Finding Optimal Paths on Terrain Maps using Ant Colony Algorithm

Vinay Rishiwal ,Mano Yadav, K.V. Arya

Abstract- **This paper presents the meta-heuristic method of ant colony optimization (ACO) to find optimal paths on terrain map images. The procedure simulates decision-making process of ant colonies as they forage for food. Modifications have been made to the ACO algorithm to solve the optimal path finding problem by optimizing multiple constraints. The number of constraints considered here is two. However, it can effectively be used for more than two constraints.**

Keywords: **Ant Algorithms, Meta-heuristic, Multiple Objective Optimization**

I. Introduction

In many real life optimization problems several objectives are to be optimized. For such multi-objective problems [1] usually there does not exist a single best solution but a set of optimal solutions is achieved which are superior to the other solutions while considering all objectives.

In reference to the terrain maps objectives, more specifically, constraints can depend on factors such as time, distance, avoidance of enemies etc. [8]. A beforehand knowledge about the possible optimal path between source and destination can aid the army troops in movement. Finding the optimal path finds special utility in transportation network, communication network, trekking and in geographical areas that are unexplored.

ACO [2, 4] simulates the behavior of ant colonies in nature as they forage for food and find the most efficient routes from their nests to food sources. The decision making processes of ants are embedded in the artificial intelligence algorithm [1] of a group of virtual ants [5] which are used to provide optimal paths on terrain maps. For multiple objectives [3] more than one colony can be maintained which interact to share the information gained and hence give those paths which lie in optimal range.

Rest of the paper is organized as follows. Section II presents the problem statement. In Section III ant colony algorithm is explained. Proposed algorithm for path finding in terrain maps along with required mathematical background is discussed in Section IV. Section V presents the results and discussions on results along with conclusions is presented in Section 6.

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II. Optimal Paths Using Ant Algorithms on Terrain Maps

The task is to determine best optimal paths in between two points referred as source and destination points on a terrain map image. The algorithm uses penalty maps of the terrain maps as an input. Terrain features such as land, forest etc are identified using different colors. Each color holds a distinct penalty value for a region on terrain map with respect to constraint under consideration.

The image taken as input, act as search space for the problem. The search space can better be described as a weighted graph G = (V, E), where V represents set of nodes and E represents set of arcs. Vs and Vd are the source and destination nodes respectively and the aim is to find set of nodes between Vs and Vd such that sum of weights on connecting arcs is minimized.

For optimizing multiple constraints each arc owes a different weight for a constraint and the objective is to optimize the path for both constraints.

The concept of node i correspond to the pixel at location (x,y) henceforth traversal from node i to node j is considered as pixel (x1,y1) to pixel (x2,y2). The weightage to the arc is the penalty value provided in the penalty map for a constraint.

III. Ant Algorithm

Ant colonies, generally social insect societies, are distributed systems that, in spite of the simplicity of their individuals, present a highly structured social organization. The field of Ant algorithm studies a model derived from the observation of real ant's behavior and uses these models as source of inspiration for the solution of optimization and distributed control problems.

Ant Colony Optimization (ACO) is a paradigm for designing meta-heuristic algorithms [6,7] for combinatorial optimization problems. The essential trait of ACO algorithms is the combination of a priori information about the structure of a promising solution with a posteriori information about the structure of previously obtained good solutions.

Meta-heuristic algorithms[1, 7] are algorithms which, in order to escape from local optima, drive some basic heuristic: either a constructive heuristic starting from a null solution and adding elements to build a good complete one, or a local search heuristic starting from a complete solution and iteratively modifying some of its elements in order to achieve a better one.

A. Forging Behavior of Ants

When an ant locates a food source it carries a food item to the nest and lays pheromone along the trail[1, 3] .Forager ants decide which path to follow based on pheromone concentration on different paths. Paths with larger pheromone concentration have a higher probability of being selected. As more ants follow a specific trail the desirability of that is reinforced by more pheromone being deposited by foragers which attracts more ants to follow that path.

B. Pheromone Updation

Once all the ants have completed their tour the pheromone on the edges is updated [1, 7]. Each of the pheromone value is initially decreased by a certain percentage. Each edge then receives an amount of additional pheromone proportional to the quality of solutions to which it belongs.

