

# ANT COLONY OPTIMIZATION FOR FINDING BEST ROUTES IN DISASTER AFFECTED URBAN AREA

F Samadzadegan<sup>a</sup>, N Zarrinpanjeh<sup>a\*</sup>, T Schenk<sup>b</sup>

<sup>a</sup>Department of Geomatics Eng., University College of Engineering, University of Tehran

<sup>b</sup>Department of Geology 876 Natural Sciences Complex, University at Buffalo, Buffalo, NY 14260

**KEY WORDS:** Disaster Management, Best Routes, High Resolution Satellite Imagery, Ant Colony Optimization, Fuzzy Inference Systems

## ABSTRACT:

This paper is dedicated to post disaster road network verification and routing using High Resolution Satellite Imagery (HRSI) and Ant Colony Optimization (ACO) algorithms. By determination of damage degree to each road element using satellite information, a modified ACO algorithm is designed and applied to find best routes with respect to each road's length and damage degree. The mentioned algorithm's innovative aspect is evident in the invented transition rule. Finally, finding best route from any source to destination is conducted not only on the basis of shortest path but also according to the current functionality and exploitability of the network. As experimented, it is observed that ACO algorithm is able to present more reliable paths compared to deterministic solutions where damaged roads are absolutely crossed off the network. Moreover, considering the flexibility of ACO in tuning parameters the algorithm is able to perform routing in case of deploying various vehicles for different operations.

## 1. INTRODUCTION

Road's network also known as transportation lifeline, has been referred as a critical factor in social and economical life of residents and a vital tool for deploying goods and services in every part of the city. When the functionality of road's network is put to the test by the hazardous powers of nature, such as earthquakes, floods and many similar devastating disasters, the criticality of such infrastructure is more vividly exposed. The functionality of city roads network is more deeply realized when all missions of post disaster rescue and relief is totally constructed on the basis of a reliable transportation system. Therefore, receiving updated information about the city roads network and also proposing managing systems to optimize the functionality of such vulnerable facilities are two most critically important issues.

High resolution satellite imageries, capable of providing accurate and timely information about the affected area, are totally believed to propose a hand to solve road map updating solution. Along with these enriched sources of information, soft computation approaches are also considered to propose more comprehensive algorithms and more robust solutions such as Fuzzy Inference Systems (FIS) (Samadzadegan et al., 2008).

Regardless of how important post disaster map updating seems, processing the received information to reduce the effects of disaster in terms of facilitating emergency transportations is a matter of importance. Therefore, a decision making system is totally needed to define routes between destinations in the affected region with respect to the results of map updating from satellite imageries. The same as map updating soft computation approaches are also hired in order to provide optimized solutions. Ant Colony Optimization (ACO) is one of the most recent approached in solving optimization problems which are

based on the collective behavior of ants living in colonies, finding shortest path between nest and food source (Dorigo et al., 2004).

In this paper defining principles of ACO, the proposed novel routing method specially designed to fit the needs of disaster affected area is defined. To reach this cardinal goal a specific ACO system is designed and developed to carry out post disaster conditions. Finally the proposed method is experimented and discussed.

## 2. ANT COLONY OPTIMIZATION

ACO is a part of swarm intelligence (also known as collective intelligence) which is inspired from the collective behavior of ants living in colonies in finding shortest path between nest and food source. The novelty of this foraging behavior of ants rises from the fact that the collective behavior of some unintelligent decentralized small entities results in intelligent outputs. ACO tries to mimic real ant actions to solve combinatorial optimization problems (Engelbrecht, 2007).

The ACO structure is composed of a set of agents also known as ants, randomly situated in the environment which is supposed to be a graph made up of nodes and arcs. According to agents' properties, these ants are capable of moving, sensing and acting in the environment. As ants take any random path a kind of chemical substance, known as pheromone which is detectable by other ants is laid on the trail. As pheromone accumulates when a path is used by multiple ants and as it evaporates by the time, and furthermore as ants tend to choose the path with higher amount of pheromone, the shortest path is selected. According to the extended Bridge Experiment (Goss et al., 1989) it is observed that path selection is biased towards the shortest path, since ants which follow the shortest path

return to the nest earlier than ants on the longer path. The pheromone on the shorter path is therefore reinforced sooner than that on the longer path (Engelbrecht, 2007).

