposed by connecting the initial node with each extended node.

Figure 1 shows an example of the space partition. The black filled circle represents the obstacle, the yellow box represents the starting position of the unmanned vehicle, and the target position is represented by the green filled five-pointed star.

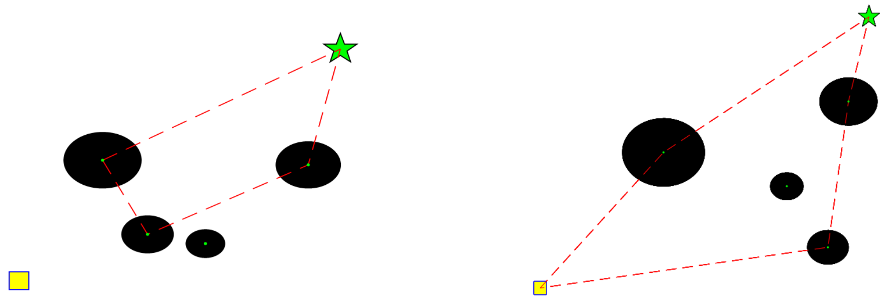


(a) (b) (c)

FIGURE 1. Schematic diagram of space partition

In the early stage of space partition, the standard PSO is used to obtain a group of feasible path groups from the starting point to the target point (as shown in Figure 1(a)). Connecting the centers of two obstacles we obtain a circle center line (as shown in Figure 1(b)), and the position of the target point is defined as the initial node (defined as the parent node). The next extended node is defined as the child node. When the circle center line has the most intersection points with the feasible path group, the center of the circle is taken as the child node of the parent node (such as child node 1 and child node 2). The child nodes are taken as the parent nodes to connect the next child node. The starting coordinate point is the final node (as shown by the black line arrow pointing in Figure 1(c)).

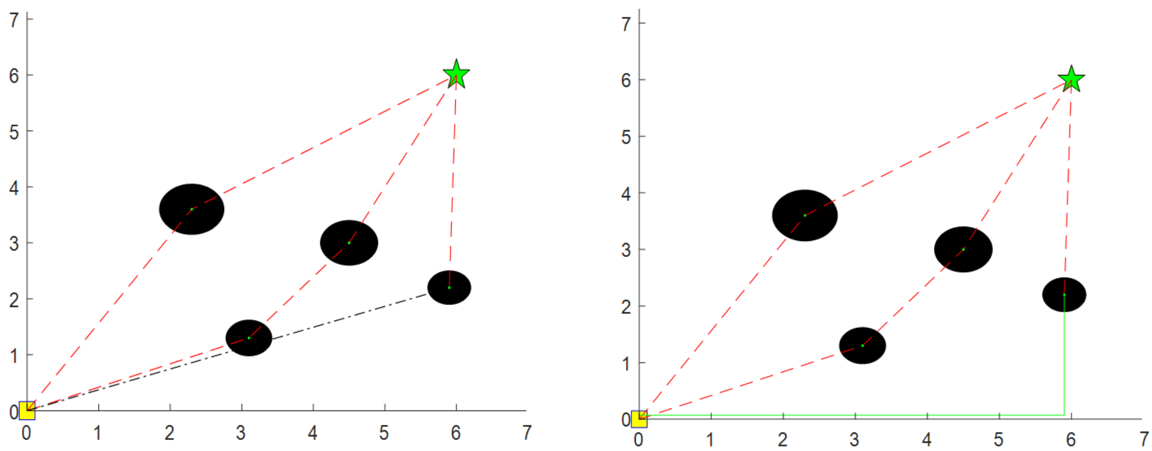
Among them, each node can only be a child node of one parent node (except the start and goal points), which can prevent the closed space (without the start point) in the process, as shown in Figure 2(a). At the same time, each node needs to be traversed. That is, the decomposed sub-region must be a single connected region to avoid the emergence of multiple connected region (as shown in Figure 2(b)).



(a) (b)

FIGURE 2. Two infeasible circumstances in space partition

2.2. **Consideration of spatial boundaries.** In the process of space partition, the boundary line in the spatial region is considered to avoid the appearance of multiple connected regions. The boundary line is taken into account. In Figure 3, a partition method is given to take the boundary line into account. In Figure 3(a), no feasible sub-region can be formed because the connecting line (black dashed line) has to pass through the obstacle. Moreover, the boundary region should be considered, as shown by the green edge line in Figure 3(b), so as to form a complete spatial sub-region.



