AN IMPROVED ANT COLONY SYSTEM ALGORITHM FOR ROBOT PATH PLANNING AND PERFORMANCE ANALYSIS

Xiao-Ming You,* Sheng Liu,** and Chen Zhang*

Abstract

An improved ant colony system (ACS) algorithm to solve the mobile robot path planning problem is presented. In the algorithm, a new heuristic operator is adopted to achieve a balance between population diversity and the convergence rate. It complements the algorithm to avoid running into the local optimum and to improve the solution quality. A heuristic path selection strategy is proposed to guide the algorithm to fast convergence. We adopt the MAKLINK graph and grids to establish the environment model, and the simulation research indicates that the proposed algorithm is effect. It can improve the solution quality and has better performance in search efficiency compared with other path planning methods. We also analyse the performance of the modified ACS algorithm and demonstrate that the novel algorithm can obtain the optimal solution for mobile robot path planning problems with faster convergence speed and better solution quality under different complex environments.

Key Words

Computing intelligence, ant colony system, heuristic operator, robot path planning, environment model

1. Introduction

Robotics is attracting widespread interest in different fields including industrial application, environmental exploration, and others [1]. Mobile robot path planning is a fundamental study in the field of mobile robots. Path planning is where the robot can navigate safely and find a motion path with minimum energy consuming from one point to the other [2].

Recently, the research of artificial intelligence has developed rapidly, and many intelligent algorithms, including neural networks, genetic algorithms, particle swarm optimization, ant colony systems (ACS) [1], *etc.*, have been applied to path planning in mobile robots. At the same time, these methods are inefficient, have poor global search abilities, and are insufficiently adaptable to complex domains. Improved ant colony optimization has drawn increasing attention from researchers and has been used in a variety of applications [2]–[27], including mobile robot path planning problems [6]–[13]. The algorithm has several advantages including strong robustness, excellent distributed computing, easy integration with other algorithms, and strong global optimization performance. However, the ant colony algorithm is also easily trapped in the local optimum in robot path planning problems. The heart of the matter is achieving a balance and compromise between population diversity and the convergence rate, which can prevent falling into the local optimum or allow escape from it. This paper addresses the problem of robot path planning using a heuristic operator-based ACS algorithm. The heuristic operator can achieve a balance between population diversity and the convergence rate.

This article has two main contributions:

(1) We propose an improved heuristic operator-based ACS algorithm for robot global path planning. First, we adopt the MAKLINK graph [6] and grids [7] to establish the environmental model, and then we use the modified ACS algorithm to obtain the global optimal path. In the modified ACS algorithm, a new heuristic operator which balances population diversity with the convergence rate is defined. It complements the modified ACS to avoid getting trapped in the local optimum and improves the solution quality.

(2) We present extensive simulation experiments to evaluate the performance of the modified ACS algorithm and compare it against Algorithms 2 and 3. We show that the modified ACS algorithm clearly outperforms Algorithms 2 and 3 using a heuristic path selection strategy. Furthermore, it is an effective algorithm for robot path planning under more complex environments. (In this paper, Algorithms 1–3 denote the algorithm in this paper and the algorithms in [6], [7], respectively.)

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Recommended by Dr. Xiaonv Hu

(DOI: 10.2316/Journal.206.2018.5.206-0071)

2. Related Work

The first ACO algorithm, called the ant system (AS), was applied to the traveling salesman problem (TSP) by Dorigo [4]. The ACS is one of the most successful ACO algorithms, and it achieves a much better performance than the AS. In the original ACS, when ant k move from city I to city j, the movement depends on the rule called pseudorandom proportional rule, it can be described as [4]

$$j = \begin{cases} \arg\max \left\{ \tau_{il} [\eta_{il}]^{\beta} \right\} l \in N_i^k, & \text{if } q \leq q_0; \\ J & \text{otherwise.} \end{cases} \tag{1}$$

where q is a random number rolled in the range of 0 and 1, q_0 $(0 \leq q_0 \leq 1)$ is a parameter, and J is a random number determined by the probability distribution as (with $\alpha = 1$)

$$\mathrm{p}_{ij}^k = \frac{[\tau_{ij}]^{\alpha} \, [\eta_{ij}]^{\beta}}{\sum_{l \in N_i^k} [\tau_{il}]^{\alpha} \, [\eta_{il}]^{\beta}}, \quad \text{if } j \in N_i^k \tag{2}$$

where $\eta_{ij} = 1/d_{ij}$ is the heuristic value to provide priori information, α and β are used to determine the relative influence of the pheromone trail and the heuristic value. Also, N_i^k is the feasible neighbourhood as a set of cities ant k can visit when it located at city i. τ_{ij} represents the pheromone from node i to node j. After constructing its tour, only the ant to find the best path to the current loop is allowed to update the pheromone by applying the pheromone updating rule (3), which accelerates the convergence of the algorithm to some extent.