IV. ACO FOR PATH FINDING

Using ACO an ant simulates an agent to search a path between source and destination points. Initially, each ant starts at the source point and the set of nodes included in its tour is empty. The ant selects the next node to visit from the list of feasible locations based on transition probability and directional biasing. Transition probability[1, 5] maintains a balance between pheromone intensity (history of previous successful moves) and heuristic information (expressing desirability of the move). The next pixel is chosen on the criteria of maximum probability obtained for that move. The process is repeated till the destination point is found.

The algorithm constructs a complete tour for the first ant prior to the second ant starting its tour. This continues until a predetermined number of ants, say m, each construct a feasible route.

After finding the best path for both constraints separately, the paths are chosen as optimal if they are with in the allowed range of penalty value for different constraint.

The range depends on maximum penalty value of a constraint computed after each iteration .Only the chosen optimal paths are reinforced with pheromone concentrations. Pheromone concentration is reduced at the end of each iteration[1].

To optimize two constraints, a separate ant colony has been assigned the responsibility of optimizing each constraint. Colonies cooperate to find a solution that optimizes all constraints by sharing information about the solution obtained by each colony.

The algorithm is iterated for ten times and during each iteration, fifty ants are used to find fifty distinct paths.

A. Transition probability

Transition probability primarily helps in finding location of the new pixel in the movement of ants and is defined [1] as

$$p_{i,j} = \frac{(\tau_{ij}^{\alpha})(\eta_{ij}^{\beta})}{\sum(\tau_{ij}^{\alpha})(\eta_{ij}^{\beta})} \qquad (1)$$

Where,

ψ, ratio of ant index to the total number of ants

τ_1, pheromone matrix element (x,y) for constraint 1

τ_2, pheromone matrix element (x,y) for constraint 2

η_1, desirability of pixel (x,y) for constraint 1

η_2, desirability of pixel (x,y) for constraint 2 α, parameter to control the influence of τ

value taken for $\alpha=7$

β, parameter to control the influence of η

value taken for $\beta=3$

Here constraints are factors which restrict the movement on terrain. They could be water bodies, forest, hills etc. Penalty represents the cost of moving through constraints. Value of penalty may depend on various issues such as time, distance etc. taken under consideration.

B. Calculating Directional Probability (Biasing for the direction of destination)

The directional probability [1] increases the chances to choose the next pixel that is in the direction of destination. The movement in east-west direction is decided by,

east-west direction,

$$ew = (x2-x)*constt / penalty[k][x][y] \qquad (2)$$

Similarly north-south direction is given by,

$$ns = (y2-y)*constt / penalty[k][x][y] \qquad (3)$$

$$xlim[k] = \begin{cases} xlim[k] - ns, & x = s, se, sw;\ where\ ns < 0 \\ xlim[k] + ns, & x = n, ne, nw;\ where\ ns < 0 \\ xlim[k] - ew, & x = n, nw, sw;\ where\ ew < 0 \\ xlim[k] + ew, & x = n, ne, se;\ where\ ew \geq 0 \end{cases}$$

where,

n, north ***e,*** east ***s,*** south ***w,*** west

ne, north-east

se, south-east

nw, north-west

sw, south-west

k, constraint

x, x-coordinate

y, y-coordinate

x2, x-coordinate of destination

y2, y-coordinate of destination

xlim[k],Determine directional probability in direction x for constraint k.

A. Pheromone Update

$$\tau_{x,y} = \rho\tau_{x,y} + \Delta\tau_{x,y} \qquad (4)$$

where,

$\tau_{x,y}$ amount of pheromone on a pixel (x,y) for each constraint

ρ, rate of pheromone evaporation

$\Delta\tau_{x,y}$, amount of pheromone deposited, typically given by

$$\Delta\tau_{x,y}^{k} = \begin{cases} \frac{1}{L_k}, & if\ pixel\ (x,y)\ \mathbf{is\ visited} \\ 0, & otherwise \end{cases}$$

where,

$\boldsymbol{L_k}$ is the cost of the k^{th} ant's tour (weighted mean penalty).