(a) (b)

FIGURE 3. (color online) Considering the circumstance of the boundary region

After using the space partition, more detailed search range can be obtained. The complexity of path search can be reduced, and the refined search can be carried out. It can avoid the problem of local optimal solution, and improve the search efficiency.

2.3. **Hierarchical processing of energy consumption.** In the process of path searching, a safe area around the obstacle is set, and the energy loss caused by obstacle avoidance near the obstacle of unmanned vehicles is taken into account. The value of energy consumption in different ranges is determined by setting up the safety energy consumption level. The energy consumption factor is added in the constraints of particle update. It makes the search under the constraints of multiple factors. There are two steps in this process.

1) Three different levels of safety range are drawn according to the radius (r) of the obstacles. The width of the safety region (ring region in Figure 4) is $0.2r$, $0.3r$, $0.5r$, and the boundary of the region is defined as L_1, L_2, and L_3.

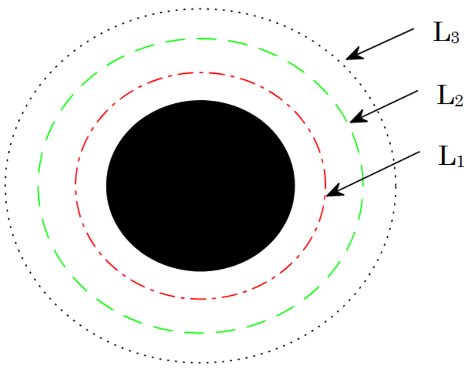


FIGURE 4. Schematic diagram of energy consumption level

2) Setting the weight of energy consumption: in the loop (r, L_1), the weight of energy consumption is K_1. In the loop (L_1, L_2), the energy consumption weight factor is K_2. In the loop (L_2, L_3), the energy consumption coefficient is K_3. The range outside L_3 is the normal driving energy consumption. Obstacle avoidance fails when the vehicle is within the obstacle.

The formula to solve the energy consumption is as follows:

$$E = E_{path} + E_r = e_0 L_{path} + K_i R_r = e_0 \sum \sqrt{\left(x_{t+1}^i - x_t^i\right)^2 + \left(y_{t+1}^i - y_t^i\right)^2} + K_i R_r \quad (1)$$

where E_{path} represents the energy consumption in the non-obstacle space, E_r represents the energy consumption in the loop (r, L_3), e_0 represents the energy consumption factor in the non-obstacle space, L_{path} represents the total path length of the unmanned vehicle in the non-obstacle space, K_i represents the energy consumption weight factor, and R_r represents the path length in the loop (r, L_3).

3. Particle Swarm Gravitational Search Algorithm Based on Fractional Order. The environmental map is refined by the space partition method. We combine the PSO with the gravitational search algorithm and the fractional calculus in the refined search stage, which improves the global convergence. The energy consumption problem is introduced and the position of the PSO is dynamically adjusted and updated.

The standard velocity update and position update of PSO are as follows:

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 \left(p_{best} - x_i^t\right) + c_2 r_2 \left(g_{best} - x_i^t\right) \quad (2)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (3)$$

where ω represents the inertia weight, p_{best} represents the best position searched by the ith particle, g_{best} represents the best position searched by the group, x_i represents the current position of the particle, v_i represents the particle velocity, c_1 and c_2 are the particle learning factors, r_1 and r_2 represent the random number between 0 and 1.

It is assumed that there is an attractive force between the particles. The force is proportional to the mass of the particle itself and inversely proportional to the distance between the particles. The force can attract the particles to approach the global optimal position. Then, the particle gravitational search algorithm is formed. The velocity update formula is as follows:

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 a_t + c_2 r_2 \left(g_{best} - x_i^t\right) \tag{4}$$

where a_t is the acceleration of each particle, and M_t is the mass of each particle.

$$a_t = \frac{F_t}{M_t} = \frac{F_t}{\left(\frac{m_t}{\sum m_t}\right)} \tag{5}$$

and

$$F_t = \sum \varepsilon G_t \frac{M_i^t M_j^t}{L_{ij}} \left(x_i^t - x_j^t\right) = \sum \varepsilon g e^{-\rho \frac{t}{T}} \frac{M_i^t M_j^t}{L_{ij}} \left(x_i^t - x_j^t\right) \tag{6}$$

$$m_t = \left| \frac{f_t - f_{best}}{f_{best} - f_{worst}} \right| \tag{7}$$

where f_t is the fitness, f_{best} and f_{worst} are the best and worst fitness of the particle swarm, respectively. F_t is the force of other particles on the current particle, ε is a random number, L_{ij} is the Euclidean distance between particles, and G_t is the gravitational constant depending on constants g and ρ. In addition, t and T denote the current iteration number and the maximum iteration number, respectively.