$$\tau_{ij}(t) = (1 - \varphi)\tau_{ij}(t) + \varphi \Delta\tau_{ij}(t) \tag{3}$$

$$\Delta\tau_{ij}(t) = \Delta\tau_{ij}^k(t) \tag{4}$$

with φ in $(0,\ 1)$, $\Delta\tau_{ij}(t)$ is the quantity of pheromone produced by ant k on the edge (i, j) between iteration t and $t + 1$. Apart from the global update rule, ACS also uses the ant cycle updating rule. An ant cycle system information update model is

$$\Delta\tau_{ij}^k(t) = \begin{cases} \dfrac{1}{L_k} & \text{arc}(i, j) \text{ belong to best loop} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where L_k denotes the total length of the current best tour T^+.

Global optimal path planning is an important problem in the navigation of mobile robots. Numerous methods to solve robot path planning have been attempted [6]–[12], [24]–[31]. For instance, in [8], the author proposed an ant algorithm based on rolling planning for a mobile robot path planning problem in an environment where the global information was unknown. In [9], the authors presented a differential evolution chaos ant colony optimization algorithm to plan an optimal collision-free path for a mobile robot in a complicated static environment. The simulation results indicated that an optimal and safe path for the robot to move on could be rapidly obtained even in a complicated geographical environment. In [10], the authors utilized the locations of the start and the goal to build an environmental model based on the simplified visibility graph. In their algorithm, the local path information was integrated with the initialization of the pheromone and the selected probabilities of the paths, resulting in improved convergence speed and avoidance of premature phenomenon as far as possible. In [12], the modelling method based on the agent was introduced to construct the ant colony foraging behaviour model. The simulation results showed that the foraging behaviour model of ant can help to find the optimal path in a complex environment fastly.

3. The Heuristic Operator-based ACS Algorithm

3.1 Modified ACS Algorithm

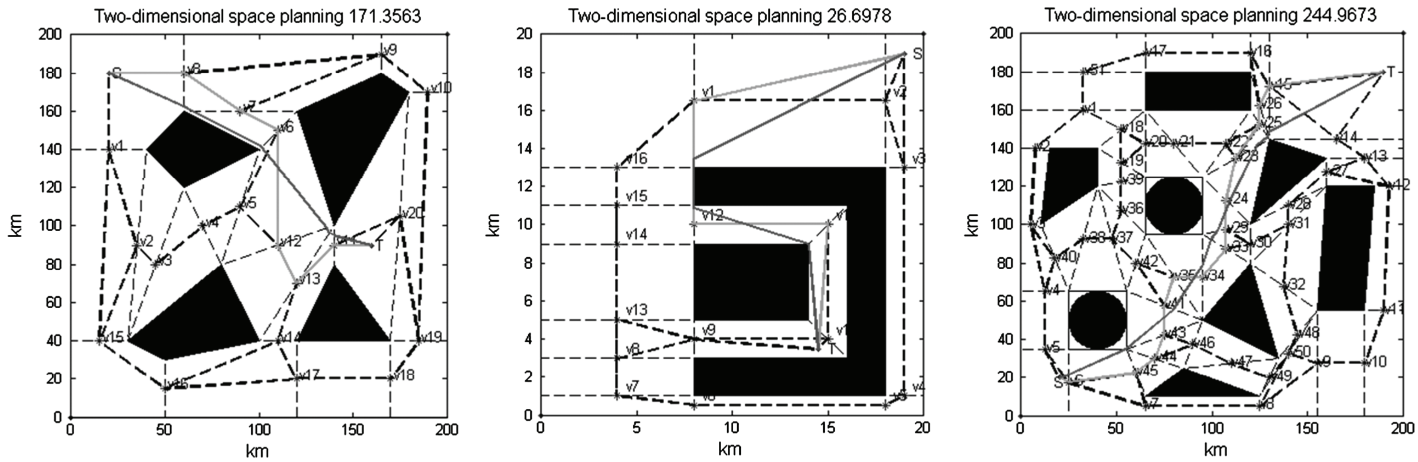
The framework of the modified ACS algorithm is given as follows:
Step 1. Initialize pheromone trails; initialization of populations; and set the iteration number $i = 0$.
Step 2. Put the starting point into tabu_k, choose one subsequent node j to move according to

