Improved Black Hole Algorithm for Intelligent Traffic Navigation

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Abstract

Traffic navigation is an important part of intelligent transportation systems (ITSs). In this paper, we propose a novel algorithm for path searching based on an improved black hole (BH) method to enhance the real-time navigation efficiency. The original BH algorithm is optimized firstly. Parallel evolution, and information exchange strategy inspired by the quasi-affine transformation evolution (QUATRE) algorithm, allow agents with effective information to search the solution space quickly and effectively that can prompt the convergence speed and expand the diversity of solutions. At the same time, strengthen the exploitation around the global best solution also can enable agents to find the target quickly. The performance of our algorithm can be confirmed by CEC 2017 benchmark functions. For practical purposes, the optimal path should not only consider the shortest distance, but also the minimum fuel consumption. Besides, the effectiveness and timeliness are of great significance for real-time path navigation. In the simulation system, our proposed algorithm can reduce the error rate of navigation to find a realistic path. The results indicate that the proposed algorithm for navigation is effective and stable.

Keywords: Black hole, Traffic navigation, QUATRE algorithm, Route optimization

1 Introduction

In recent years, traffic congestion, known as the disease of big cities, has become a focus of government and public concern. Especially in the traffic rush hour, how to steer clear of the congested road, with a shorter distance and less fuel consumption reaching the destination, that has become a path optimization problem [1-11]. We need to take into account the distance between nodes and the congestion of the road, as well as the consumption of gasoline, to find the optimal solution with a balance of these factors. The traditional algorithms [7-8], such as the greedy algorithms and dynamic programming algorithms, have good performance when the problem scale N is not very large, but now it is confronted with the challenge of the expansion of urban traffic scale.

Group-based optimization algorithms in evolutionary computation with meta-heuristic characteristics play an important role in solving these problems, which is mentioned above. And those algorithms have good performance compared with other algorithms. Particle swarm optimization algorithm [1-2], ant colony optimization [5, 12], cat swarm optimization algorithm, ebb-tide-fish-inspired algorithm [4], monkey king evolutionary algorithm [6], and black hole algorithm are all examples. Because of modern cities with a large number of traffic intersections, grid management is more in line with reality. Thus, based on previous research, this paper improves the black hole algorithm and builds on that and a mesh model of the urban traffic to propose a novel path optimization algorithm.

In the grid, there is more than one possibility of node arrangement of the shortest path from node a to node b. Besides, the path between any two points can be extended to all points arrangement in the area [4]. The shorter the distance between the two points, the less fuel consumed, but the congestion of intersections can not be ignored considering the reality. If a node is in the state of congestion, the road to that node is in a jam, and the amount of gasoline consumed increases. So, the fuel consumption that from point a to point b is made to be an appraisal criterion of the optimal solution.

The path can be expressed as G (V, E) according to the graph theory, V represents the set of all nodes contained in the path, and E represents edges between two adjacent nodes [7]. A new method, which bases on a mapping between V and E, is used to reduce the scope of solutions. Also, the necessity of information communication to population-based algorithms is one of the characters of the heuristic algorithms that make the ratio of better solutions increase gradually, expand

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the diversity of swarm and lead solutions to the expected direction [13-17]. A new strategy inspired by the QUATRE algorithm [18] is adopted in the process of evolution to boost information exchange. In the simulation experiment, our proposed algorithm has a better performance in finding available navigation compared with the Floyd-Warshall algorithm in large-scale problems.

2 Relate Works

2.1 Latest Achievements About BH Algorithm and PSO

In the field of evolutionary algorithms, as well-known, particle swarm optimization (PSO) is irreplaceable. It is nature-inspired and performs well compared with traditional methods in solving a series of realistic problems of domains about engineering and network applications, etc. In recent years, the PSO algorithm is still one of the most widely used swarm intelligence based algorithms, which draws support from other methods, theories, and techniques, for instance, Taguchi method, evolutionary game theory, a Pareto based approach, adaptive angle division, fuzzy clustering method, and cooperative method. And besides, the hybrid model combining different algorithms also played a promoting role in its evolution.