By Equation (4), we obtain the following form:

$$v_i^{t+1} - \omega v_i^t = c_1 r_1 a + c_2 r_2 \left(g_{best} - x_i^t\right) \tag{8}$$

Inertia weight ω is a random number between 0 and 1. When the value is 1, the left side of Equation (8) can be expanded with the help of fractional calculus, as shown in the following equation:

$$\begin{aligned} & v_i^{t+1} - \omega v_i^t = c_1 r_1 \left(p_{best} - x_i^t\right) + c_2 r_2 \left(g_{best} - x_i^t\right) \\ & v_i^{t+1} - \alpha v_i^t - \frac{1}{2!}\alpha(1-\alpha)v_i^{t-1} - \frac{1}{3!}\alpha(1-\alpha)(2-\alpha)v_i^{t-2} - \frac{1}{4!}\alpha(1-\alpha)(2-\alpha)(3-\alpha)v_i^{t-3} \\ & - \frac{1}{5!}\alpha(1-\alpha)(2-\alpha)(3-\alpha)(4-\alpha)v_i^{t-4} = c_1 r_1 a + c_2 r_2 \left(g_{best} - x_i^t\right) \end{aligned} \tag{9}$$

In the above equation, α is a random coefficient. A performance with good convergence performance can be obtained by selecting a value between 0 and 1.

The fractional calculus is introduced in the velocity update term, while the particle velocity update is associated with the history term of the previous four moments.

We introduce a dynamic parameter to adjust the particle update search step size. It is necessary to appropriately increase or decrease the step size in each iteration to obtain a more accurate solution. At the same time, it can adaptively adjust the position update parameters in the iterative process.

$$\beta = sig\left(\frac{E(x_{id})}{E(x_{id})_{avg}}\right) \tag{10}$$

where $E\left(x_{id}\right)$ is the energy consumption and $E\left(x_{id}\right)_{avg}$ is the average energy consumption.

Then, the particle position update term is as follows:

$$x_i^{t+1} = \beta x_i^t + v_i^{t+1} \tag{11}$$

The schematic diagram of the algorithm flow is shown in Figure 5.

