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A path planning method using adaptive polymorphic ant colony algorithm for smart wheelchairs

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ABSTRACT

In many cases, users of smart wheelchairs have difficulties with daily maneuvering tasks and would benefit from an automated navigation system. With multi-colony division and cooperation mechanism, the polymorphic ant colony algorithm is helpful to solve optimal path planning problems by greatly improving search and convergence speed. In this paper, a path planning method for smart wheelchairs is proposed based on the adaptive polymorphic ant colony algorithm. To avoid ant colony from getting into local optimum in the process of reaching a solution, the adaptive state transition strategy and the adaptive information updating strategy were employed in the polymorphic ant colony algorithm to guarantee the relative importance of pheromone intensity and desirability. Subsequently, the search ant maintains the randomness for the search of the global optimal solution, and then the deadlock problem is solved by means of the direction determination method that improves the global search ability of the algorithm. The target path planning and obstacle path planning are respectively carried out by using the adaptive polymorphic ant colony algorithm. Experimental results indicate that the proposed method provides better performance than the improved ant colony algorithm and the polymorphic ant colony algorithm. Furthermore, the efficiency of finding an optimum solution is higher than the average polymorphic ant colony algorithm. The proposed method, which achieves superior performance in path planning for smart wheelchairs, is even racing ahead of other state-of-the-art solutions. In addition, this study reveals the feasibility of using it as an effective and feasible planning path tool for future healthcare systems.

1. Introduction

Smart wheelchairs give people with disabilities not only mobility but also the necessary help and support to handle daily living activities. The smart wheelchair combines a variety of research fields, such as machine vision [1], robot navigation and positioning [2], pattern recognition [3], multi-sensor fusion [4] and human-machine interface [5]. Especially in automatic navigation, accurate path planning results will greatly improve the performance of a smart wheelchair [6]. It is desirable to use reliable path planning methods to enhance awareness of the status of contemporary smart wheelchair technology, and ultimately increase the functional mobility and productivity of users. Intelligent optimization algorithms, which are simple, efficient and adaptive, have been introduced to solve path planning problems, especially in infrastructures and facilities for healthcare [7–9]. Ant colony optimization is an intelligent search algorithm developed by Marco Dorigo's doctoral thesis from a long-term observation of ant colony foraging behaviors [10]. Different from other path planning techniques, for instance, heuristic search or potential fields, it is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs. Hence ant colony algorithm has widely used in transportation, logistics and distribution, network analysis, pipeline and other fields in recent years [11,12].

At present, a large number of scholars are doing applied research on the ant colony algorithm. For instance, Xia et al. studied the issues of dynamic nature, instability and multi QoS property restrictions of Web service in the process of services combinatorial

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optimization, and proposed a multiple pheromone dynamically updated ant colony algorithm [13]. Sheng et al. proposed a credible service discovery method based on the improved ant colony algorithm for the service discovery problems in the unstructured P2P networks [14]. Luo et al. proposed an improved ant colony algorithm based on dynamic node planning for the problem of selection of optimal measuring points for analog circuit [15]. Shan et al. employed the ant colony algorithm to the smart wheelchair path planning method to solve the problems of local optimal in the path search process for the smart wheelchair [16]. Mohamed et al. proposed multi-division vehicle routing problems based on the hybrid ant colony algorithm by combining local search and basic ant colony algorithm [17]. Although the ant colony algorithm is widely used, and reflects good search features during the path optimization, it has shortcomings of likeliness to fall into local optimum and long search time, etc [18,19].

In traditional ant colony algorithms, the paths are gradually explored by ants and the search efficiency of the algorithms is low. To solve this problem, many scholars put forward some improved methods to cope with such problem. Yao et al. put forward the adaptive parallel ant colony algorithm [20]. With the aid of this method, it can determine the optimal combination of parameters depending on the search stage to avoid stagnation to a certain extent. Hu et al. applied dynamic calls and the rule of increase of pheromone on the optimal path into the basic ant colony algorithm, and proposed the optimal path model with a number of path quality constraints [21]. Du et al. designed the improved polymorphic ant colony algorithm based on the secondary annealing mechanism according to the advantages of the polymorphic ant colony algorithm and the simulated annealing algorithm, allowing the pheromone release to reflect the path quality better than before [22]. Li et al. introduced the roulette method to the state transition rule, and classified the search into local search and global search. By doing so, it avoid the algorithm from falling into local optimum [23]. Yang et al. proposed the improved ant colony algorithm by combining group intelligence and local search, effectively solving the multi-dimensional problem in the traveling salesman problems [24].

Containing a variety of ant colonies and pheromones, the polymorphic ant colony algorithm combines local search and global search, allowing the searching speed and convergence speed to be greatly improved [25–27]. In this paper, an adaptive polymorphic ant colony algorithm is proposed to solve the path planning problem in smart wheelchairs. The search ant makes state transition according to the pseudo-random rule, and combines the state transition strategy and the adaptive parallel strategy of the search ant during the search to get the adaptive state transition strategy and the adaptive information strategy to avoid the algorithm from falling into local optimum. By employing the direction determining method, the deadlock problem was properly addressed and the increased efficiency of global search in a complex environment is achieved. The adaptive polymorphic ant colony algorithm proposed is applied separately to the target path and obstacle path planning experiments, and the experimental results are compared with the results obtained from the improved ant colony algorithm and the general polymorphic ant colony algorithm. The comparison shows, that the adaptive algorithm in this paper is better to implement the path planning for smart wheelchairs with fewer iterations and higher search efficiency.