Inspired by particle swarm optimization, a lot of nature-inspired algorithms were proposed in the last decades. The BH algorithm is a good example. Many variants of the BH algorithm have solved the problem not only confined to a single-objective problem, but also in the direction of multi-objective. They are applied in wireless sensor networks, image processing, multi-objective based dynamic workflow in cloud computing and solving the set covering problem, etc. In this work, a novel improved BH algorithm is utilized to optimize the routing problem.

2.2 Some Concepts Related to Our Work

Manhattan distance is also known as city block distance [19-20]. It represents the distance between points in the grid of city streets. Figure 1 gives a vivid display of the Manhattan distance. In our simulation system, the shortest distance between any two points is the Manhattan distance. And in information theory, Hamming distance [21-22] and information entropy are useful measurement methods. The former is used to measure the account of different letters in the corresponding places of two strings in the same length. And the other reflects the state of the population reach the expectation of us or not [23-24].

The city block distance with k-dimension between two points, a and b, is calculated as:

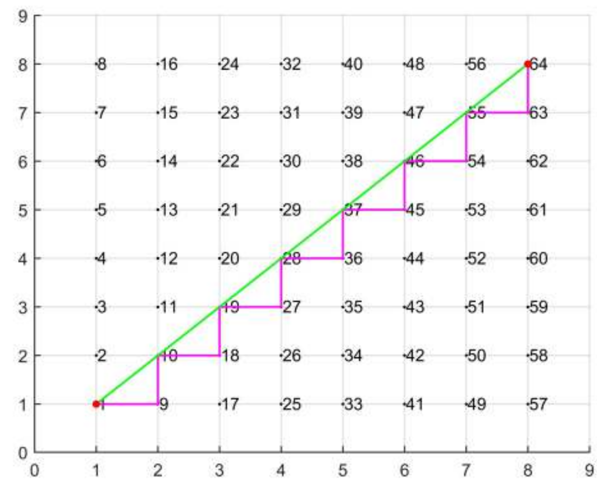


Figure 1. The Manhattan distance of any two nodes. The green solid line represents the Euclidean distance, and the magenta represents the Manhattan distance

$$D_{ab} = \sum_{j=1}^{k} |a_j - b_j| \tag{1}$$

The formula for information entropy is as follows:

$$E(X) = -\sum_{i=1}^{m} p(x_i) \cdot \log p(x_i) \tag{2}$$

with m dimensions, x_i is the value of each dimension. p indicates the probability of occurrence of x.

2.3 QUATRE Algorithm

The QUATRE algorithm [18, 25-29] is a swarm-based algorithm, which mainly applies the quasi-affine transformation method to the evolution process of the population, which enhances the information exchange between sub-groups as shown in Equation (3). The matrix S represents the population. W is a random binary matrix. It can be obtained through the row or column transformation of the lower triangular matrix. The elements in $\tilde{W}$ are opposite to the corresponding elements in W. This can be seen in Equations (4) and (5). And the E is the guiding matrix, which is the wind vane of the population evolution. It can be generated by different strategies. The symbol "•" in Equation (3) denotes ".*" in Matlab. Particles can learn from each other with new experiences and strengthen cooperation through information exchange, which has effectiveness in preventing evolution from stagnating due to information asymmetry. Thus, our proposed algorithm uses a parallel strategy, and each subgroup provides a guiding matrix generated using a new scheme. And then sub-groups learn the advanced experience with each other through the exchange of guiding matrix randomly. The mapping of the QUATRE algorithm is shown below:

$$S = W \bullet S + \tilde{W} \bullet E \tag{3}$$

$$W = \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix} \tag{4}$$

$$\tilde{W} = \begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{bmatrix} \tag{5}$$

3 Black Hole Algorithm and Its Improvement

3.1 Black Hole Algorithm

Inspired by the black hole phenomenon, the black hole algorithm has been created [30-32]. And it is also an algorithm based on swarm with some similar characters to particle swarm optimization [33]. The population is consists of candidate solutions for the problem that will be solved. The candidate individual with the optimal value so far in one generation, which has been calculated by the fitness function, is supposed to be the black hole. The remaining candidate solutions are set to ordinary stars. Because of the powerful attraction from the black hole, all-stars move toward it. But this group behavior brings a drawback that easily causes the population to fall into the state of local optimum. The best way to solve this problem is to increase the diversity of solutions. So, a method to imitate a phenomenon of the event horizon of the black hole is applied to the BH algorithm. In other words, if the distance between a candidate solution and the black hole is too close, this candidate will be replaced by a new solution randomly generated in the search scope. The evolution of the black hole algorithm is as follows:

Step 1: initialize the location of the population with Equation (7) in the search range randomly.