B. Proposed Algorithm for Path Finding

1. Read the image.
2. Read the penalty map for *penalty1* and *penalty2*
3. Input source and destination points.
4. for iteration 1 to 10 do
5. for penalty 1 to 2 do
6. for ant *n*=1 to 50 do
   a. Initialize directional probability, *clim* in 8 directions
   b. Increment the probability in direction of destination
   c. While
      -set xlim=clim (clim is initialized by 10000)
      -Increment the probability in direction of destination.
      -Reduce probability depending on the penalty value in that direction
      -Calculate probability according to ACO in 8 directions.
      -Depending on probability choose next pixel
   until end point is reached or the path length exceed the threshold value
   d. Remove loops from the path.
   e. Calculate *penalty1*, *penalty2*
7. Choose best solution for penalty 1.
8. Choose best solution for penalty 2.
9. Compare paths against their counter penalty
   a. Store optimal path lying under the allowed range.
10. Display the path
11. Update pheromone content on each selected path.
12. end
13. end

V. Results

In the input terrain map white region have minimum penalty value for both the constraints in Fig. 1 through Fig. 4 and penalty increases as shade becomes darker for both constraints. Fig. 1 shows the original image where blue circle shows the starting pixel vs and red circle showing the destination pixel vd. When the proposed algorithm is applied on this image any number of iterations may be performed but here results are shown only after single iteration. In any iteration out of 50 searched paths only 10 paths are chosen by optimizing a single constraint. After 10 optimal paths are chosen for each constraint, 10 best optimal paths are chosen optimizing both the constraints. Fig. 2 shows the optimal paths for first constraint after one iteration and the optimal paths for the second constraint are shown in Fig. 3. Finally the overall 10 optimal paths have been shown in Fig. 4. In the implementation it is considered that these paths tend to follow white region avoiding colored region thus minimizing overall penalty of movement.

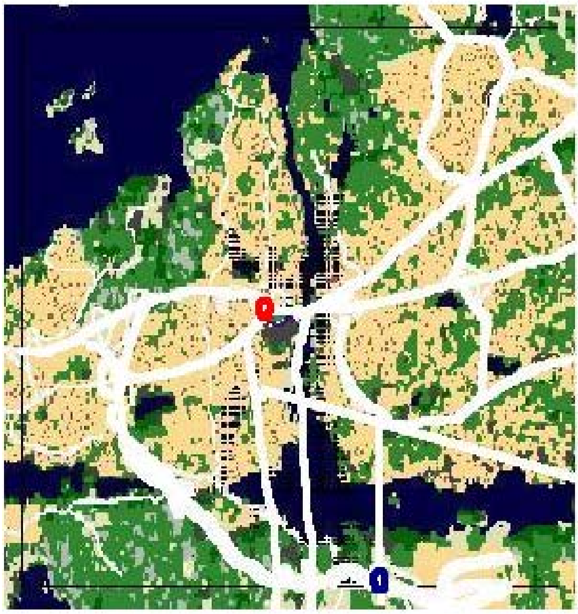

Figure. 1: Original Image of a given terrain map

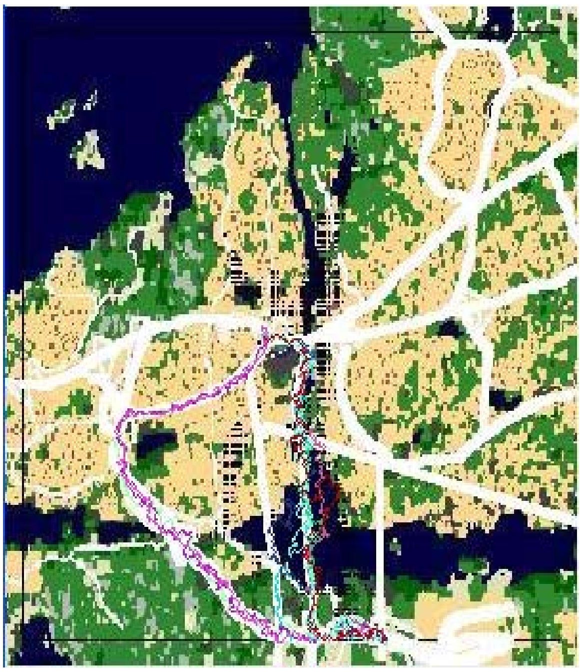

Figure 2: Optimal paths for constraint one after single iteration.