2. Polymorphic ant colony algorithm

The multi-colony ant colony is introduced into the polymorphic ant colony algorithm based on the basic ant colony algorithm, which includes scouts, search and worker ants. Scouts take the path node of each wheelchair as the center and leave the investigation elements during the investigation, so that search ants may make a choice when they arrive at the path node. Scouts and search ants work in the polymorphic ant colony and perform tasks as follows:

Scouts: The scouts (quantity: m) are placed separately on the path nodes of the wheelchairs (quantity: n), and each scout investigates the path nodes of the other wheelchair (quantity: $n-1$), taking the path node of the wheelchair as the center, and combines the result of the investigation with the existing information to constitute the investigation element referred to as $s[i][j]$ and marked on the path from the path node i to the path node j. $s[i][j]$ $(i, j = 1, 2, \ldots, n-1, i \neq j)$ is calculated by the following formula:

$$s[i][j] = \begin{cases} \dfrac{d_{ij}^{\min}}{d_{ij}}, & \text{path node } j \text{ is in the selectable range of the path node } i \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where d_{ij} the total path of the selected ant; $d_{ij}^{\min}$ is the minimum distance to the other $n-1$ path nodes when taking the wheelchair path node i as the center.

Based on this result, the information amount on each path at the initial time is set firstly as follows:

$$\tau_{ij}(0) = \begin{cases} C \cdot s[i][j], & s[i][j] \neq 0 \\ \dfrac{C \cdot d_{ij}^{\min}}{d_{ij}^{\max}}, & \text{otherwise} \end{cases} \tag{2}$$

where $d_{ij}^{\max}$ is the maximum distance to the other $n-1$ path nodes when taking the path node i as the center. C is the information amount on each path at the initial time.

Search ant: the adaptive transition probability $p_{ij}^{k}(t)$ of ant k $(k = 1, 2, \ldots, m)$ from the path node i to the path node j in the search process is calculated as follows:

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\tau_{ij}(t)^{\alpha} \cdot \eta_{ij}(t)^{\beta}}{\sum\limits_{h \notin tabu_k} \tau_{ih}(t)^{\alpha} \cdot \eta_{ih}(t)^{\beta}}, & j \notin tabu_k \text{ and } s[i][j] \neq 0 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where $\tau_{ij}(t)$ is the information amount on the path (i, j) at the time t; $\eta_{ij}(t)$ is the heuristic function, and its expression is $\eta_{ij}(t) = \frac{1}{d_{ij}}$; α is the information heuristic factor, representing the relative importance of the path; β is the desired heuristic factor, representing the relative importance of the visibility; $tabu_k$ is the taboo collection, and t is the amount of evolution generation.

After all the ants complete a cycle, the pheromone on each path is updated as the following formula:

$$\tau_{ij}(t+1) = \begin{cases} \rho \cdot \tau_{ij}(t) + (1-\rho) \cdot \Delta\tau_{ij}(t), & s[i][j] \neq 0 \\ \rho \cdot \tau_{ij}(t), & \text{otherwise} \end{cases} \tag{4}$$

Where ρ is the pheromone evaporation factor, $1-\rho$ is the pheromone residual factor; in order to prevent the unlimited accumulation of information, the value range of ρ is $P \subset [0, 1)$; $\Delta\tau_{ij}(t)$ is the amount of information released by all the ants on the path (i, j) in this cycle, and $\Delta\tau_{ij}(t) = \sum\limits_{k=1}^{m} \Delta\tau_{ij}^{k}(t)$.

$\Delta\tau_{ij}^{k}(t)$ is the amount of information released by ant k on the path (i, j) in this cycle, and its formula is as follows:

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \dfrac{Q \cdot (d_{ij}^{\min}/d_{ij})}{L_k}, & \text{ant } k \text{ goes through } (i, j) \text{ and } s[i][j] \neq 0 \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where Q is a constant, t is the evolution generation, and L_k is the length of the journey traveled by ant k.

3. Adaptive polymorphic ant colony algorithm

In the polymorphic ant colony algorithm, search ants may still fall into local optimum in the range determined by the investigation elements, and the pheromone intensity and the desired intensity are ignored in the iterations. Based on polymorphic ant colony algorithm, the adaptive parallel rule and the pseudo-random proportion rule are introduced in this paper to effectively avoid the problem of local optimum in the search process. Search ants makes a state transition in accordance with the pseudo-random rule in the search stage while adopting the adaptive parallel strategy to determine the optimal combination parameters in the state transition functions. The state transition rule adopted is as follows:

$$S=\begin{cases} \underset{j\in allowed_k}{arg}\ \max\left\{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}\right\}, q<q_0 \\ p_{ij}^{k}(t), \text{otherwise} \end{cases} \tag{6}$$

where q is the random number uniformly distributed in [0,1], $q_0=1-e^{-1/K}(K=1, 2, \ldots, N)$, and N is the iteration number.