Step 2: evaluate the fitness value of every individual and select the suitable one to be the black hole.

Step 3: all of the candidate solutions are moving toward the location of the black hole as Equation (6). $X_j(g)$ denotes jth individual in the gth generation. X_b represents the best solution as so far in one generation, namely the black hole, and the *rand* is a random number between 0 and 1. If a candidate reaches a better position compared with the black hole, it will become the new black hole.

$$X_j(g+1) = X_j(g) + rand \times (X_b - X_j(g)) \tag{6}$$

Step 4: a candidate solution will obtain a new position in search scope randomly with Equation (7) if it is within the event horizon of the black hole.

$$X = X_l + rand \times (X_u - X_l) \tag{7}$$

where X_u denotes the upper bound, X_l denotes the lower bound, and *rand* is a random number between 0 and 1.

Step 5: continue to Step 2 when the termination condition is not met, otherwise, end the loop.

3.2 Our Proposed Algorithm

This section mainly describes the modification of the black hole algorithm. Our proposed algorithm uses parallel evolution [17, 34-38], each sub-group has a black hole, and the particles in the sub-groups move with Equation (6). The new method and information exchange strategy are applied to Step 4 of the black hole algorithm to accelerate convergence and achieve a more precise search. In Step 4, the limitation of the event horizon is ignored, and the position of the particle closest to the black hole is replaced by Equation (8). The X_g is the global best solution, which means the new particle around the global optimal. This method can speed up convergence.

$$X = X_g + rand \times (X_u - X_g) \tag{8}$$

Information exchange plays a vital role in population evolution. It can reduce the time consumption of exploration in the non-focus area and spend more time focus on the search of the key area [18]. With the help of the exchange mechanism of quasi-affine transformation, the search scope is gradually reduced and gradually close to the optimal. The key to this process lies in the selection of a guiding matrix. In the proposed algorithm, the concept of information entropy is introduced that comes from information theory and reflects the state of a population that the swarm is close to the optimal solution or not [23-24]. Calculate the information entropy of population in each dimension and then compare the value of individuals and the black hole in the corresponding dimension, if the value of the individual is less than that of the black hole, the information entropy in corresponding dimension plus a constant number, otherwise, minus the same number. In this paper, this number is 0.5, which get by comparison. The information entropy generates the guiding matrix through Equations (9)-(11) and determines its leading direction. The *Ent* denotes the information entropy in dimensions and E represents the guiding matrix. C_1 and C_2 are vectors. D denotes the number of the dimension.

$$C_1 = 0.1 \times Ent \tag{9}$$

$$C_2 = ones(1, D) - C_1 \tag{10}$$

$$E = C_1 \times X + C_2 \times X_g \tag{11}$$

Finally, we use Equation (3) for information exchange between subgroups. For example, suppose there are three sub-groups, E_1 is the guiding matrix of sup-group 1, it exchanges information to a sub-group randomly selected from sub-group 2 or sub-group 3.