$$j = \begin{cases} \arg\max \left\{ [\tau_{il}][\eta_{jl}]^{\beta} \right\}, & q \leq q_0 \\ J(p_{ij}^k) & q > q_0 \end{cases},$$
$$q_0 = q_0 \times \left(1 - \frac{1}{\lg_2(1 + n_i)}\right) \times \theta \tag{6}$$

where q_0 is a heuristic roulette selection parameter, n_i is the number of iterations, and θ is the accelerating convergence factor. Finally, put node j into tabu_k.
Step 3. Loop (Step 2) until each ant finds the target point, calculate the tour length L_k of ant k, and record the current optimal solution L_b.
Step 4. Update the pheromone intensity of each arc (i, j) on the best ant tour L_b using the global pheromone updating rule.
Step 5. The number of iterations plus 1.
Step 6. If the number of iterations meets the termination condition or all of the ants find the same solutions, output the best solution.
Step 7. To clear the tabu_k of each and move to (Step 2).
End.

3.2 Heuristic Operator Analysis

The heuristic operator plays an important role in an evolutionary algorithm. In (1), by roulette selection, the parameter q_0 determines the movement strategy of the ants (use the greedy method or explore other paths). In other words, the tuning parameter q_0 adjusts the degree of exploration and can have a choice in whether to improve the convergence or the diversity. Thus, the heuristic roulette



(a) Environment 1 (b) Environment 2 (c) Environment 3

Figure 1. Simulation environment. The red line shows the path generated by the heuristic ACS algorithm (Algorithm 1).

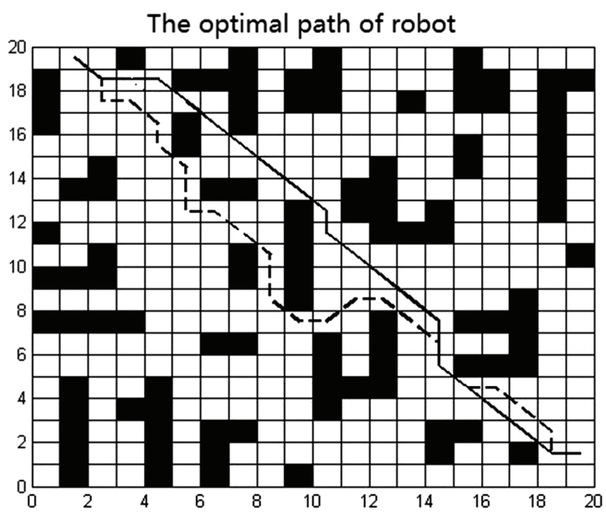


Figure 2. The solid line shows the optimal path generated by the heuristic ACS algorithm (Algorithm 1) under complex environment 4.

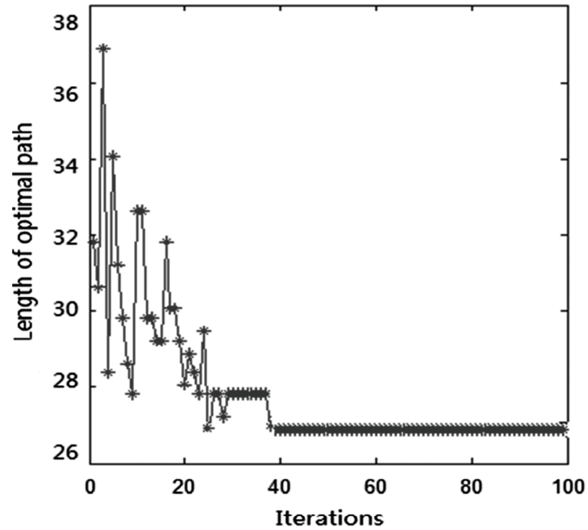


Figure 3. The convergent curve of Algorithm 1 under complex environment 4.

selection operator (6) presented in this paper sets a smaller value to increase the diversity of the population in the early evolution, while a greater value should be set to fasten the convergence in the later stage of evolution. The performance of the heuristic operator will be demonstrated in the experiments in the next section (Figs. 9 and 10).

