Wireless Pers Commun
https://doi.org/10.1007/s11277-017-5229-5

Off-road Path Planning Based on Improved Ant Colony Algorithm

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Abstract Optimal vehicle off-road path planning problem must consider surface physical properties of terrain and soil. In this paper, we firstly analyse the comprehensive influence of terrain slope and soil strength to vehicle's off-road trafficability. Given off-road area, the GO or NO-GO tabu table of terrain gird is determined by slope angle and soil remolding cone index (RCI). By applying tabu table and grid weight table, the influence of terrain slope and soil RCI are coordinated to reduce the search scope of algorithm and improve search efficiency. Simulation results based on tracked vehicle M1A1 in off-road environment show that, improved ant colony path planning algorithm not only considers the influence of actual terrain and soil, but also improves computation efficiency. The time cost of optimal routing computation is much lower which is essential for real time off-road path planning scenarios.

Keywords Off-road mobility · Path planning · Ant colony · Terrain slope · Remolding cone index

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Published online: 13 February 2018

1 Introduction

The path planning algorithm in off-road environment faces a lot of challenges [1–4]: the terrain slope is varied which limits or influences vehicle movement severely; the soil types are complicated and inevitably affected by climate and rainfall [5], the strength of soft or solid soil causes multiple block or delay for vehicle trafficability [6]. To plan an off-road path, if real car and driver are applied to test, it will be costly in manpower, material and financial resources. Moreover, the safety of vehicles and personnel can not be guaranteed. As a result, it's necessary to investigate an optimized path planning method accommodating real terrain and soil conditions well.

The essence of present optimal path planning problem [7–9] is planning out a reasonable path from start point to end point under known limitation of road network topological structure. A large number of experts and scholars have carried out the research on this question and proposed numerous algorithms [10], such as genetic algorithm, particle swarm optimization, neural network, visibility graph and colony optimization. The off-road path planning problem in this paper is different from above work in two aspects: First of all, in off-road environment, there is no road. Any point in given terrain is available as part of path which means the choice space of path planning algorithm is tremendous. Secondly, considering terrain slope as one important influence factor for vehicle's movement, the search space of path planning problem in this paper is 3-Dimensional. To achieve quick movement and efficiently fulfil kinds of tasks, the optimal off-road path planning problem in 3-Dimensional space not only requires finding a least-cost trafficable path of vehicle, but also requires computation time is as short as possible, i.e. in real-time.

Ant colony algorithm [11–13] is a new kind of evolutionary algorithm which plays an important role in solving the traveling salesman problem [14], the shortest path search problem [15], etc. The main problem of ant colony algorithm is how to improve global search ability and convergence speed. To find the global optimal path, the search space of algorithm should be as large as possible, however to reduce computation time, the random search should converge to best solution quickly. In this paper, to solve contradictions between the algorithm's randomness and the pheromone update intensity, an improved ant colony algorithm is proposed. A 3-Dimensional model of terrain surface is firstly set up which partitions the continuous terrain into discrete grids. By applying theoretical analysis and simulation experiment, the tabu tables of slope and soil are set up which determine the GO/NO GO property of terrain-vehicle relationship. Based on the tabu table, the tremendous search space for ant colony algorithm is reduced significantly which improves the algorithm runtime efficiently. Moreover, the influence of slope is quantitatively expressed as weight value in path point selection and path distance calculation, which effectively avoid too high slope and reduce time cost of vehicle movement. The scheme of pheromone update is elaborately designed to improve algorithm converge speed.

The simulation results based on Matlab software tool demonstrate that improved ant colony algorithm (IACA) proposed in this paper is a good solution for path planning problem in off-road environment. Comparing IACA with traditional Dijkstra algorithm, the results show that IACA is more efficient with much lower time cost which is essential for real time off-road path planning scenarios. The reminder of this paper is organized as follows. In Sect. 2, we introduce the knowledge of terrain trafficability, such as the slope computation and weight assignment, the soil classification and influence on vehicle movement. We propose the improved ant colony algorithm (IACA) in Sect. 3. In Sect. 4, simulations are carried out to test the performance of IACA. Experimental results are presented for IACA and traditional Dijkstra algorithm. We conclude this paper in Sect. 5.