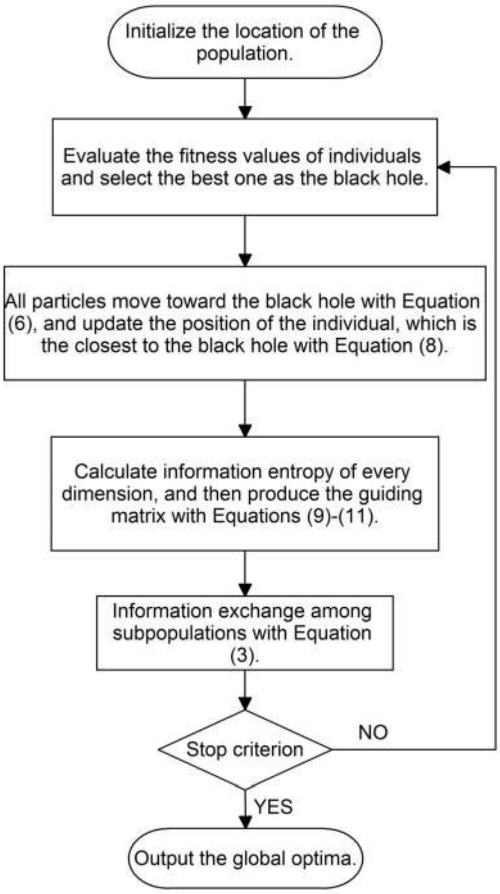


Figure 2. The flow chart of the improved black hole algorithm

4 Experimental Results

In this section, the validity and stability of our proposed algorithm have been proved through the CEC 2017 test set [39] and a simulation test of intelligent traffic navigation.

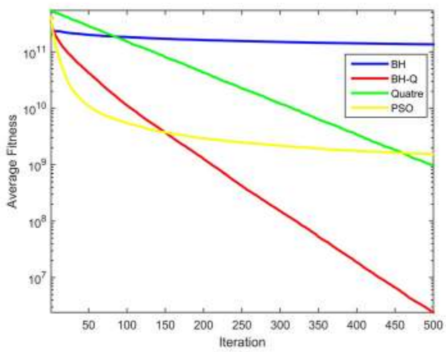
4.1 The Results of Test Functions

To make the test results more convincing, we choose the CEC 2017 test set, a black box test to confirm the performance of our proposed algorithm. The CEC 2017 contains 30 test functions, which are divided into four categories, such as unimodal, simple multimodal, hybrid and composition. But the second test function is eliminated since its unstable performance. Our proposed algorithm has a comparison with the BH algorithm, QUATRE algorithm, and the original PSO. And the basic PSO is a classic algorithm based on swarm with some common features of population-based heuristic algorithms. Each algorithm runs the function independently 30 times to ensure that there is no mutual interference. The dimension is design to 100 and the population size is 300 to prove our algorithm has advantages when dealing with large-scale problems. The comparison result of the average optimum between our algorithm and the other compared algorithms has been demonstrated in Table 1. And the bold denotes the stronger competitiveness of our proposed algorithm.