4. Performance Evaluation

4.1 Simulation Model

In this section, a performance evaluation study of the hybrid ACS algorithm should be presented with three environments of different complexities illustrated in Fig. 1.

All simulations are implemented on a PC with an Intel Core i2 CPU @ 1.8 GHz and 3 GB of RAM under Windows 8.1.

Furthermore, we conducted other simulation experiments under different complex environments and the map has been divided as 20×20 grids [7]. Figures 3, 5, and 7

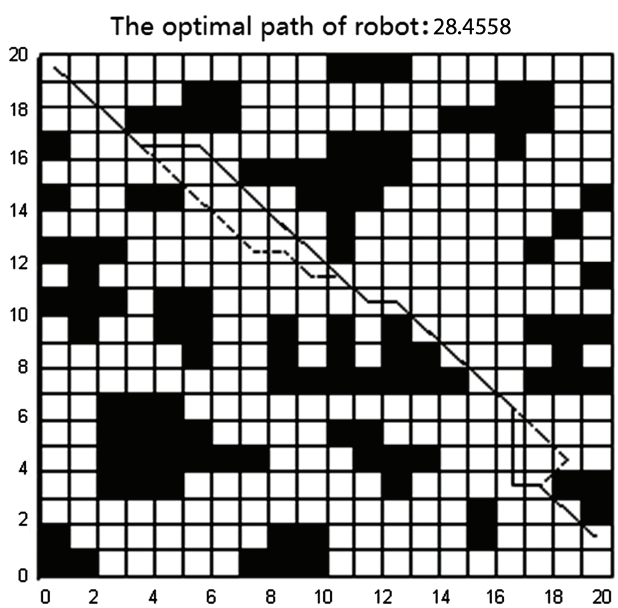


Figure 4. The solid line shows the optimal path generated by the heuristic ACS algorithm (Algorithm 1) under complex environment 5.

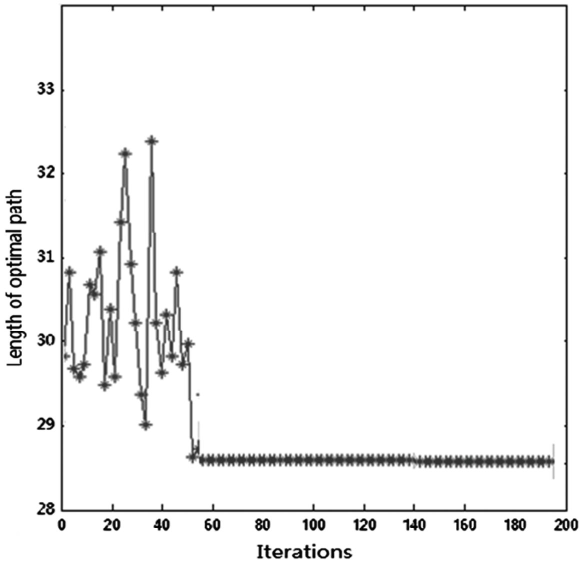


Figure 5. The convergent curve of Algorithm 1 under complex environment 5.

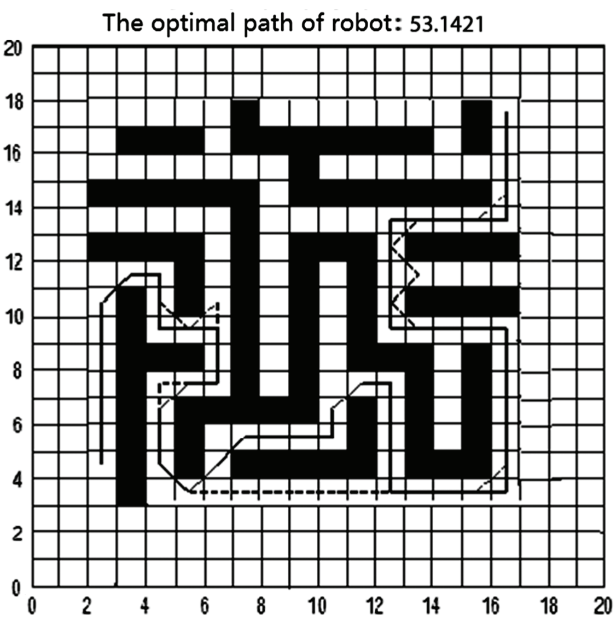


Figure 6. The solid line shows the optimal path generated by the heuristic ACS algorithm (Algorithm 1) under complex environment 6.