2 Terrain Trafficability

The term “terrain trafficability” is commonly used to denote the terrain component of the environment which affects ground vehicle mobility [16, 17]. Terrain includes the material that comprises the terrain (soil, snow, vegetation) as well as the geometry of the terrain surface (slope, topography) [18, 19]. The ability of the terrain to support and provide traction for vehicle operation is called trafficability. In trafficability studies, the emphasis is on the interaction between vehicle and the surface material, including obstacles and topography on vehicle mobility. The properties of terrain surface influence off-road vehicle performance a lot [20], especially for vehicle trafficability.

The major terrain factors which influence vehicle ground trafficability include slope, soil (type and strength), surface material, obstacle description, snow, vegetation, and hydrology, etc. The primary determinants of terrain trafficability in most settings are slope, surface material (including soil type/strength). So in this paper, we mainly consider the influence of slope and soil on the GO/NO GO property of a given terrain.

2.1 Slope Computation and Weight Assignment

Slope is the aspect with respect to direction of travel. In off-road environment, terrain slope influences the mobility of vehicle a lot. Take Abrams tank M1A1 as example, if the upward slope is bigger than 30° it will surpass the climbing limit of M1A1 and make it stop. Based on the gird model composed by uniform square, the 3-Dimensional terrain map is constructed which has the advantages of simple data structure, strong regularity and efficient data index.

Considering the important influence of terrain slope, the given off-road terrain is firstly modelled in 3-Dimensinal and the continuous terrain is discretely stored in data table; Secondly, the gird model is used. A gird is represented by the coordinates of its center point. The slopes of present grid to its neighbour eight girds are computed, based on which the slope table is determined. Considering the actual climbing capacity of given vehicle, such as Abrams tank M1A1, the trafficability weight table named *slopeW* is set up. In this table, if the slope is bigger than the maximum upward climbing angle or smaller than the minimum downward climbing angle, the weight value in table *slopeW* is set to zero meaning this neighbour grid is NO GO. Else, the slope angle is partitioned into many grades, each of which is assigned a different weight value ranging from 0 to 1. Generally speaking, the harder slope for vehicle to climb, the lower weight is set for corresponding gird.

Supposing the area projected by a vehicle is a grid unit. The four vertexes of gird (i, j) are $(P_{i,j}, P_{i+1,j}, P_{i+1,j+1}, P_{i,j+1})$ and the corresponding heights are $(H_{i,j}, H_{i+1,j}, H_{i+1,j+1}, H_{i,j+1})$. So the center point $P_{i,j}{}'$ of this grid and its height $H_{i,j}{}'$ is defined in formula (1) and (2).

$$P'_{i,j} = (P_{i,j} + P_{i+1,j} + P_{i+1,j+1} + P_{i,j+1})/4 \tag{1}$$

$$H'_{i,j} = (H_{i,j} + H_{i+1,j} + H_{i+1,j+1} + H_{i,j+1})/4 \tag{2}$$

In this paper we mainly analyse the off-road mobility of M1A1 tank, when the tank is commanded to move, it’s necessary to constantly compute the slope towards the direction of travel and judge the trafficability between neighbour grids. The slope is a metric of earth surface curvature at given point it's composed of two factors: slope size and slope direction.

In the algorithm of slope calculation, based on the present grid represented by its center point $P_{i,\ j}{}'$, the slope values of its neighbour eight grids are computed, as shown in Fig. 1.

Take grid $P_{i,\ j}{}'$ to its dead ahead grid $P_{i,\ j+1}{}'$ as example, its slope computation method is in formula (3).

$$G_{i,j,1} = \frac{H'_{i,j+1} - H'_{i,j}}{L} \tag{3}$$

L is the width of grid unit, from formula (3) and Fig. 2 it's obvious to see that $G_{i,\ j,\ 1}$ is essentially the tangent value of slope angle α from present grid $P_{i,\ j}{}'$ to its dead ahead grid $P_{i,\ j+1}{}'$.