According to this rule, whenever the ants select which path node to move to, a random number is generated in [0,1], and then the transition direction is determined based on the state transition rule. The adaptive transition probability $p_{ij}^{k}(t)$ can be calculated as follows:

$$p_{ij}^{k}(t)=\begin{cases} \dfrac{\tau_{ij}(t)^{\frac{4\alpha t}{N}+1}\cdot\eta_{ij}(t)^{\frac{2\beta t}{N}+1}}{\sum\limits_{h\notin tabu_k}\tau_{ih}(t)^{\frac{4\alpha t}{N}+1}\cdot\eta_{ih}(t)^{\frac{2\beta t}{N}+1}}, & j\notin tabu_k \text{ and } s[i][j]\neq 0 \\ 0, \text{otherwise} \end{cases} \tag{7}$$

where $\tau_{ij}(t)$ is the information amount on the path (i, j) at the time t; $\eta_{ij}(t)$ is the heuristic function, and its expression is $\eta_{ij}(t)=\frac{1}{d_{ij}}$; a is the information heuristic factor, representing the relative importance of the path; β is the desired heuristic factor, representing the relative importance of the visibility; $tabu_k$ is the taboo collection, t is the evolution generation, and N is the maximum evolution generation.

In the polymorphic ant colony algorithm, the search ant will leave the pheromone in a possible optimal solution path while ignoring the other paths, which may lead to a final solution which may not be the best one. To avoid this, this paper introduces the adaptive information update strategy, and the adaptive information amount is determined by the following formula:

$$\Delta\tau_{ij}^{k}(t)=\begin{cases} \left(\dfrac{[Q\cdot(d_{ij}^{\min}/d_{ij})]}{\sum\limits_{k=1}^{l}d_{k}^{L}}\cdot\dfrac{1}{L_{best}}\right)^{\frac{2t}{N}+1}, & k \text{ goes through}(i, j) \text{ and } s[i][j]\neq 0 \\ 0, \text{otherwise} \end{cases} \tag{8}$$

where Q is a constant, t is the evolution generation, N is the maximum evolution generation, L_{best} is the current optimal path length, L is the optimal path among the first l paths, and d_k^L is the unsorted path length.

Adaptively updating the amount of information in the search process avoids the ignorance of the paths because less pheromone are left on them, and also prevents the pheromone from decreasing

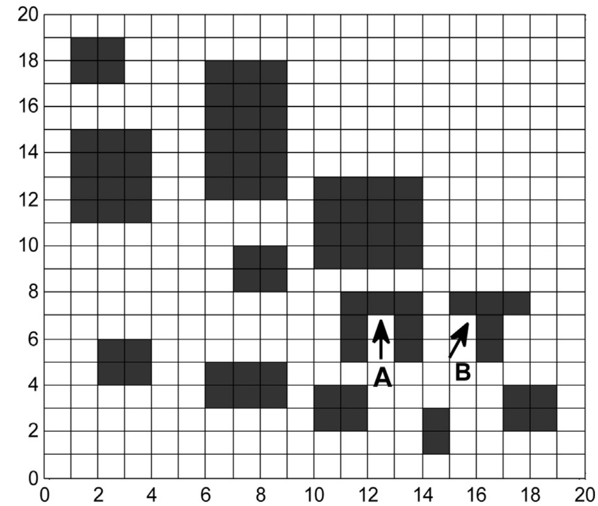

Fig. 1. The smart wheelchair falls into deadlock.

with the increase of the number of iterations [28,29]. However, the ant colony may fall into a deadlock when encountering a complex environment during the path search. With the grid length set as 1 m, the algorithm falls into the deadlock state if the smart wheelchair cannot move to the other positions around when it continues to travel at point A and point B in the direction of the arrow in Fig. 1.

In order to solve the deadlock problem, Wang et al. adopted *Early Death* method [30]. The main idea of their method is to make the ant in the deadlock dead, so it stops updating the pheromone of the path already traveled. When lots of ants are in the deadlock state, this method is not conducive to the global optimum search and it also reduces the diversity of path solutions. Hong et al. solved the problem by *Fallback* method [31,32]. When an ant is in deadlock, do not make it die but allow it to take a step back and continue the search.

In this paper, the direction determination method is a tool to deal with deadlock, in which the taboo table is updated when the ant is in deadlock, and the pheromone on the edge of deadlock is punished so that the ant may adjust the forward direction in the original position and find a direction where there is no obstruction, and then moves on in this direction, as shown in the arrow in Fig. 2.