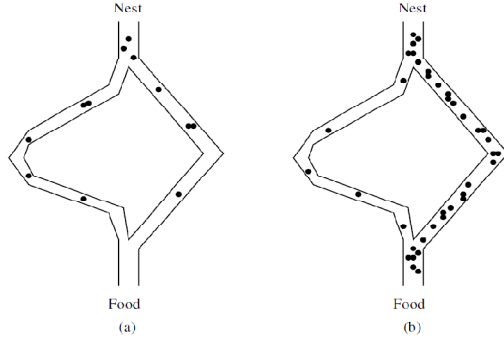


Figure1. Extended bridge experiment (Engelbrecht, 2007).

Artificial ants, designed on the basis of foraging behavior, are capable of finding shortest path in the network of roads between two specific start and destination points. At first a number of  $k$  ants are deployed on the start node and all arcs throughout the environment are assigned with an initial pheromone value. Then ants are randomly or heuristically (considering tabu lists) deployed throughout the network. Each ant chooses next arc under rules known as transition rules which consider the pheromone value and some other external facts such as length or cost. The simplest transition rule only accounts the pheromone value on each arc.

$$P_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}^\alpha(t)}{\sum_{j \in N_i^k} \tau_{ij}^\alpha(t)} & \text{if } j \in N_i^k \\ 0 & \text{if } j \notin N_i^k \end{cases} \quad (1)$$

Where  $P_{ij}^k(t)$  is the probability of choosing arc  $ij$  by ant  $k$  which is positioned on node  $i$  where  $N_i^k$  is the set of feasible arcs to node  $i$ .  $\tau_{ij}$  is the pheromone value on arc  $ij$  and  $\alpha$  is a tuning parameter. There are also other transition rules which account external knowledge such as length or cost such as equation(2) (Engelbrecht, 2007).

$$P_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}^\alpha(t) \eta_{ij}^\beta(t)}{\sum_{u \in N_i^k} \tau_{iu}^\alpha(t) \eta_{iu}^\beta(t)} & \text{if } j \in N_i^k \\ 0 & \text{if } j \notin N_i^k \end{cases} \quad (2)$$

where  $\eta_{ij}$  is the cost or length value on arc  $ij$  and  $\alpha$  and  $\beta$  are tuning parameters which reflect the influence of pheromone value on the decision in comparison with the external knowledge.

When all ants reach destination point, the pheromone value on each arc is updated on the basis of the length (Euclidean or any other definable distances) of the path each ant has passed. The shorter the path with respect to length or cost, the higher the pheromone updating amount. The updating amount would be the sum of all updating values for each  $k$  ants.

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{n_k} \Delta\tau_{ij}^k(t) \quad (3)$$

To prevent premature convergence, pheromone values on arcs are allowed to evaporate before being reinforced on the basis of the constructed path.  $\rho$  represents the rate at which pheromone is evaporated (Engelbrecht, 2007). Pheromone update and evaporation is done when all ants have reached the destination node.

$$\tau_{ij}(t) \leftarrow (1 - \rho)\tau_{ij}(t) \quad (4)$$

In the next iteration, once again a number of  $k$  ants are deployed and the same procedure is executed until a satisfying number of ants (all on them) converge to an identical path between start and destination points.

### 3. ACO BASED ROUTING IN DISASTER AFFECTED AREA

As previously mentioned the process of routing in the disaster affected area considers performing two cluster of processing. First to receive a comprehensive update about the current situation of roads network using information from HSRI via road verification and extraction algorithms under the title of road destruction assessment and second to facilitate finding best routes through designing special artificial ants to perform ACO with respect to the specifications of the affected region

#### 3.1. Road Destruction Assessment

Road destruction assessment is totally devoted to provide a comprehensive knowledge about the current situation of road elements throughout the city. The same as many change detection approaches this process needs pre and post-disaster spatial information sources such as satellite images and maps. In this approach pre-event vector map and post event satellite images of the corresponding region is considered to extract road pixel by overlaying map and image and then to evaluate the extracted road elements comparing the information to training data (Samadzadegan et al., 2008). In this approach each road element in the vector map is assigned to a destruction value which determines how severe a specific road is damaged. Values close to 0 mean more damage and values close to 1 show less damage logically. To have more comprehensive judgment of the suffered damage by any road elements, car shade and occlusion from elevated objects such as trees and buildings should be accounted. The flowchart of road destruction assessment method is depicted in figure 2.