Similarly, other slope values of neighbour grids are computed in formula (4) to (10), the serial number of neighbour grids are defined in Fig. 1.

$$G_{i,j,2} = \frac{H'_{i-1,j+1} - H'_{i,j}}{\sqrt{2}L} \tag{4}$$

$$G_{i,j,3} = \frac{H'_{i-1,j} - H'_{i,j}}{L} \tag{5}$$

$$G_{i,j,4} = \frac{H'_{i-1,j-1} - H'_{i,j}}{\sqrt{2}L} \tag{6}$$

$$G_{i,j,5} = \frac{H'_{i,j-1} - H'_{i,j}}{L} \tag{7}$$

$$G_{i,j,6} = \frac{H'_{i+1,j-1} - H'_{i,j}}{\sqrt{2}L} \tag{8}$$

$$G_{i,j,7} = \frac{H'_{i+1,j} - H'_{i,j}}{L} \tag{9}$$

$$G_{i,j,8} = \frac{H'_{i+1,j+1} - H'_{i,j}}{\sqrt{2}L} \tag{10}$$

For M1A1 tank, the maximum upward climb angle is 31° and corresponding value $G_{i,\ j,\ k}$ is $\sqrt{3}/3$; when $G_{i,\ j,\ k}$ is smaller than 0, it means the tank is moving downward.

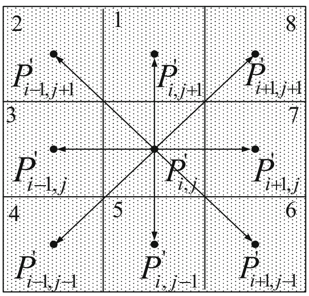

Fig. 1 3 × 3 grid representation

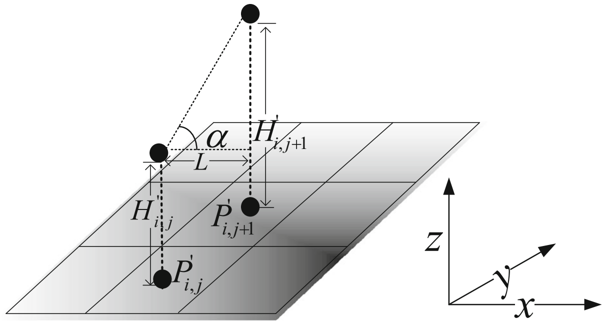

Fig. 2 Calculation of slope value

Supposing the minimum downward slope value is − 60° with corresponding $G_{i,\ j,\ k}$ value $-\sqrt{3}$. Base on the experimental results of M1A1, the slope tabu table *slope* and slope weight table *slopeW* are set up.

For tabu table *slope*(i', j') with slope value $G_{i,\ j,\ k}$: If $G_{i,j,k} \in \left[-\sqrt{3}, \sqrt{3}/3\right]$, *slope*($i'$, j') = 1, means gird k is trafficable for tank; else *slope*(i', j') = 0, means gird k is untrafficable. Here, (i', j') is the 2-Dimensional index of neighbor grid $P_{i',\ j'}{}'$ in algorithm data table storing the given terrain surface.

The grade partition of slope angle from − 60° to 30° and corresponding weight in table *slopeW* is defined in Table 1.

2.2 Soil Influence on Trafficability

The commonly used soil types are defined by the Unified Soil Classification System (USCS) [21]. In USCS, soil types are composed of two letter connotative symbols composed of a prefix and a suffix. The prefix indicates the main soil type and the suffix indicates subdivisions of these main groups, as shown in Table 2.

Remolding Cone Index (RCI) is the most important characterization of soil strength. The Cone Index (CI) characterizes the in situ shear strength of a soil. It is obtained by the measurements performed using a specific device, the cone penetrometer. The behaviour of the soil under repetitive loadings is described by the Rated Cone Index (RCI) which is measured using the same cone penetrometer but the soil is compacted by applying a defined number of blows. The Mobility Index, (MI), represents a parameter that is related to the Vehicle Cone Index (VCI) performance of the vehicles running on fine-grained soils. It is composed of many traction parameters influencing vehicle characteristics [22].