The application of this method to solve the deadlock problem aims at improving the ability of global search of the algorithm,

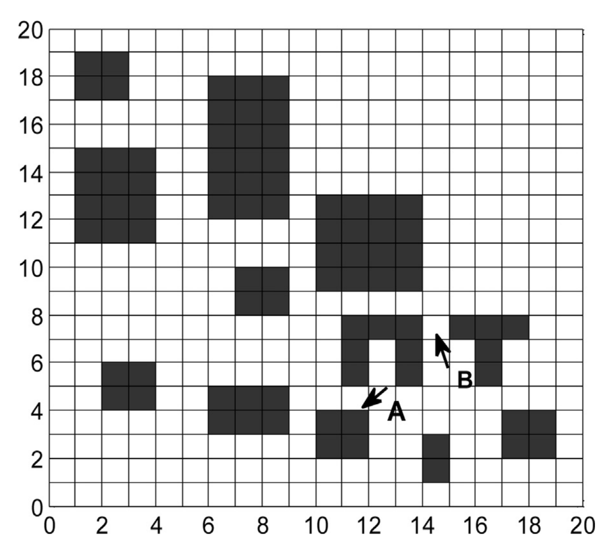

Fig. 2. The intelligent wheelchair searches the direction without obstacles.

and effectively reducing the possibility of the other ants to fall into deadlock in the same position. Its pheromone penalty function is:

$$\tau_{rs} = (1-\lambda)\tau_{rs} \quad (9)$$

where $(1-\lambda)$ is the corresponding penalty coefficient.

The specific steps of the adaptive polymorphic ant colony path planning method are as follows:

Step 1 Environmental modeling is made using the grid method, and constant Q, amount of information C, and the maximum evolution generation N and the wheelchair starting position are initialized;

Step 2 The m (quantity) scouts are placed separately in the n (quantity) path nodes, and each scout investigates the nodes of the other $(n-1)$ paths with the path node as the center; the investigated elements are calculated as Eq. (1), and the results are put in the $S[i][j]$;

Step 3 The amount of information on each path at the initial moment is set according to Formula (2), and the initial value of the evolution generation NC is set as 0;

Step 4 The initial position of each search ant is randomly selected and placed in its corresponding *tabu* table;

Step 5 The position where search ant k will be transferred is calculated according to Eq. (6), and is set as j; the previous position is set as i, and j is placed into the corresponding *tabu* table of the search ant k until each search ant completes a cycle to obtain a solution; if ant k falls into deadlock in the path search, the direction determining method will be employed to deal with the deadlock;

Step 6 The objective function value L_k (k = 1, 2, ..., m) is calculated for each search ant, and the current optimal solution is recorded;

Step 7 If the specified evolution generation has been reached or the obtained solution has no significant improvement in the last several generations, execute Step 9; otherwise, modify the pheromone concentration of each path according to Eq. (8);

Step 8 Set $\Delta\tau_{ij}$ as 0, clear the *tabu* table; update the evolution generation from $NC+1$ to NC, and return to Step 4;

Step 9 Output the optimal solution.

4. Experimental results

The traveling salesman problem (TSP) asks for an optimal tour through a specified set of points [33]. To solve a particular instance of the problem, it is necessary to find a shortest tour and verify that no better tour exists. Some techniques can be employed in the Concorde code for the TSP, focusing on the difficult verification task [34]. A typical one is to select a path for the wheelchair to visit every point exactly once and return to the initial position. Lots of previous work has touched the quite old scenario and many solutions are available, such as ant colony algorithm and its derivative algorithms.

The simulated coordinates (in m) of 20 points are (0.5, 0.5), (1, 0.7), (0.7, 0.5), (0.2, 0.9), (0, 1), (0.1, 0.6), (1, 0.2), (0.6, 0.7), (0.9, 0.2), (0.8, 0.3), (0.3, 0.8), (0.7, 0.3), (0, 0.2), (0.3, 0.4), (0.8, 0.8), (0.5, 0.9), (1, 0.9), (0.1, 0.4), (0.2, 0.9) and (0.9, 0.7), respectively. The application effects of the adaptive polymorphic ant colony algorithm (APACA) are compared with those of other TSP-based methods, including original ant colony algorithm (OACA), improved ant colony algorithm (IACA), general polymorphic ant colony algorithm (GPACA), and adaptive polymorphic ant colony algorithm (APACA). The essential parameters are set as follows: the number of ants m = 120, the number of iterations N = 200, the information heuristic factor α = 1, the desired heuristic factor β = 5, the pheromone evaporation coefficient ρ = 0.9, the constant Q = 100, the information amount on each path at the initial time C = 3. The

Table 1
Application effects of TSP-based algorithms.

Algorithm	Optimal path length/m	Number of Iterations
OACA	4.1725	60
IACA	4.1725	20
GPACA	4.1585	15
APACA	4.1585	6

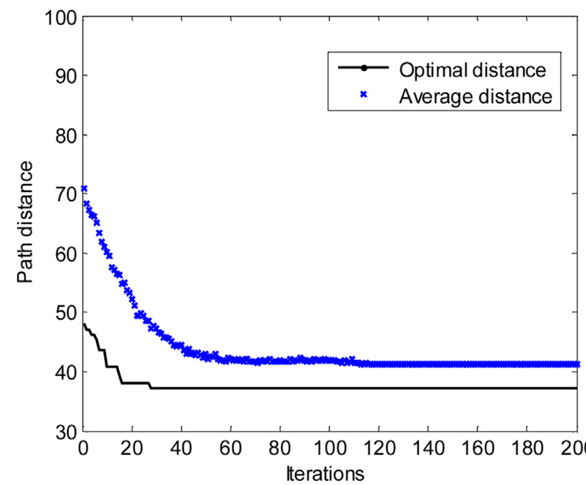

Fig. 3. The evolution curve of path distance by IACA.

optimal path lengths and the numbers of iterations by above four TSP-based algorithms are shown in Table 1, respectively.