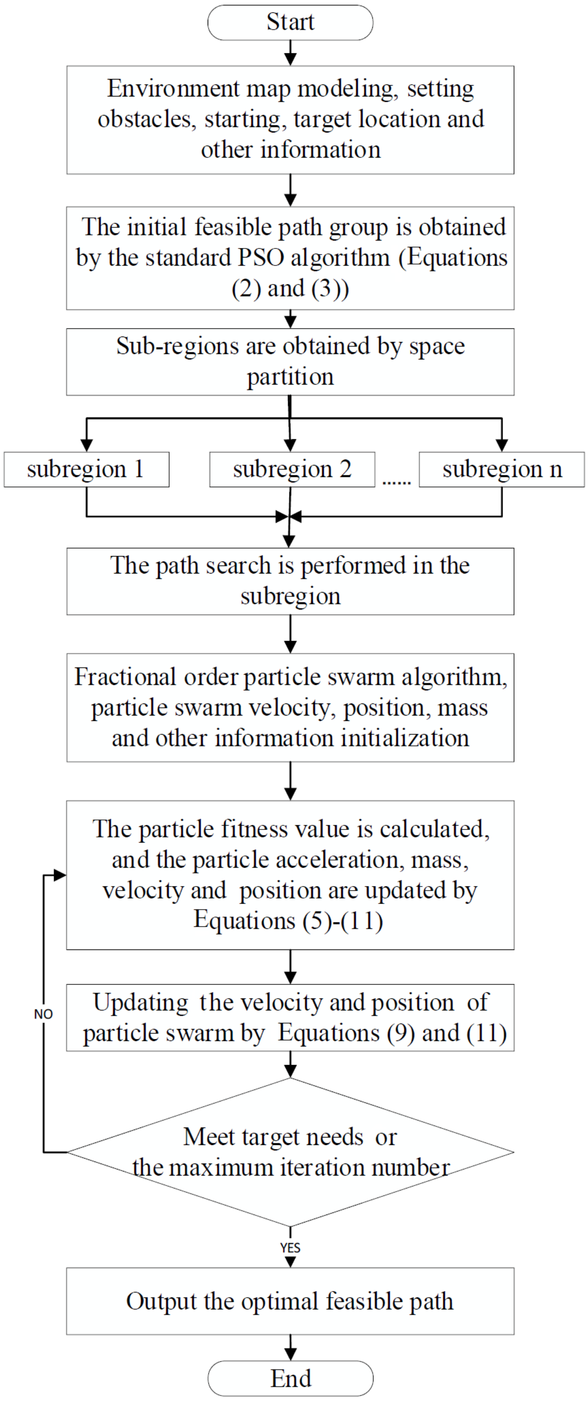


Figure 5. Flowchart of the algorithm

The steps of overall algorithm are as follows.

Step 1: Initialize the environmental map information and the location of the start and end points.

Step 2: Some initial feasible paths are obtained by PSO (Equations (2) and (3)), and the environmental map is divided into different sub-regions by using the space partition method.

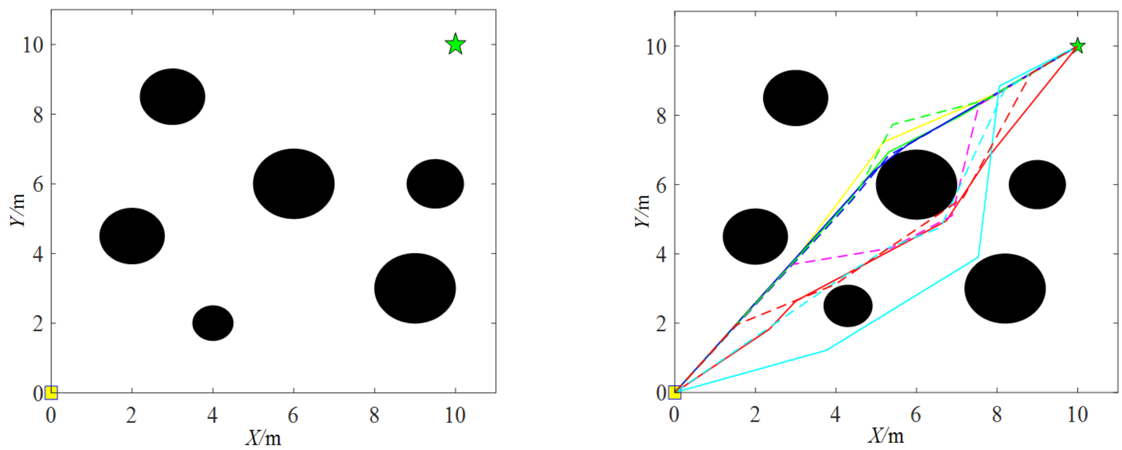
Step 3: PSO is combined with gravitational search algorithm, and fractional calculus. The energy consumption constraints are introduced to form a hybrid algorithm for path search in sub-regions.

Step 4: Initialize the velocity, position, and acceleration of the particle swarm.

Step 5: Calculate and update the mass, acceleration, velocity, and position of the particle by using Equations (5)-(11).

Step 6: The position and velocity of the particle swarm are updated continuously by using Equations (9) and (11). The iteration ends/the optimal feasible path is searched, and the final result is output.

4. **Experimental Simulation.** The environmental map is shown in Figure 6, and the specific specifications are set as follows: 1 in the environmental map represents 1 m. The coordinates of the starting point and the target position are selected as $(0,0)$ and $(10,10)$, respectively (marked by the yellow box and the green five-pointed star, respectively). The search range is set in the interval of 11×11. In the environmental map, six circular obstacles of different sizes (black) are set, and the coordinate positions are $(2.0,4.5)$, $(3.0,8.5)$, $(4.0,2.0)$, $(6.0,6.0)$, $(9.0,3.0)$, and $(9.5,6.0)$. The corresponding radii are 0.8, 0.8, 0.8, 0.5, 1.0, 1.0, 0.7. In addition, the parameters in the algorithm are usually chosen to be the commonly used values in PSO, which are $c_1 = c_2 = 2$, $r_1 \in (0,1)$, $r_2 \in (0,1)$. Through the comparison of experimental results, the population size and the number of population iterations are selected. Table 1 gives two of the groups of data.