depict the convergent curve of Algorithms 1 and 3 in the grid environment of Figs. 2, 4, and 6, respectively. It costs just a few iterations for Algorithm 1 to converge.

The simulation results show that the proposed algorithm is effective. Compared with other path planning method, it has better performance in its solution quality and can improve the convergence speed.

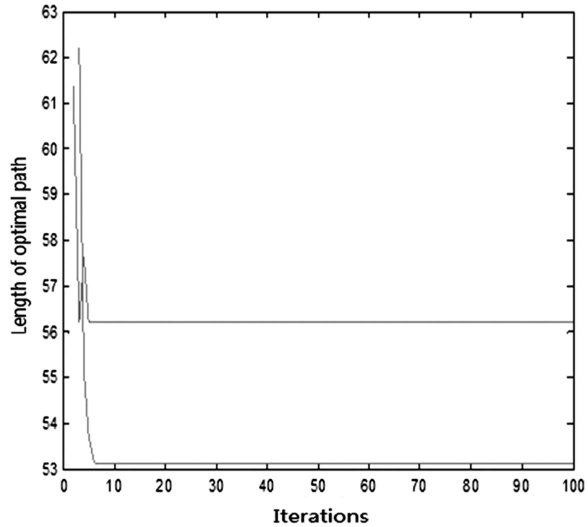


Figure 7. The convergent curve of Algorithm 1 and Algorithm 3 under complex environment 6.

Table 1
Parameter Specifications

Parameters	Value
m: number of ants	20
α: pheromone trail coefficient	1
β: heuristic coefficient	2
q_0: selection threshold	0.9
θ: accelerating convergence factor	0.9
φ: evaporation trail	0.2
τ_0: the initial pheromone value	0.0003
NC: number of iterations of the modified ant algorithm	200

4.2 Simulation Results and Analysis

In this section, we provide a broad simulation study to illustrate the efficiency of the modified ACS algorithm. The parameters of the algorithm are presented in Table 1.

First, we present a comparison of Algorithms 1 and 2 to demonstrate the advantage carried out by Algorithm 1. From Table 2, we notice that the lengths of the paths generated by Algorithms 1 and 2 for environments 1 and 2 are close. Yet, for environment 3, Algorithm 1 generates better solutions in just a little greater time than Algorithm 2. Figure 8 shows the convergence processes of the optimal solutions generated, respectively, by the two algorithms for environment 3.

Second, we present a comparison of Algorithms 1 and 3. From Table 3, we notice that Algorithm 1 generates better solutions in fewer iterations than Algorithm 3.

Table 2
Comparison of Algorithm 1 and Algorithm 2

Environments	Path Lengths		Execution Times	
	Algorithm 1	Algorithm 2	Algorithm 1	Algorithm 2
Environments 1	171.3563	171.6162	3.776	3.569
Environments 2	172.0817	172.5877	2.642	2.456
Environments 3	246	253	4.558	3.788

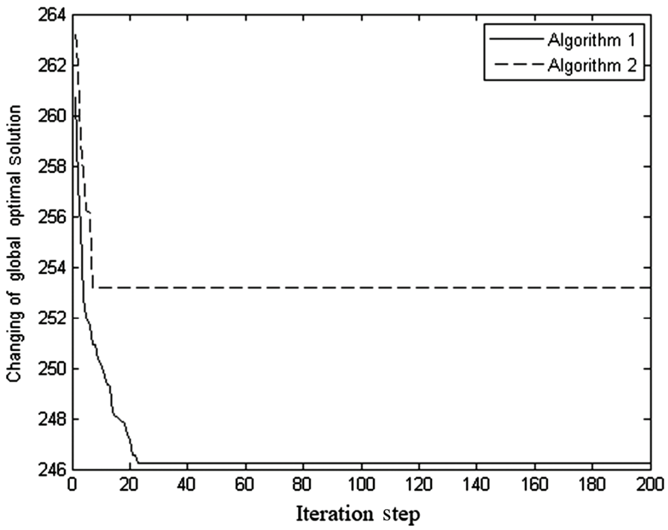


Figure 8. Convergence curve of the optimal solution variation in both the algorithms for environment 3.