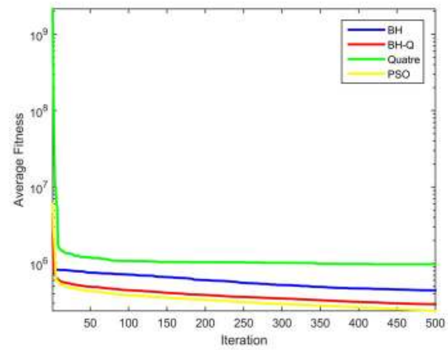
Table 1. The average of best value

F	BH	BH-Q	QUATRE	BH-Q	PSO	BH-Q
f1	1.3563E+11	**2.4097E+06**	9.4477E+08	**2.4097E+06**	1.5227E+09	**2.4097E+06**
f3	4.4394E+05	**2.9019E+05**	9.7350E+05	**2.9019E+05**	2.3843E+05	2.9019E+05
f4	3.1337E+04	**8.2778E+02**	9.8621E+02	**8.2778E+02**	1.1146E+03	**8.2778E+02**
f5	1.7754E+03	**1.0575E+03**	1.5105E+03	**1.0575E+03**	1.3187E+03	**1.0575E+03**
f6	6.9547E+02	**6.3341E+02**	6.2032E+02	6.3341E+02	6.6228E+02	**6.3341E+02**
f7	3.1279E+03	**1.8783E+03**	1.8675E+03	1.8783E+03	2.1976E+03	**1.8783E+03**
f8	2.2399E+03	**1.4170E+03**	1.7989E+03	**1.4170E+03**	1.6480E+03	**1.4170E+03**
f9	6.1947E+04	**2.2310E+04**	2.2493E+04	2.2310E+04	4.9976E+04	**2.2310E+04**
f10	3.0354E+04	**1.4012E+04**	2.9865E+04	**1.4012E+04**	2.0561E+04	**1.4012E+04**
f11	1.2740E+05	**3.7677E+03**	8.6571E+04	**3.7677E+03**	8.0041E+03	**3.7677E+03**
f12	7.2762E+10	**3.9067E+07**	1.6655E+09	**3.9067E+07**	1.0254E+09	**3.9067E+07**
f13	1.2439E+10	**1.0069E+04**	5.0778E+05	**1.0069E+04**	1.2082E+07	**1.0069E+04**
f14	8.5879E+06	**9.0633E+05**	2.0620E+06	**9.0633E+05**	2.2590E+06	**9.0633E+05**
f15	3.5719E+09	**3.8148E+03**	2.1383E+05	**3.8148E+03**	8.1457E+05	**3.8148E+03**
f16	1.4636E+04	**5.1860E+03**	1.1274E+04	**5.1860E+03**	6.4420E+03	**5.1860E+03**
f17	4.3402E+04	**4.5323E+03**	8.6962E+03	**4.5323E+03**	5.5035E+03	**4.5323E+03**
f18	8.1866E+06	**1.1841E+06**	1.5009E+07	**1.1841E+06**	3.1443E+06	**1.1841E+06**
f19	3.4282E+09	**3.6418E+03**	2.2678E+04	**3.6418E+03**	8.5932E+06	**3.6418E+03**
f20	6.7077E+03	**4.3320E+03**	7.0997E+03	**4.3320E+03**	5.2846E+03	**4.3320E+03**
f21	4.3872E+03	**2.9334E+03**	3.3457E+03	**2.9334E+03**	3.3891E+03	**2.9334E+03**
f22	3.3341E+04	**1.7471E+04**	3.1906E+04	**1.7471E+04**	2.4030E+04	**1.7471E+04**
f23	6.7399E+03	**3.4349E+03**	3.8210E+03	**3.4349E+03**	4.3274E+03	**3.4349E+03**
f24	1.0346E+04	**4.1739E+03**	4.3634E+03	**4.1739E+03**	4.9025E+03	**4.1739E+03**
f25	1.2174E+04	**3.5359E+03**	3.7149E+03	**3.5359E+03**	3.7280E+03	**3.5359E+03**
f26	3.7380E+04	**1.7572E+04**	1.7482E+04	1.7572E+04	1.9701E+04	**1.7572E+04**
f27	1.1179E+04	**3.9651E+03**	3.2000E+03	3.9651E+03	3.9378E+03	3.9651E+03
f28	1.8647E+04	**3.6375E+03**	3.3000E+03	3.6375E+03	3.8087E+03	**3.6375E+03**
f29	2.2402E+04	**6.8545E+03**	1.0162E+04	**6.8545E+03**	9.4832E+03	**6.8545E+03**
f30	1.1863E+10	**4.2841E+04**	2.1819E+05	**4.2841E+04**	5.6804E+07	**4.2841E+04**

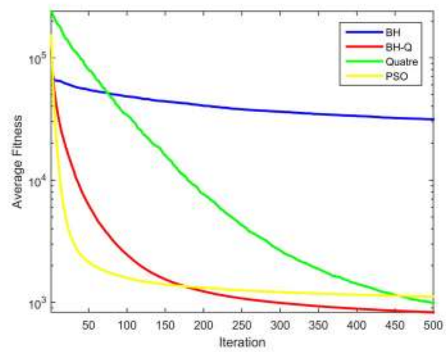
At the same time, the convergence characteristics of the four algorithms have been compared. The comparison figures of eight functions shown in Figure 3, they are F1, F3, F4, F10, F11, F20, F21 and F30, the first and last of each category. The BH-Q denotes our algorithm. On the whole, the convergence rate of our proposed algorithm performs well in all functions except the 27th and 28th. In brief, our algorithm has advantages in dealing with large-scale problems, both in accuracy and in convergence speed.