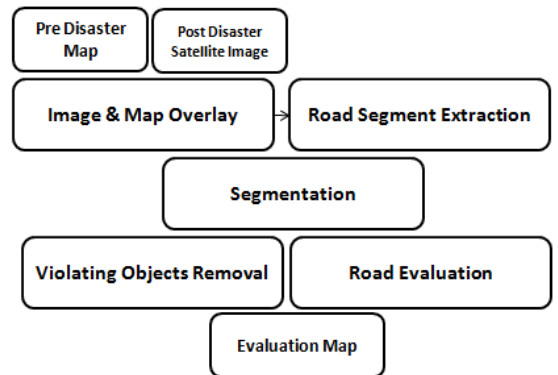


Figure 2. The flowchart of destruction assessment process

After overlaying image and vector data corresponding region of any road element in the vector map is extracted. Then the image of the extracted road is segmented into regions to generate image objects to upgrade image analysis of the region into object level processing. In other words each region in the image could be considered as a potential object at the scene. Then the image objects are searched for all possible objects such as vegetation, occlusion, shade and car. Removing such objects which violate the process of detection of undamaged and damaged roads is necessary. After removing violating objects all remaining regions are divided into damaged and undamaged road entities.

To evaluate the current situation of the road, in terms of inspecting objects along the central axis of each road element, the number of pixels of each object type is counted perpendicular to main central axis. So a profile of each object is computable and the final evaluation is done considering each profile. The values of each profile are introduced to a fuzzy inference system and as a result an evaluation profile for each road element is computed. The overall value for each road is computed using equation (5).

$$\zeta_{ij} = c / \sum (1 - k)^\gamma \quad (5)$$

Where  $\gamma$  is a tuning parameter and  $k$  is the evaluation value of the profile for each pixel along the road axis. The idea of using such equation lies beneath the fact that lower values of  $k$  mean road damage and consequently road blocks.  $C$  is a constant value. This function implicitly tries to propose a measure to brighten the existence of any road blocks.

### 3.2. ACO Based Routing

Receiving a comprehensive knowledge about the damage to road network throughout the city an ACO based routing method is designed to take the destruction information along with distance or other cost parameters to find most optimized routes. Figure 3 shows the flowchart of the proposed method for finding best routes between places.

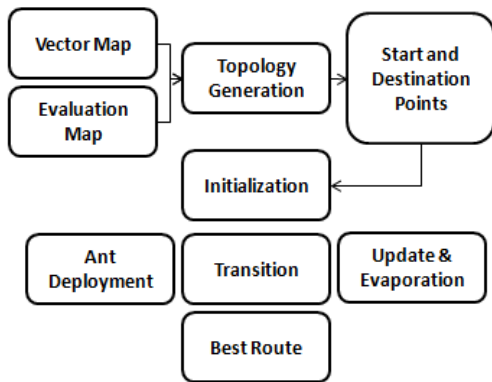


Figure 3. The flowchart of finding best routes between points.

The algorithm receives vector map and also evaluation from previous processing as input data. To prepare ACO for finding

best routes the topology between road elements in the map should be generated. This guides ant to understand the feasible arcs to each node and move throughout the network.

According to the flowchart two specific start and destination points should be marked to define the problem. At the next level, ants are deployed from start point throughout the network. In this specific algorithm a random deployment is considered. According to the random deployment ants are allowed to choose arcs several times. Only choosing the arc through which the ant has reached the current node is prohibited.