If the RCI of soil is bigger than VCI of vehicle, the vehicle can go through soil; else, the soil will be too soft for vehicle to go and vehicle will sink into soil. The VCI of M1A1 tank has been experimented and determined, whose VCI_1 is 25 and VCI_{50} is bigger than 50. Here VCI_1 means go through the soil only once while VCI_{50} means the vehicle repeatedly go through the soil for 50 times.

Base on the experimental results of M1A1, the soil tabu table *soil* is set up.

For *soil*(i', j') in tabu table: If RCI(i', j') > VCI_{50}, *soil*(i', j') = 1, means soil in gird k is trafficable for tank; else *soil*(i', j') = 0, mean soil in gird k is untrafficable. Here, (i', j') is the 2-Dimensional index of neighbor grid $P'_{i\prime,j\prime}$ in algorithm data table storing the given terrain surface.

In [23] the empirical formula relationship among RCI, moisture percent and clay percent is established in formula (11).

Table 1 Slope partition and weight assignment

Slope	≤ − 60	− 60 to − 40	− 40 to − 30	− 30 to − 20	− 20 to − 10	− 10–0	0–5	5–15	15–20	20–25	25–30	≥ 30
slopeW	0	0.8	0.85	0.9	0.95	1	1	0.95	0.9	0.85	0.8	0

Table 2 USCS soil types

USCS code	Description
GW	Well-graded gravels
GP	Poorly-graded gravels
SW	Well-graded sands
SP	Poorly-graded sands
SM	Silty sands
SC	Clayey sands
CL	Inorganic clays of low to medium pasticity
CH	Inorganic clays of high pasticity
MH	Inorganic silts
ML	Inorganic and very fine sands

$$RCI = \exp\left(4.605 + \frac{2.123 + 0.008C - 0.693\ln M}{0.149 + 0.002C}\right) \tag{11}$$

RCI is the Remolding Cone Index of soil; *C* is the percent of clay; *M* is moisture percent, %.

Formula (11) can be deformed into formula (12).

$$RCI = exp(a + blnM) \tag{12}$$

In formula (12), $a = 4.605 + \frac{2.123+0.008C}{0.149+0.002C}$ and $b = \frac{0.693}{0.149+0.002C}$ are variables determined by soil type; *M* is moisture percent, %.

According to the classification of USCS, *a* and *b* values for different soil types are shown in Table 3.

The relationship between *RCI* and moisture percent *M* for different soil types are simulated and depicted in Fig. 3.

3 Algorithm Construction and Description

Ant colony algorithm is a new kind of evolutionary algorithm which is brought forward by Dorito it comes from the study of ants searching for food problem. Ant colony algorithm is a kind of adaptive distributed algorithm; it is also a kind of random search algorithm.

Table 3 a, b values for different soil types

USCS type	*a*	*b*
SM + SC	11.3445	− 2.4497
CL	15.2821	− 3.4542
CH	13.0541	− 2.5091
MH + CH	12.2076	− 1.9434
ML	11.7046	− 2.3319
ML + CL	13.8927	− 3.0272
MH	21.6000	− 4.6228

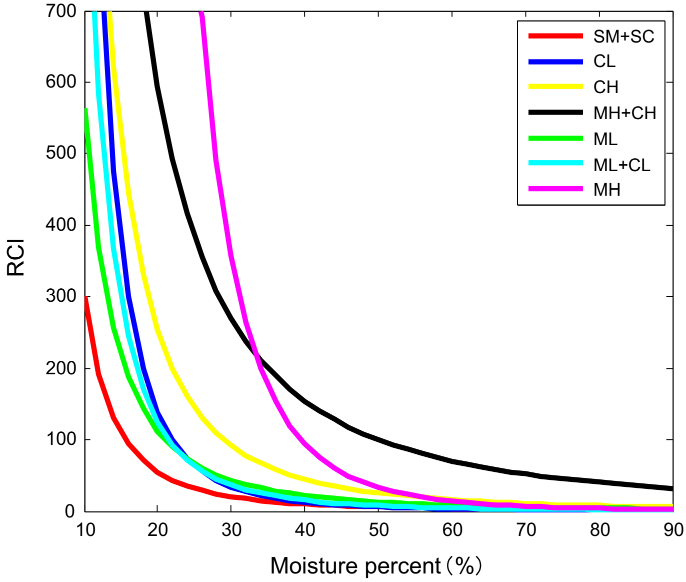

Fig. 3 Relationship between RCI and moisture percent

Different from traditional path planning algorithms, the algorithm designed for off-road path must consider not only the path length but also the trafficability of terrain, i.e., the GO/NO GO property of terrain gird. Based on above analysis of terrain slope and soil strength, we explicitly introduce the improved ant colony algorithm (IACA) to solve off-road path planning problem in this section.