Evidently, APACA provides the shortest optimal path length and the least number of iterations. It is superior to OACA, a very fundamental TSP-based method, and the other two solutions evolved from OACA. Not only that, the focus of this paper lies in solving optimal path planning problems of automated navigation systems for smart wheelchairs. In formal experiment, we set up 15 items and each item represents a point. A person in the smart wheelchair picks up each item starting from one point, and the ultimate target is to find the shortest path for the wheelchair to pick up all the items. The position coordinates (in m) of the fifteen items are A (2, 8), B (0, 4), C (1, 6), D (3, 5), E (4, 2), F (6,2), G (3, 0), H (10, 4), I (4, 3), J (2, 1), K (7, 0), L (9, 4), M (11, 3), N (13, 2), and O (5, 1), respectively.

The application effects of the adaptive polymorphic ant colony algorithm are compared with those of the other typical path planning methods. Experimental parameters are set as follows: the number of ants m = 120, the number of iterations N = 200, the information heuristic factor α = 1, the desired heuristic factor β = 5, the pheromone evaporation coefficient ρ = 0.9, the constant Q = 100, the information amount on each path at the initial time C = 3. The evolution curves of distance paths by IACA, GPACA and APACA are shown in Figs. 3–5, respectively. In addition, the performance comparison of IACA, GPACA, and APACA is shown in Table 2.

In Fig. 3, the optimal solution obtained by IACA iterated to about 30 times, and in Fig. 4, the optimal solution obtained by GPACA iterated to about 10 times while the optimal solution obtained by APACA iterated to about 5 times in Fig. 5. In Table 2, the optimal path distance for the smart wheelchair obtained by IACA and GPACA is 37.2991 m, and the optimal path distance obtained by APACA is 36.9428 m. The optimal path obtained using the algorithm presented in this paper is optimized by 0.3563 m compared to the shortest path obtained using the previous two algorithms, especially the worst solution and the average solution of the optimal path are better than IACA.

Regarding to the solving efficiency of the optimal solution, the optimal solution was obtained after about 5 iterations using

Table 2
Performance comparison of IACA, GPACA and APACA in path planning.

Algorithm	Optimal distance/m	Average distance worst solution/m	Average distance optimal solution/m	Optimal path
IACA	37.2991	70.0112	43.3014	H→L→F→O→E→I→D→A→C→B→J→G→K→N→M
GPACA	37.2991	46.9854	42.2154	L→H→M→N→K→G→J→B→C→A→D→I→E→O→F
APACA	36.9428	47.1254	42.8912	L→H→M→N→K→O→G→J→B→C→A→D→I→E→F

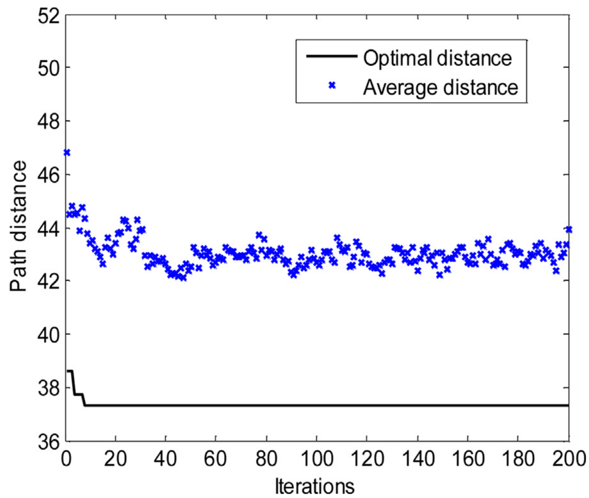

Fig. 4. The evolution curve of distance by GPACA.

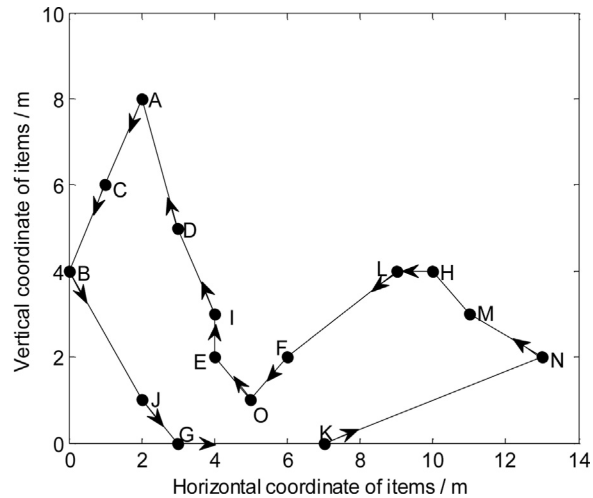

Fig. 6. The shortest path searched by IACA.