At each node ant chooses next arc with respect to the pheromone value and evaluation degree. The innovative aspect of this algorithm in comparison with other proposed ACO-based solution is considered in the transition rule ants obey to choose arc at each node, presented in equation (6).

$$P_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}^\alpha(t) \eta_{ij}^\beta(t) \zeta_{ij}^\gamma}{\sum_{u \in N_i^k} \tau_{iu}^\alpha(t) \eta_{iu}^\beta(t) \zeta_{iu}^\gamma} & \text{if } j \in N_i^k \\ 0 & \text{if } j \notin N_i^k \end{cases} \quad (6)$$

$\zeta_{ij}$  is the evaluation value of each road element. The pheromone update uses Ant-density method mentioned in equation (7). This means that the pheromone updating value is added by  $Q$  for link  $ij$  if the link occurs in any path.

$$\Delta \tau_{ij}^k(t) = \begin{cases} Q & \text{if link } ij \text{ occurs in path } x^k(t) \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

Moreover, evaporation mechanism follows a conventional procedure as mentioned in equation (4). The algorithm continues iteration by iteration until all ants follow the same path which will be considered as the best route between nodes.

## 4. EXPERIMENT AND RESULTS

To inspect the capabilities of the proposed method evaluating road elements and finding best routes using ACO approaches, experiments and tests are performed utilizing pre-event digital vector map and post-event QuickBird Pan sharpened high-resolution satellite images of the city of Bam located south west of Iran, regarding to the devastating earthquake strike in December 2003.

To extract road segment the algorithm is tuned to extract start end nodes from digital map and road width from attribute. If no attribute exists for any road segment the algorithm allocates a presumed width automatically. The extracted road segment is projected on satellite image and corresponding pixels are extracted and individually prepared for further processes.



Figure 4. High resolution satellite Imagery and overlaid digital vector map.

According to the destruction assessment flowchart in figure 2, violating objects are detected and removed layer by layer. Each layer of the engine is comprised of a Fuzzy Inference System which is capable of recognizing objects in the image computing specific number of descriptors. These prominent descriptors are indicated in Table 1. In this case, three layers of Fuzzy Inference Systems are proposed to detect cars, shades and road non-road regions.

Table 1. Descriptors used for surface analysis (Samadzadegan et al., 2008)

Layer	Descriptors
Car	Mean , StdDev
Shade	Mean , StdDev Semivar1
Road	Mean, Dissimilarity Semivar1 Contrast

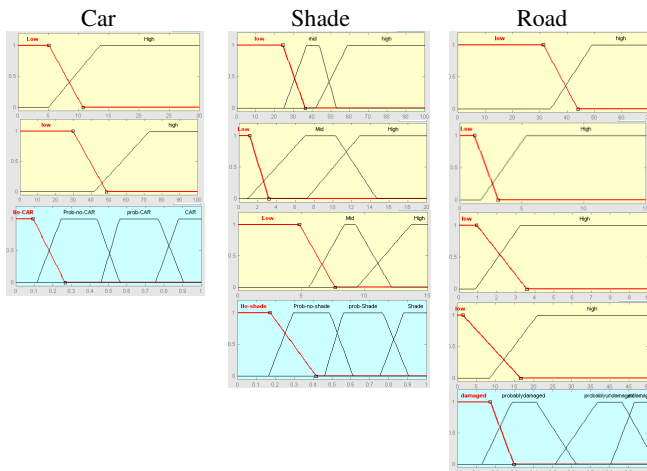


Figure 4. Membership functions for each fuzzy engine

Through another Fuzzy Inference System, cars, shades and road engine results are put together and a verification value is generated for every point on the axis. Higher values of this measure indicate the validation of the road at each point. This profile of values is then converted to an evaluation value using

equation (5) to generate evaluation map. The stated procedure is performed to all road elements in the area the evaluation degree of all arcs are generated.

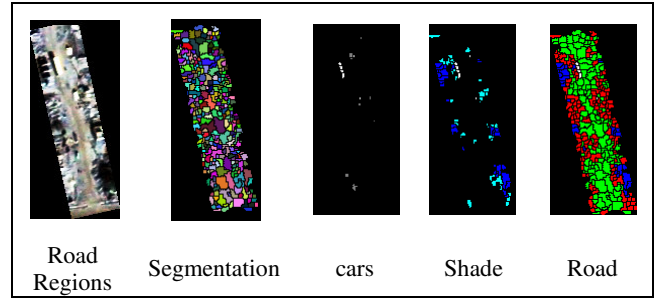


Figure 5. The results of road analysis of a road element.