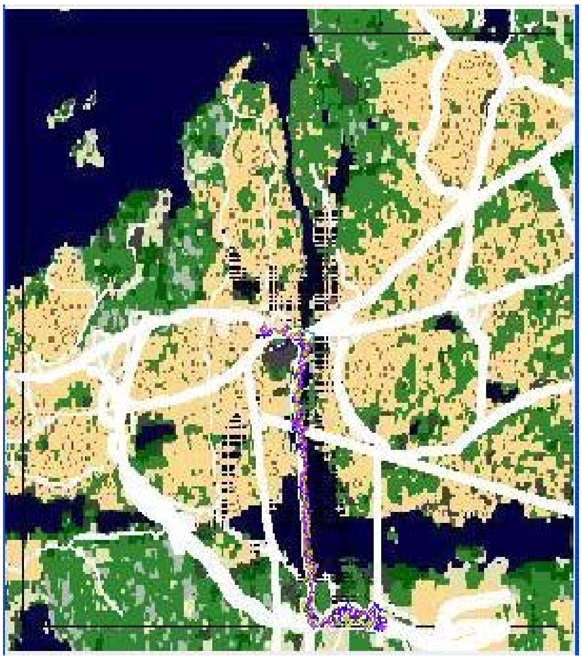

Figure 3: Optimal paths for the second constraint

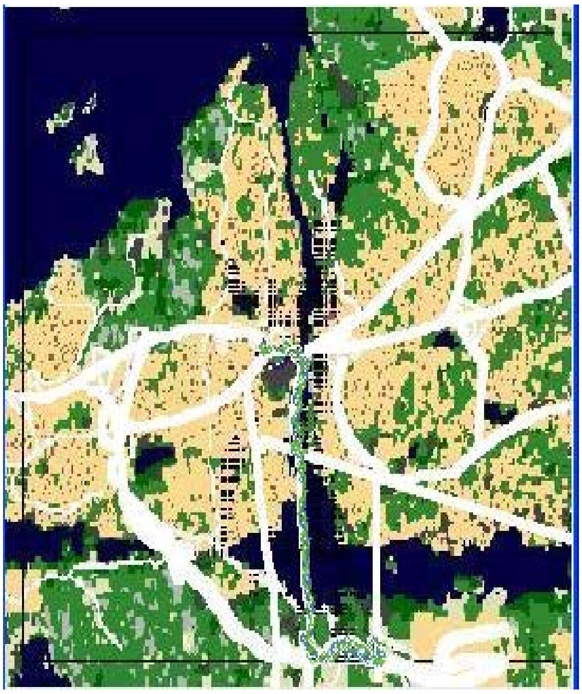

Figure 4: Overall 10 best optimal paths.

VI. Discussion and Concluding Remarks

In this paper problem of finding optimal paths in terrain maps has been addressed efficiently using ant colony algorithm. The terrain maps considered here may include so many constrains like forest, hills etc. A penalty criterion has been used to find the best optimal paths for a desired source destination pair. It is evident from the results that the proposed solution is efficient enough to find the optimal paths in the given input (original terrain map) image. While searching for the best path it is desirable to find the most distinctly different paths. In the graph two paths might differ from each other in only single node. This difference does not guarantee that the paths are distinctly different. This problem is not addressed in this implementation of the proposed solution. Optimization can be refined by zooming exploited area in the search space. Another possible improvement is that while moving on homogeneous penalty surface an ant may avoid computing transition probability to choose next pixel to move instead proceed in the same direction. Therefore, the proposed algorithm can be used efficiently for finding optimal paths on the terrain maps.

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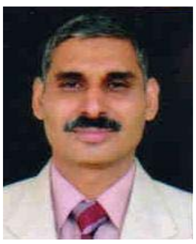

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