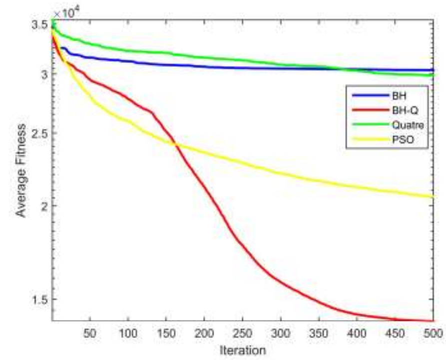
(a) F1



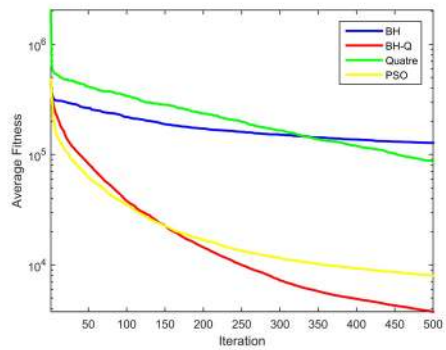
(b) F3



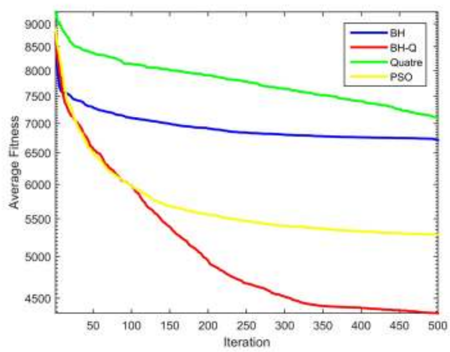
(c) F4



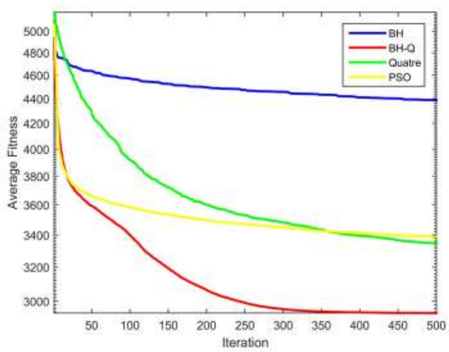
(d) F10



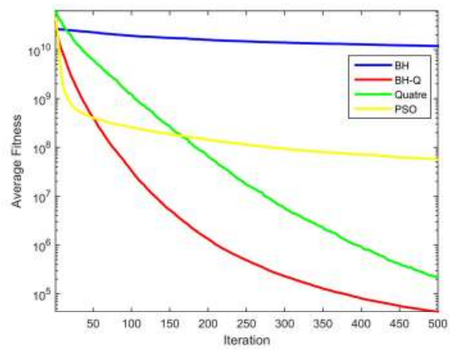
(e) F11



(f) F20



(g) F21



(h) F30

Figure 3. The convergence curve of function

4.2 The Results of Simulation Experiment

In this simulation experiment, nodes of the grid regard as the traffic intersections of a big city and mesh edge regard as streets. At a certain time, if a node is congested, the edge leading to the node is also considered to be congestion. Fuel consumption increases under congestion. For ease of calculation and understanding, the weight of distance and fuel consumption of mesh edge is set to one under normal traffic conditions, but the latter is placed at two when it is under congestion. The purpose of this simulation is to test the effectiveness of our proposed algorithm for finding the optimal path from node *a* to node *b*. The solution should have a shorter distance and less gasoline consumption, and more importantly, it must be along streets because you can't cross over the wall.

The path is an arrangement of all nodes in the grid, which has assigned to the ordinary star. The black hole denotes the optimal path. Our proposed search algorithm based on the improved black hole algorithm is as follows:

Step 1: determine the relative position of the starting and end of the path. Divide the grid into four quadrants centered on the starting point as shown in Figure 4. The direction is different depending on the quadrant where the endpoint of the path locates.

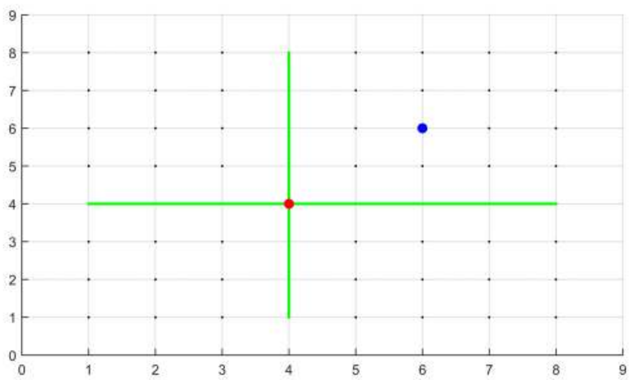


Figure 4. The quadrant diagram. The red "●" denotes the start and the blue is the end. The green axis divides the plane into four parts, which are the first, second, third and fourth quadrants in counterclockwise direction respectively

Step 2: narrow down the search area of solutions based on the results of the first step and the Manhattan distance. There are two directions for each point along the shortest path direction to choose from. For example, there are 2^{n-1} sequences for the shortest path containing n points. So the solution is limited to the scope of the shortest path from *a* to *b*. And then calculate the fitness value of individuals, the fuel consumption of *a* to *b*, to find the black hole.