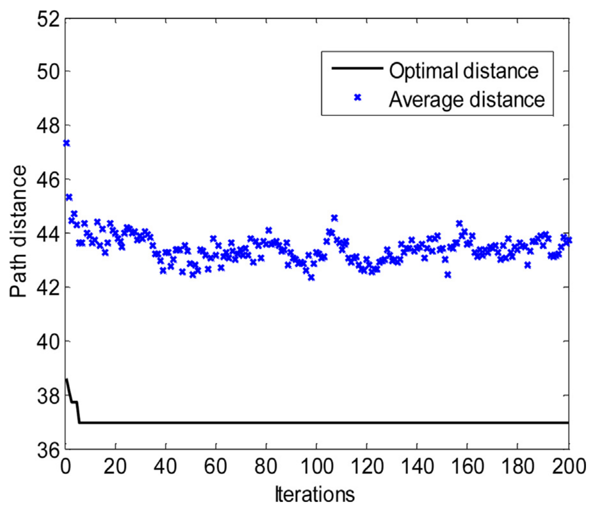

Fig. 5. The evolution curve of distance by APACA.

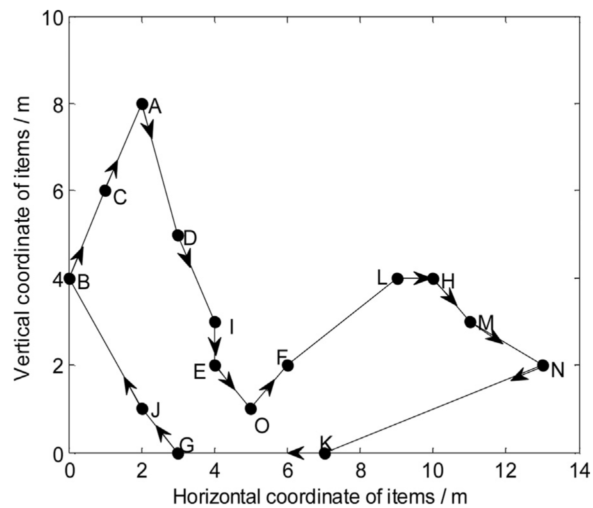

Fig. 7. The shortest path searched by GPACA.

the algorithm in this paper. However, the optimal solutions were obtained using IACA and GPACA after about 30 and 10 iterations respectively, resulting in the optimal solution and the efficiency using the algorithm in this paper are better than IACA. Accordingly, the shortest paths obtained from the above algorithms are shown in Figs. 6–8, respectively.

TPS mainly focuses on optimal path choice, while the problem described in this paper includes not only optimal path choice, but also obstacle avoidance problem of smart wheelchairs. The comparison of the performance of IACA, GPACA, and APACA has been executed in the obstacle path planning for the smart wheelchair. The experimental parameters are as follows: the number of ants $m = 50$, the number of iterations $N = 100$, the information heuristic factor $\alpha = 1$, the desired heuristic factor $\beta = 5$, the pheromone evaporation coefficient $\rho = 0.8$, the constant $Q = 1$, and the information amount on each path at the initial time $C = 3$. The obstacle path optimization curves of IACA, GPACA, and APACA are shown in Figs. 9–11, respectively.

In Figs. 9–11, the optimal path distances obtained from the three algorithms are respectively 30.38 m, 29.21 m and 28.038 m. The path distance obtained from APACA is better than IACA and GPACA. It is evident that APACA dose plays an important role in finding an optimal path for the smart wheelchair. The corresponding convergence curves of IACA, GPACA, and APACA are shown in Figs. 12–14, respectively. The results of obstacle path planning for the smart wheelchair using the three algorithms are shown in Table 3.

According to Figs. 12–14, APACA and GPACA achieve optimal value after about 40 times, so its iteration effect is better than IACA. According to the convergence curves in Figs. 12–14, APACA proposed in this paper obtains the optimal path distance with the least amount of iterations. According to the data in Table 3, the optimal path length of IACA and GPACA is much longer than the

Table 3
Results of obstacle path planning using IACA, GPACA and APACA.

No.	IACA			GPACA			APACA		
	The optimal length/m	Iterations	<35 m iterations	The optimal length/m	Iterations	<35 m iterations	The optimal length/m	Iterations	<35 m iterations
1	32.46	25	25	29.32	15	15	28.128	16	5
2	30.38	15	6	29.24	8	2	29.012	17	8
3	33.56	8	5	30.12	21	11	30.891	23	11
4	37.24	25	>40	36.87	38	>40	28.038	25	13
5	32.14	6	6	39.25	17	>40	28.321	4	4
6	36.45	26	>40	29.36	8	8	29.782	9	4
7	30.47	15	10	29.21	14	14	30.442	25	9
8	41.31	25	>40	38.02	26	>40	29.361	11	6
9	36.43	12	>40	29.45	2	2	28.291	8	8
10	43.13	22	>40	36.24	7	>40	29.571	21	11