3.1 The Basic Description of Algorithm

Simulating the process of ant feeding and taking the complex terrain surface into consideration, the path planning algorithm searches the "shortest" path from the start point to the end point. Ants leave a kind of chemical called pheromone to communicate and collaborate with each other. The higher a path pheromone concentration is, the shorter the corresponding path is. Based on this positive feedback of learning information, the ants will eventually find the best path from the nest to food source.

For a given 3-Dimensional terrain with different surface characterization, the aim of path planning is to find the optimal path with length as short as possible and efficiently avoid crossing the places the vehicle can not go, such as slopes beyond vehicle move ability and soil which is too weak to support vehicle travel. The model of off-road terrain is based on the set of discrete points, each of which represents a terrain grid. In traditional ant colony algorithm, the pheromone is stored in the edge connecting different nodes. If the pheromone is also stored in the edge between discrete terrain grid points, since the terrain and the size of discrete point set partitioned from it are usually large, with the increase of terrain scale the computation space complexity increases sharply which is unacceptable. As a result, the ant colony algorithm designed for terrain path planning utilizes grid representation and stores pheromone in discrete terrain grid. Moreover, the algorithm assumes that the vehicle just moves one grid at each step and the movement between neighborhood grids is independent of time.

3.2 The Improved Ant Colony Algorithm

3.2.1 The Choice of Path Point

Assuming the present grid of ant position is (i, j), the probability of choosing neighbor grid (i', j') as its next step is $P(i', j')$. Based on the choice probability of each neighbor grid, the next grid to move is determined by roulette mode. $P(i', j')$ is defined in formula (13).

$$P(i',j') = \begin{cases} \dfrac{ph(i',j')^{\alpha} * H(i',j')^{\beta}}{\sum\limits_{(i',j') \in neighbor(i,j)} ph(i',j')^{\alpha} * H(i',j')^{\beta}} & H(i',j') \neq 0 \\ 0 & H(i',j') = 0 \end{cases} \tag{13}$$

$ph(i', j')$	Pheromone concentration of grid (i', j'), the value will gradually decay with the pass of time;
α	Importance degree of $ph(i', j')$, this value can be adjusted through experiments;
β	Importance degree of $H(i', j')$ that can be adjusted through experiments;
$H(i', j')$	A heuristic function taking slope and soil tabu table into the gird (i', j') weight consideration, see formula (14)

$$H(i',j') = \begin{cases} \dfrac{J * gridW(i',j')}{\Delta D + Q(i',j')} & slope(i',j') = 1 \& soil(i',j') = 1 \\ 0 & else \end{cases} \tag{14}$$

J	Coefficient of $gridW(i', j')$;
$\triangle D$	The actual distance from grid (i, j) to (i', j');
$Q(i', j')$	The euclidean distance from (i', j') to the end point (i_{end}, j_{end})
$gridW(i', j')$	The weight assigned to grid (i', j') according to the slope and soil. Here $gridW(i', j')$ is equal to $slopeW(i', j')$ because the soil influence is simplified to GO/NO GO judgment of vehicle

3.2.2 The Update of the Pheromone

Pheromone in ant colony algorithm is used to attract ant for searching path, its update include local pheromone update and global pheromone update. Local pheromone update demands each ant updates the grid pheromone after going through. To increase the search probability of other grids haven't been travelled yet and reach global search, the local update of travelled grid must reduce its pheromone. The formula of local update is in formula (15).

$$ph(i,j) = (1 - decr) \quad * ph(i,j) \tag{15}$$

decr is volatility coefficient of pheromone ranging of [0,1].