Step 3: increase the chance of finding the best solution through the local search modal. Calculate the Hamming distance between each individual and the black hole, and randomly exchange two points of the candidate path, one is the same as the corresponding point from the black hole, but the other is different.

Step 4: exchange information according to Equation (3). Calculate the information entropy of every individual. Then the candidate solution is compared with the corresponding location of the black hole. If it is the same, the information entropy adds a constant number; otherwise, subtract the same number. Choose individuals with large information entropy to form the guiding matrix.

The optimal navigation found using our proposed search algorithm is shown in Figure 5. The red "*" represents the node under congestion. The green "●" denotes the start of a path and the magenta is the finish. The blue solid line shows the navigation.

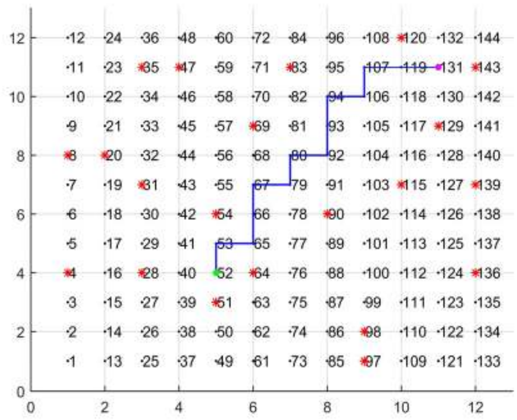
Floyd-Warshall algorithm is a dynamic programming algorithm, which is used to solve the shortest path problem of all node pairs [8]. The weight matrix of fuel consumption as the adjacency matrix of the algorithm since the path weight between adjacent points in the grid all equal one.

To verify the effectiveness and stability of our algorithm when dealing with large-scale problems, four different scale matrices as the experimental platform, such as the 8×8, 12×12, 20×20 and the 30×30. And ten different node pairs in four different directions are selected respectively in a platform. Also, our proposed search algorithm and the Floyd algorithm run independently. Figure 6 shows the operation results that the number of the effective path found by our algorithm is significantly higher than that of the Floyd algorithm in the same condition, especially when the grid nodes in the large-scale.

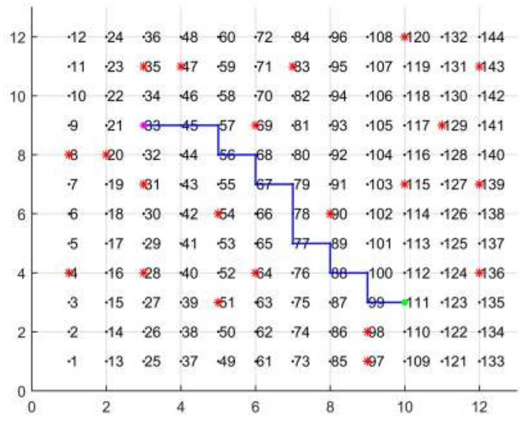
As shown in Figure 7, the proportion of the effective path decreases as the increase of the grid node scale gradually at the same time. But this trend runs slowly for our algorithm, and the ratio is always at a high level compared with the Floyd algorithm. In brief, our proposed algorithm has a good performance on different scale platforms, not on the effectiveness but also the robust.