(a) (b)

FIGURE 6. Environmental map

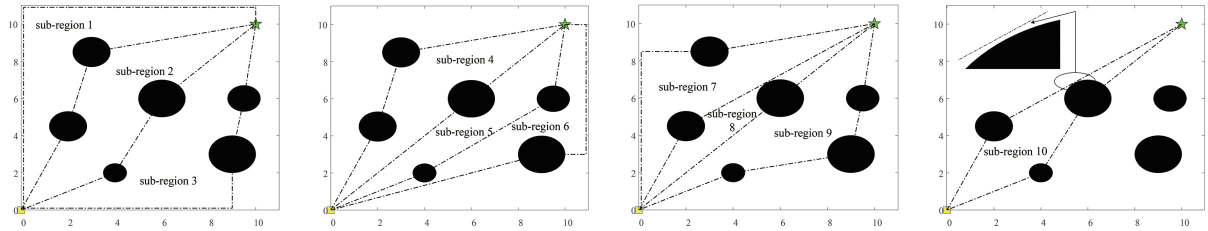
TABLE 1. Comparison results of some parameters

Iteration number	100				200			
Population size	40	80	100	200	40	80	100	200
Path length/m	15.13	16.4	15.15	14.81	16.07	15.39	15.37	14.94
Time/s	1.2	2.05	2.39	4.38	2.04	3.5	4.77	10.58

In Table 1, with the same number of iterations, more populations lead to longer search time. For the same population, if the number of iterations increases, the search time will also increase. During the experiment, we find that the solution is unstable if the number of iterations is too small or the population size is small. Based on the comprehensive analysis, the number of populations is selected as 80 and the number of iterations is selected as 200.

The environmental map is shown in Figure 6(a). Some initial feasible paths are obtained by the standard PSO, as shown in Figure 6(b).

The region is divided into different sub-regions by using the space partition (overlapping spaces are allowed between sub-regions). The results are shown in Figure 7.

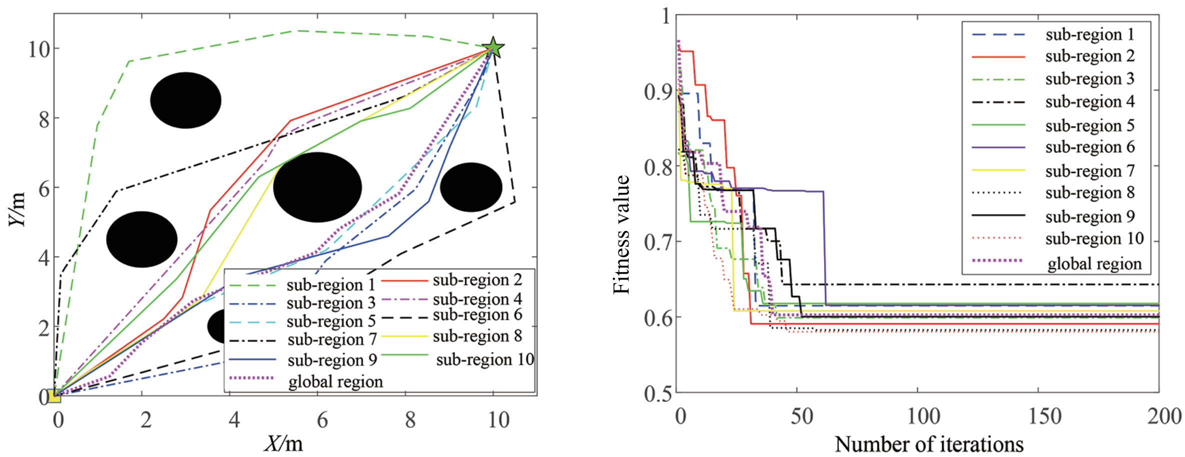


(a) (b) (c) (d)

FIGURE 7. Different sub-regions

4.1. **The obtained feasible paths in different regions.**

When verifying the feasibility of the algorithm, the feasible path results of each sub-region and the global region (the global region means that there is no space partition method used in path planning) are obtained and shown in Figure 8.



(a) (b)

FIGURE 8. (color online) Feasible paths in each sub-region and the global region

Figure 8(a) shows the feasible paths of each sub-region and the global region. Figure 8(b) contains the corresponding fitness curve.

Table 2 records the experimental results, including the feasible path length, total energy consumption and iteration number.

According to the results in Table 2, sub-region 9 has the shortest length. Sub-regions 2 and 3 have lower energy consumption. Sub-regions 2 and 7 have better performance.

Among them, the feasible path in sub-region 2 performs best. It is better than the result generated by other sub-regions. Compared with the experimental results obtained by the global region, the path length is 1.1% shorter than the latter, the energy consumption is reduced by 16%, and the number of iterations is less than that of the global search. In a word, our result has good global convergence, path accuracy, and less energy consumption.