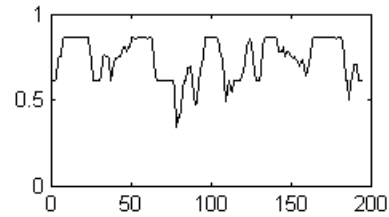


Figure 6. The result of road evaluation for road element

To test ACO for post disaster routing the basics of such computational solution is developed using Matlab as a toolbox. The toolbox is specially designed to handle ACO based procedures for various applications. Figure 7 shows a simple example of the routing considering parameters depicted in table 2.

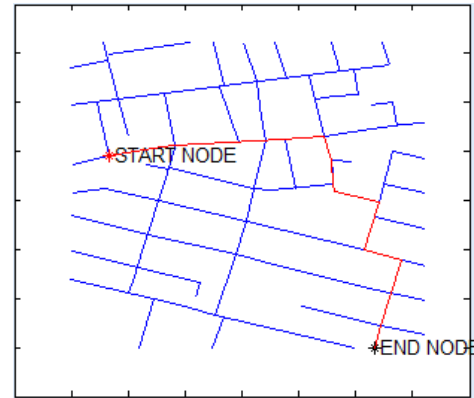


Figure7. An example of routing in post disaster area.

Table 2. Parameters tuned for routing.

Parameters	Values
Initial Pheromone	100
Initial Number of Ants	60
Max Iteration	10
Deployment	Random
$\alpha$	0.5
$\beta$	0.5
$\gamma$	2
$\rho$	0.2
$c$	100
$Q$	1

Tuning  $\alpha$ ,  $\beta$  and  $\gamma$  directly affects the results of routing. Lower values of  $\alpha$  and  $\beta$  compared to  $\gamma$  tune algorithm to emphasize the effect of evaluation map to routing in comparison with length and pheromone intensity. This can be simply used for routing with respect to specifications of the vehicle. As a matter of fact, routing for heavy vehicles is more sensitive to destruction assessment as these vehicles are larger in size and have more movement limitations. Decreasing the value of  $\gamma$  means that the vehicle can handle road block relatively better.

## 5. CONCLUSIONS

In this paper, a method for road evaluation and routing in disaster affected cities is proposed. In conclusion, one might consider that the novelty of the approach arises from the emergence of the following items.

- 1- Using satellite imagery as prominent information source to receive post disaster evaluation of roads in the affected regions.
- 2- Considering an ACO approach for finding best routes in disaster affected area.

ACO solution for post-disaster routing seems to be efficient in term of providing the capability of routing in case of different routing missions. In other words, this method also accounts damaged roads as far as they might be exploitable by measuring the damage degree and routing with respect to these items rather than eliminating the damaged roads from the functional networks.

Proposed idea in this research is considered as the first endeavors in using ACO solution for such purposes. The most important challenge of this study could be summarized in how parameters of each section are tuned. Regardless of how successfully an expert can provide information for tuning parameters, using training datasets for parameter tuning seems efficient although finding or generating such training data is a matter of challenge.

## REFERENCES

- Dorigo, M., Stutzle, T., 2004. Ant colony optimization, A Bradford Book The MIT Press, Cambridge, Massachusetts, London, England, 2004.
- Engelbrecht, P., 2007. An Introduction to Computational Intelligence Second Edition John Wiley & Sons.
- Goss, S., Aron, S., Deneubourg, J.L., Pasteels, J.M.. 1989. Self-Organized Shortcuts in the Argentine Ant. *Naturwissenschaften*, 76:579
- Samadzadegan, F., Zarrinpanjeh, N., 2008. Earthquake Destruction Assessment of Urban Roads network from High resolution satellite imagey. *Proceedings of ISPRS XXIst Congress*, Beijing, China, July, 2008.