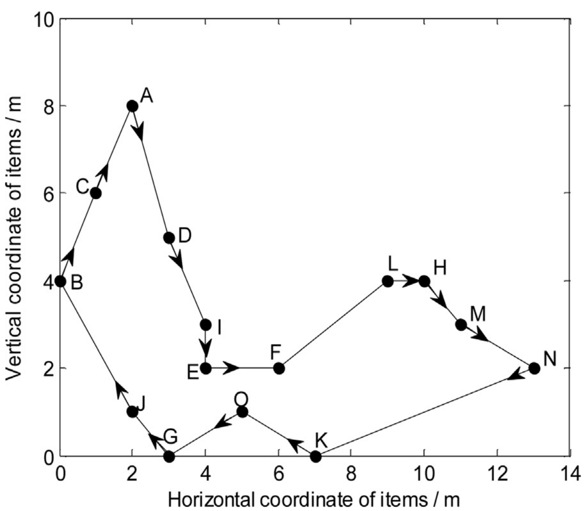

Fig. 8. The shortest path searched by APACA.

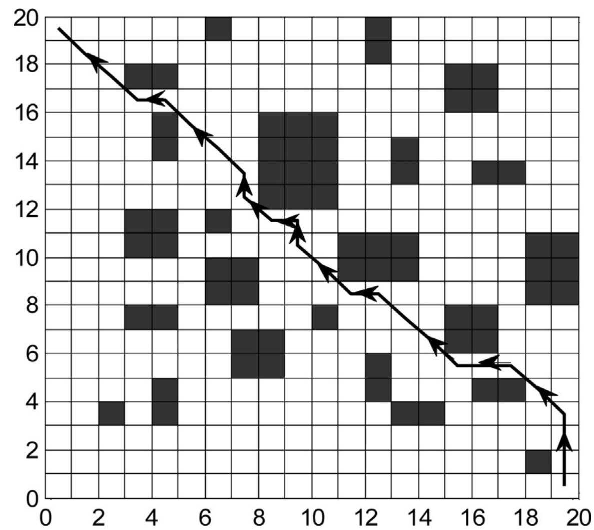

Fig. 10. GPACA path optimization curve.

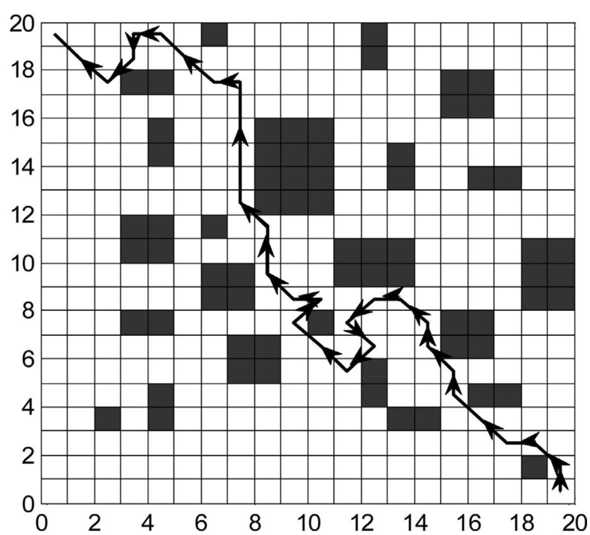

Fig. 9. IACA path optimization curve.

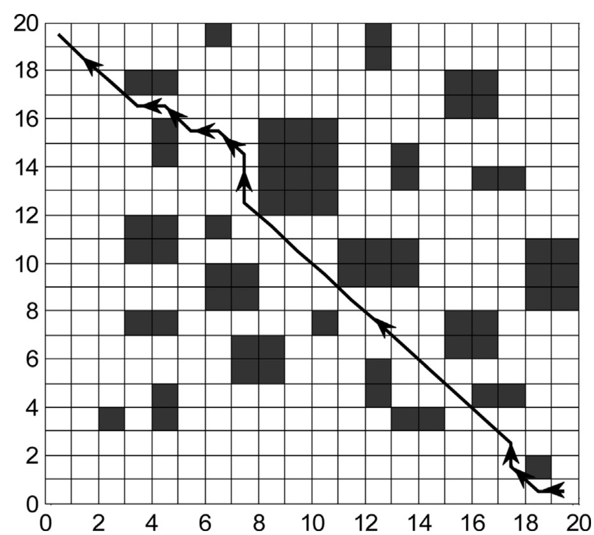

Fig. 11. APACA path optimization curve.

improved adaptive polymorphic ant colony algorithm. In the operation of 10 times, the first two algorithms have respectively 5 times and 6 times less than 35 m or less, while the third algorithm has 10 times of the calculations, results less than 35 m and the optimal path length of 28.038 m was found. The experimental results indicate that in terms of the optimal path, the convergence and the iterative effect, the obstacle path planning results obtained using the adaptive polymorphic ant colony algorithm in this paper are better than those from improved ant colony algorithm and the generally polymorphic ant colony algorithm.