Global pheromone update happens when the iterative search completed and all ants move from the start point to the end point. In order to avoid the searched solution space converges too quickly, the algorithm proposed in this paper applies the elite ant strategy in which the pheromone is updated based on the shortest path at present iteration and insure the search space of ants near the concentration of best solution. The formula of global update is in formula (16), (17).

$$ph(i,j) = (1 - rou) * ph(i,j) + rou * \Delta ph(i,j) \tag{16}$$

$$\Delta ph(i,j) = K/\min(length(m')) \tag{17}$$

rou is an adjustable coefficient of pheromone ranging of [0,1].

As pheromone concentration gradually decay with the volatility coefficient *decr*, if the size of problem is comparatively large, the pheromones of the grids haven't been searched will decrease to nearly zero and the problem will converge to non-global solution too early. To search the solution space more thoroughly, it is essential to limit the maximum and minimum value of pheromone. The limitation of pheromone value is in formula (18).

$$ph(i,j) = \begin{cases} ph_{\max}, & ph(i,j) \geq ph_{\max} \\ ph_{\min}, & ph(i,j) \leq ph_{\min} \end{cases} \tag{18}$$

3.2.3 The Path Construction

Ant colony algorithm is used to obtain the shortest path which is recorded in table Path. Path is an m × 2n matrix recording the x and y coordinate along the path ant travelled which satisfying following condition:

$$\begin{cases} Path(m', 1:2) = [i_{start}, j_{start}], & m' \leq m \\ length(Path(m', :)) = 2 * n \end{cases} \tag{19}$$

m is the number of ants, *n* is the biggest number of path grids among the searched path set, $Path(m',:)$ represents the path searched by the *m*' th ant, $length(Path(m',:))$ is the column number of the m' th path.

As the search method for ant is based on roulette mode, it is easy to be stuck in some bad point and the search process is stopped. That is to say, not all $Path(m',:)$ represents acceptable path and some of the corresponding column length of the path $length(Path(m',:))$ is not 2n. For this condition, the left elements in $Path(m',:)$ are supplemented by zero. Only the paths satisfying formula (20) are acceptable.

$$\begin{cases} j = nnz(Path(m', :));\ m' \leq m \\ Path(m', j-1) = i_{end} \\ Path(m', j) = j_{end} \end{cases} \tag{20}$$

$nnz(Path(m',:))$ represents the number of non zero elements in $Path(m',:)$. The distance $Dist(m')$ of path $Path(m',:)$ is calculated only if it satisfies formula (20). Here for the off-road path planning problem, the distance of path is a comprehensive metric of geographic length and terrain surface properties. $Dist(m')$ is defined in formula (21).

$$Dist(m') = \sum_{k=2}^{n} \frac{1}{gridW_k} \cdot l_k = \sum_{k=2}^{n} \frac{1}{slopeW_k} \cdot l_k = \sum_{k=2}^{n} \frac{1}{slopeW_k} \cdot EuclideanDist(P_{i,j}, P_{i',j'}) \tag{21}$$

l_k is the segment length (Euclidean distance) from the *k*-1th point to the *k*th point. Supposing there are n points in the path and the path is partitioned into *n*-1 segments, as shown in Fig. 4. Since the start point (i_{start},j_{start}) of ant search is fixed, the grid weight including slope and soil strength is calculated from the second point in path. $slopeW_k$ is the partial weight of grid k decided by the slope from grid k-1 to grid k. $soilW_k$ is the partial weight of grid k decided by the soil strength in grid k.

3.2.4 The Description of Algorithm

The detailed procedures of algorithm are described in Table 4.

4 Simulation Analysis

4.1 Simulation Scene and Parameters

This improved ant colony algorithm is implemented in MATLAB R2012b simulation platform. The scale of terrain surface in simulation is 210 m × 210 m × 100 m and partitioned into 21 × 21 square grid. The start point and end point of ant search are set to (10, 3) and (8, 5) respectively. The initial $ph(i, j) = 0.4$. According to references and experimental results, initial$\alpha = 3$, $\beta = 4$, $J = 200$, $decr = 0.1$, $rou = 0.4$, $K = 500$, $m = 40$, $NC_{\max} = 100$, $ph_{\min} = 0.001$, $ph_{\max} = 0.8$.