5 Conclusion

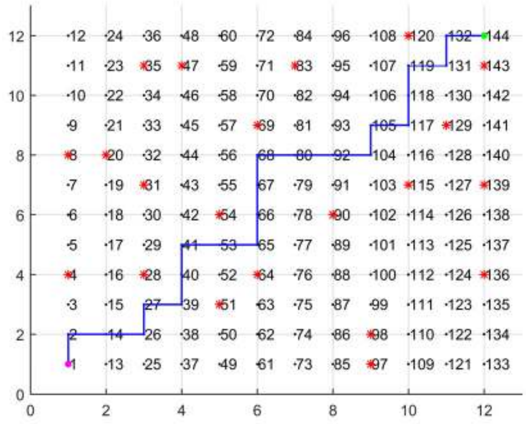
In this paper, we proposed a search algorithm of path based on an improved black hole algorithm. It is applied to the intelligent transportation system of big cities, which is a large-scale problem. A mesh is simulated large-scale traffic intersections and streets in large cities. The experimental result shows that our proposed algorithm has strong competitiveness in both effectiveness and stability. This is mainly because our algorithm not only has the group advantage of swarm intelligence algorithms but also has the characteristics of deep communication of the quasi-affine transformation. These make our algorithm get a noticeable improvement



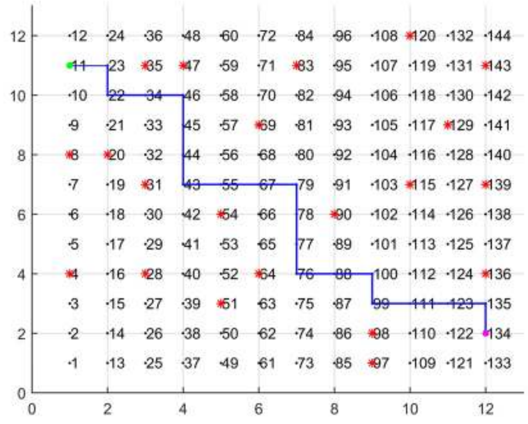
(a) The destination is in the first quadrant



(b) The destination is in the second quadrant



(c) The destination is in the third quadrant



(d) The destination is in the fourth quadrant

Figure 5. The navigation path

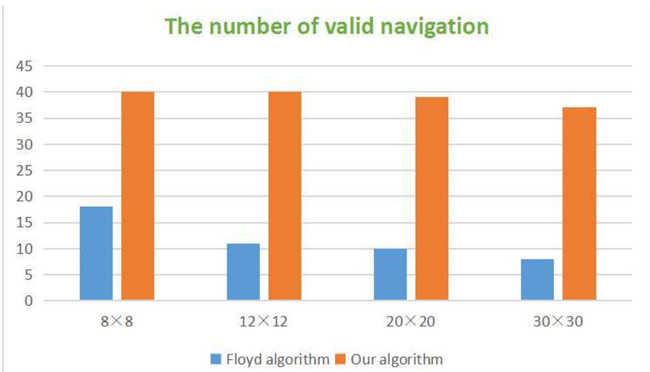


Figure 6. The comparison of the number of valid navigation with different algorithms

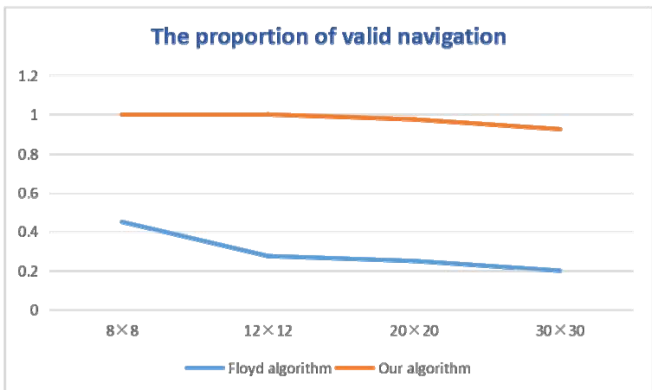


Figure 7. The comparison of the proportion of valid navigation with different algorithms

both in global and local searches. The fast convergence characteristics of our algorithm in dealing with high dimensional problems and its higher accuracy compared with other algorithms are verified by standard test functions. In future work, we will further research and improve the technology of path search and optimization, so that it can handle large-scale problems with faster speed and higher accuracy. The proposed algorithm may also be improved by implementing some hybrid methods [40-43]. Wireless sensor network has been applied to the traffic navigation [44-45], the proposed methods may combine with the techniques [46-51] so as to further improve efficiency and effectiveness of traffic navigation.

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