Obviously, the path planning results using adaptive polymorphic ant colony algorithm is better than the results with other similar algorithms. Moreover, the proposed method can help smart wheelchairs to proactively identify the best path classify the current situation where a user is standing on as sidewalk, roadway and

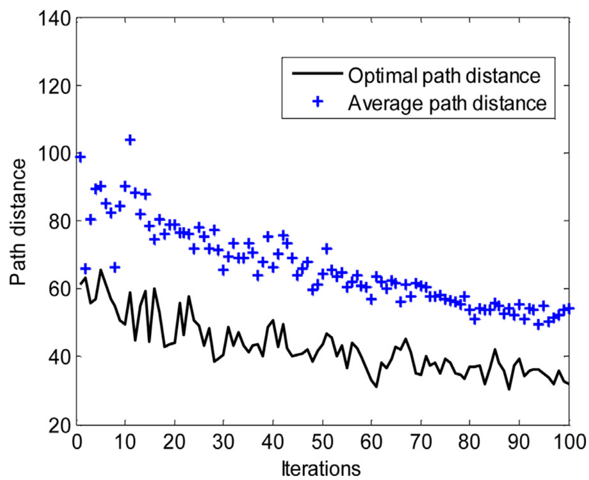

Fig. 12. IACA convergence curve.

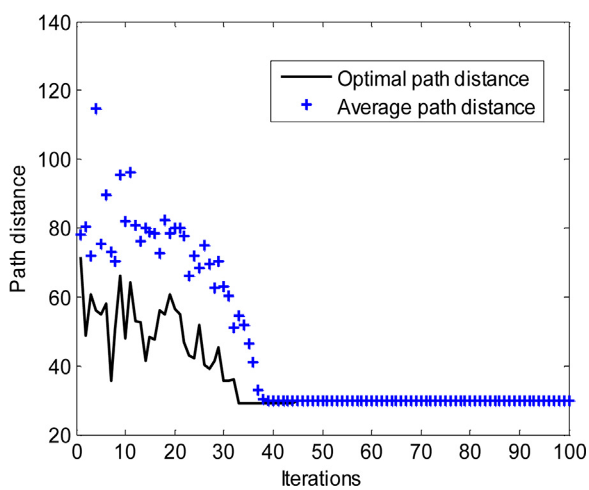

Fig. 13. GPACA convergence curve.

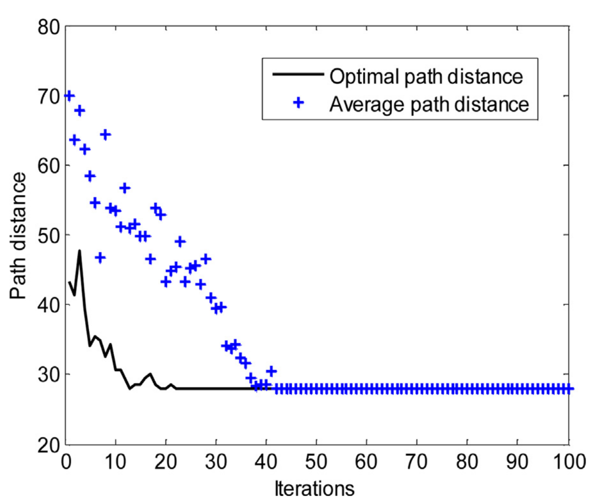

Fig. 14. APACA convergence curve.

traffic intersection, which prevents the collisions of vehicle at the traffic intersection.

5. Conclusions

In this paper, the adaptive polymorphic ant colony algorithm is proposed as a path planning method for smart wheelchairs. The search ant can determine the optimal combination parameters in accordance with actual situation and make the state transition in the search process to effectively prevent the search ant from falling into local optimum to a certain extent. The direction determining method also employed to accelerate convergence, improving the efficiency of the algorithm in searching the global optimal solution. The improved polymorphic ant colony algorithm is applied separately to the target path planning and obstacle path planning, and is compared with the improved ant colony algorithm and the generally polymorphic ant colony algorithm, respectively. Our method achieves superior performance in this challenging problem, which is even racing ahead of the recently developed state-of-the-art solutions. Additionally, this study reveals the feasibility of using it as an effective and feasible planning path tool for future healthcare systems.

It is noteworthy that in a point to point path planning, the smart wheelchair is just regarded as an idealized point rather than a practical model in our experiment. There are lots of existing models regarding wheelchair or similar. Actually, safe mission planning typically seeks to construct a route from origin to destination that minimizes the risk imposed; nevertheless, the robot has limitation in making rotation during automatic drive. In the future study, we will consider some practical models for the smart wheelchair in path planning.

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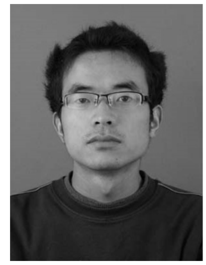

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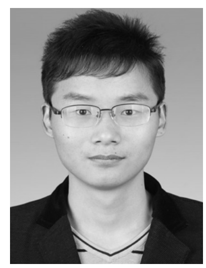

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