In simulation, the parameters of M1A1 tank acquired from actual experiments are applied. Its maximum upward climb angle is 31° and minimum downward slope value is − 60°. The slope tabu table *slope* and slope weight table *slopeW* are set up in Table 1. The VCI of M1A1 tank has been experimented, whose VCI_1 is 25 and VCI_{50} is bigger than 50.

The topographic distribution of simulation terrain is shown in Fig. 5, the different color of grid represents different height of terrain ranging from 0 to 100 m.

Supposing there are three types of soil in simulation: Inorganic silts (MH), Inorganic clays of high plasticity (CH) and Silty sands (SM), see Fig. 6. The moisture percent of soil is set to 30%, the RCI of different soil types can be calculated from Fig. 3 and the trafficability of different grid is judged.

4.2 Simulation Results and Analysis

The improved ant colony algorithm is implemented in above simulation scene and parameter setting, the running results are shown in Fig. 7. From the figure we know, due to the trafficability influence of terrain slope and soil strength, the planned optimal path is not the path with shortest physical distance directly from start point to end point. Path planning for off-road environment must satisfy vehicle trafficability firstly. While taking the slope

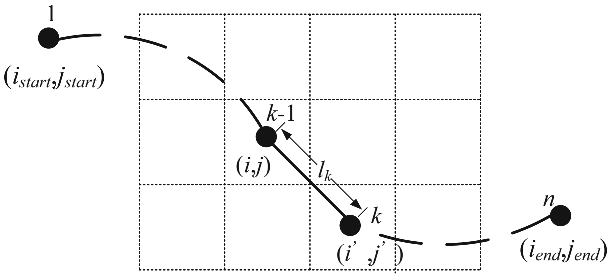

Fig. 4 Calculation of path distance

Table 4 Improved Ant Colony Algorithm descriptions

Data preprocessing for input:
  Read the height data of given terrain from 3-Dimensional maps.
  Calculate the height of grid center point according to formula (1).
  Set up a series of tables: *slopeW* table, *soilW* table, *gridW* table.

Initialize the coefficients of algorithm including:
  Parameterα, β, J, *decr*, *rou*, K and m.
  Start point (i_{start}, j_{start}) and end point (i_{end}, j_{end}).
  Initial value of $ph(i, j)$ and maximum loop count NC_{max}.
  Place all ants at the start point. Set $\triangle ph(i, j) = 0$ and $NC = 1$.

For the NCth $\in[1, NC_{max}]$ loop:
  Start all ants to move.
  For ant $m'\in[1,m]$
    Suppose its present grid is (i, j), calculate the heuristic function value $H(i', j')$ of its neighbor girds according to formula (14) and the choice probability $P(i', j')$ according to formula (13).
    Based on the calculated probability, ant m' choose its next grid by roulette mode.
    Update the local grid pheromone according to formula (15) and (18). Add the chosen grid into path table $Path(m',:)$.
    When ant m' finishes its search. Judge the feasibility of $Path(m',:)$ according to formula (20). If it is feasible, calculate the length Dist(m') of this $Path(m',:)$ according to formula (21).
  Choose the shortest feasible path found by m ants. Record this path as *Bestpath* (m'_{min},:) and its length as *Bestdist* (m'_{min},:).
  Update the global grid pheromone according to formula (16) and (17).

Choose the shortest path of NC loops as the final best path. Record this as *Bestpath* and *Bestdist*.

Output *Bestpath* and *Bestdist* as the final result of ant colony algorithm.