TABLE 2. The experimental results of different regions

Sub-region	The feasible path length/m	Total energy consumption	Iteration number
1	18.19	1.82	41
2	14.50	1.45	31
3	14.56	1.46	33
4	14.46	1.68	44
5	14.60	1.61	36
6	16.46	2.06	62
7	15.56	1.62	24
8	14.51	2.30	59
9	14.29	1.74	52
10	14.42	2.10	48
Global region	14.66	1.68	40

4.2. **Comparison with other algorithms.** In order to further discuss the feasibility of the algorithm, PSO in [15], particle swarm optimization gravitational search algorithm (PSOGSA) in [19], and the proposed algorithm (FPSOGSA) are adopted. The following results are obtained.

Figure 9(a) shows the feasible paths obtained by PSO, PSOGSA and FPSOGSA. Figure 9(b) records the fitness curve corresponding to each feasible path. Table 3 records the experimental results of feasible paths under the three algorithms, including the feasible path length, total energy consumption and iteration number.

It can be seen from Figure 9(b) that, FPSOGSA has fewer iterations. PSO and PSOGSA do not contain the energy consumption constraint in the experimental process, so they

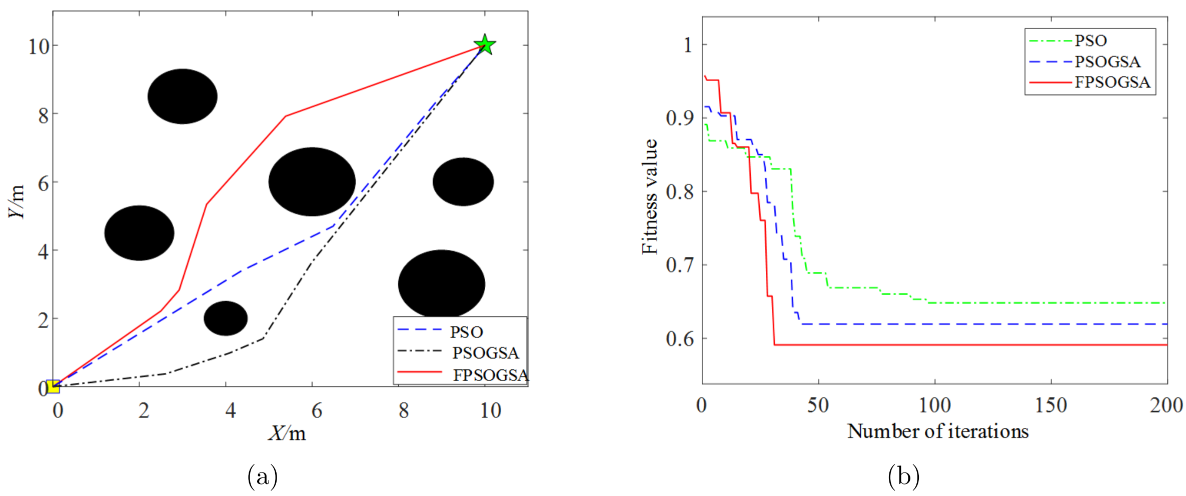


FIGURE 9. The results of PSO, PSOGSA, and FPSOGSA

TABLE 3. The experimental results of different algorithms

	The feasible path length/m	Total energy consumption	Iteration number
PSO	14.38	1.713	97
PSOGSA	14.47	1.605	43
FPSOGSA	14.50	1.450	31

have better accuracy performance (shorter path length). However, with the consideration of energy consumption, the PSO algorithm is the worst. The energy consumption of the latter two algorithms is 6.72% and 18.14%, which are less than that of PSO algorithm. Compared with the PSOGSA algorithm, the FPSOGSA algorithm reduced the total energy consumption by approximately 10.68%.

5. **Conclusions.** In order to improve the global search efficiency of path planning, this paper adopts the space partition method, which divides the global region into multiple sub-regions so as to narrow the search scope and reduce the complexity of the search. The fractional calculus is used to improve the particle velocity update term. At the same time, the search step size is dynamically adjusted by considering the energy consumption in the location update term. The final experimental results show that the proposed algorithm has the advantages of good calculation speed, better accuracy and less energy loss.

Future work will consider to apply the proposed method to more complex environmental maps, and take more constraints into account, such as turning radius, and kinematics.

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