The modified ACS algorithm has a better convergence and much greater solutions.

The operator $q_0 = q_0 \times (1 - \frac{1}{\lg_2(1+n_i)}) \times \theta$ can be viewed as a heuristic operator. It should set the value of the variable q: in the prophase, we use a smaller value of q to explore the space and to get more information globally; meanwhile, we can use a larger value of q to accelerate the convergence. The experimental results show that by using the variable q, we can obtain a better optimized result (Figs. 9 and 10).

The red line shows the result of the fixed parameter q, while the blue line shows the result of the heuristic parameter q.

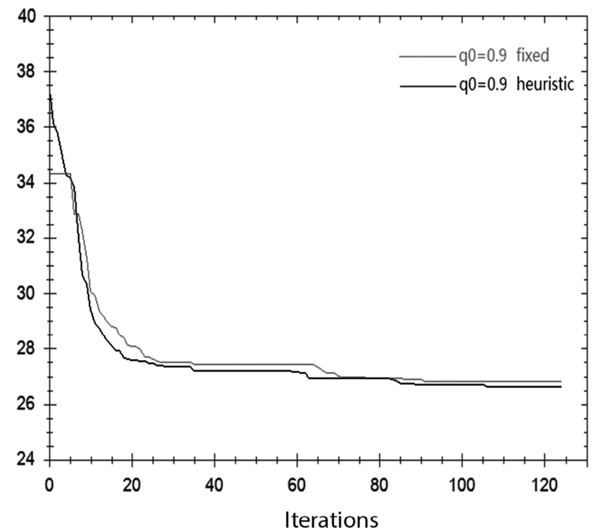


Figure 9. The average result for the complex environment 4 for different q parameters.

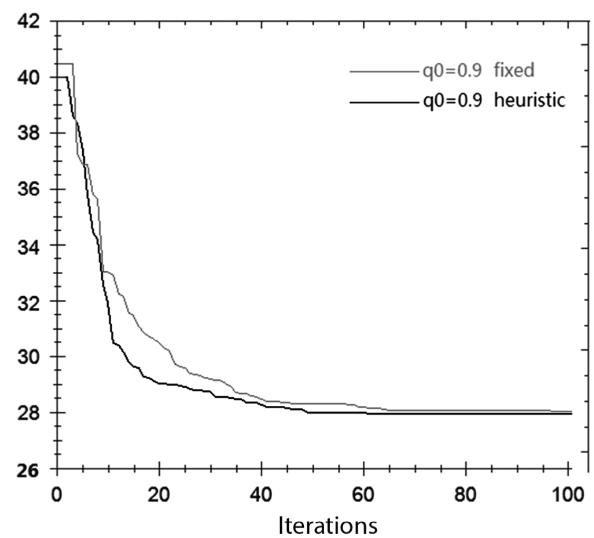


Figure 10. The average result for the complex environment 5 for different q parameters.

Table 3
Comparison of Algorithm 1 and Algorithm 3

Environments	Path Lengths		Iterations	
	Algorithm 1	Algorithm 3	Algorithm 1	Algorithm 3
Environments 4	26.6272	30.9705	40	91
Environments 5	28.4558	29.9558	50	63

5. Conclusion

This paper presents a new heuristic ACS algorithm to solve the global robot path planning problem in a static environment. The modified ACS algorithm achieves a balance between population diversity and the convergence rate. The experiment results show that the proposed algorithm can improve both the solution quality and the search efficiency, as compared with the path planning method in [6], [7]. Furthermore, the new algorithm has a better performance in global search capability, and can keep great adaptability even in more complex environments. Currently, we are working towards applying the modified ACS algorithm to dynamic environments. Furthermore, we will also consider other techniques of establishing an environmental model for robot path planning.

Acknowledgement

The authors gratefully acknowledge the support of the Natural Science Foundation of China (Grant Nos. 61673258, 61075115, 61403249).

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