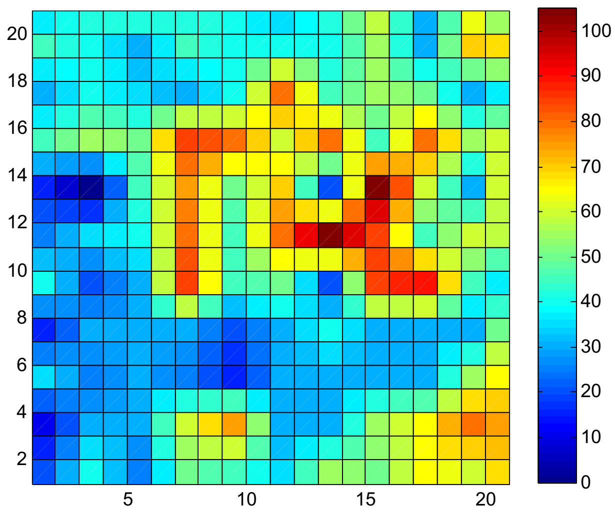

Fig. 5 Topographic distribution of terrain

weight into account of gird selection and distance calculation, the planned path mainly locates in the comparatively flat terrain with bigger RCI value.

Dijkstra algorithm is a classical shortest path planning algorithm. To test the efficiency of improved ant colony algorithm proposed in this paper, we compare these two methods in identical simulation scenes and parameter setting. The results are shown in Table 5. The

Fig. 6 Soil distribution in simulation

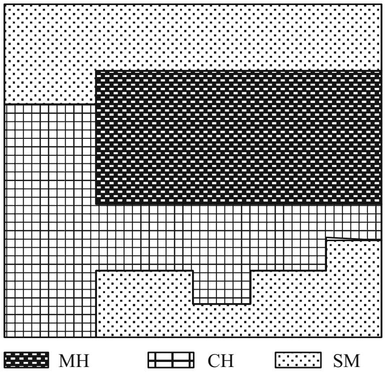

Fig. 7 Path planning result

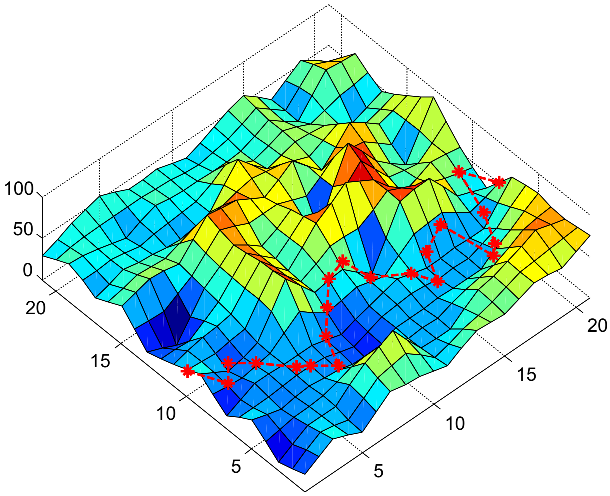

Table 5 Comparison of algorithms

Algorithm	Point number	Path distance	Search space	Time cost
Dijkstra	21	33.5	3210	300 s
IACA	21	33.5	276	21 s

term of time cost is algorithm runtime on Matlab software platform. From the results, it's obvious to see that the planned path are the same while the search space and implementation time of our algorithm are much smaller than Dijkstra. For real time path planning applications in off-road environment, running time of path planning algorithm is of essential importance. Our algorithm not only consider the trafficability of actual terrain surface, but also reduce path planning time which can be used in complex off-road terrain path planning scenarios with kinds of soil types quickly and efficiently.

5 Conclusions

In this paper, the actual trafficability influence of terrain slope and soil strength on vehicle mobility is considered in off-road path planning problem. By combining theoretical analysis with simulation experiment, the tabu table of slope and soil is set up which determines the GO/NO GO property of terrain-vehicle relationship. Considering the slope influence on vehicle mobility, the trafficable slope is furthermore partitioned into different grades with different weight. Based on these tabu table and grid weight table, an improved ant colony algorithm (IACA) is applied for 3-dimension path planning. Simulation results show that IACA is more efficient in path planning. Comparing the improved algorithm with traditional Dijkstra algorithm, numerical experiments result shows that improved algorithm can plan an optimal route with much lower time cost which is essential for real time off-road path planning scenarios.

Acknowledgements The authors acknowledge the National Natural Science Foundation of China (Grant No: 61273047), the National Natural Science Foundation of China (Grant No: 61573376).

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