A Guidance System for Wide-area Complex Disaster Evacuation based on Ant Colony Optimization

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Abstract: This paper reports the results of applying our approach discovering safe evacuation routes to practical situations. Our approach is based on the ant colony optimization (ACO) and it is practical in the light of a real case with a tsunami. ACO have been often employed for finding evacuation routes in traditional approaches, which only take advantage of ants' behavior more frequently following traces of other ants through pheromone communications. We assume that there are a lot of danger zones in the damaged area. For example Rikuzentakata is a city that extensively damaged in the 2011 Great East Japan Earthquake. In such a case, the traditional approaches may present some unsafe routes through the danger zones. We have proposed an ACO based approach that calculates evacuation routes avoiding danger zones. In our approach, evacuees can deposit deodorant pheromone around danger zones, which makes normal pheromone ineffective, so that our approach gives routes not passing through the danger zones. We have implemented our approach as a simulator, conducting experiments in the same situation as the Rikuzentakata case. Through the results of the experiments, we show that our approach decreases the number of people suffering from collapsed and burning buildings.

1 INTRODUCTION

The Great East Japan Earthquake in 2011 was recorded as an earthquake with magnitude 9.0. The earthquake destroyed all the anti-tsunami structures such as breakwaters and tide embankments, so that the tsunami following the earthquake caused enormous damage to the coastal areas. The damage that people suffer from such a wide-area disaster can be classified into three patterns: the direct disaster casualties, the damage caused by collapsing of structures and fire during evacuation, and the damage caused by the disastrous tsunami. In general, these damages do not occur simultaneously. In most cases, people saved from the first damage have to escape from the third damage while avoiding the second damage. Therefore, ideally, evacuation to safe areas should be completed before the third attack where the tsunami strikes. However, several zones damaged by an earthquake restrict the number of evacuation routes, so that it becomes difficult for people to evacuate. Thus, it is extremely important to dynamically find safe evacuation routes depending on the situation where a wide-area disaster occurs.

In this paper, we propose an algorithm of discovering safe evacuations based on the ant colony optimization (ACO) algorithm (Dorigo et al., 1996) extended for avoiding danger zones, e.g., areas with fire and other damages. Traditional approaches based on ACO presents the shortest routes to safe areas depending on strength of pheromone, which may include the danger zones. In our approach, we introduce a new repulsive pheromone called deodorant pheromone to ACO (Ohta et al., 2016).

In order to quantitatively evaluate the algorithm in realistic situations, we present complex disaster scenarios such as tsunamis. In the numerical experiments, we show that our evacuation system can find effective routes that decrease the number of people suffering from collapsed or burning structures. Also, we discuss the limitations of our algorithm.

The structure of the balance of this paper is as follows. In the second section, we describe the related work. In the third section, we provide an overview

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of the ACO and discuss issues that we need to consider during an evacuation. In the fourth section, we describe the simulation model. In the fifth section, we discuss the results of the experiments. In the sixth section, we discuss the other scenario. In the seventh section, we describe a future work and we conclude our discussion.

2 RELATED WORKS

Disaster is known to make several infrastructures unavailable, in which communication infrastructures are also included. Once access points for Wi-Fi become unavailable, we cannot take advantage of mobile devices to collect useful information for our evacuation. However, even in the cases, we may be able to construct a mobile ad-hoc network through connecting mobile devices one another, which may be effective for sharing the information. In previous works that deal with evacuation assistance, there are a lot of approaches assuming the ad-hoc network. Especially, ACO based approaches are effective to detect evacuation routes on the ad-hoc network. Avilés et al. proposed an approach for sharing information of evacuation gates on the ad hoc network. In their approach, ants and pheromone of ACO are implemented as software mobile agents, where the agents corresponding to ants dynamically guide evacuees to the evacuation gates in a floor (Avilés et al., 2014).

Asakura et al. proposed an approach that calculates evacuation routes based on ACO on a simulator, and showed the effectiveness of applying their approach to wide-scale disaster areas (Asakura et al., 2013a)(Asakura et al., 2013b).

On the other hand, Mas et al. applied their simulation-based approach, which did not use ACO, to more practical case of the Great East Japan Earthquake, and showed that the shortest evacuation routes were detected (Mas et al., 2012).

These previous works highlight just one of two issues important for evacuation support systems, which are consideration of the secondary disaster and reality of assumed scenario. Our reports in this paper provide not only remediation for the evacuation in the disaster but also experimental results based on realistic scenarios to show the effectiveness of our approach.

3 EXTENDED ANT COLONY OPTIMIZATION

This section explains the details of deodorant pheromone mentioned in Section 1 by extending the basic algorithm corresponding to traditional ACO, where the deodorant pheromone suppresses the effect of traditional pheromone in our extended ACO. Also, we describe how the deodorant pheromone is used to avoid danger zones.

3.1 Basic Algorithm

During foraging, real ants secrete a volatile chemical substance called pheromone that encourages other ants to behave cooperatively. Once an ant discovers food, it brings the food to the nest. In this process, it put pheromone on the ground to provide signposts for following ants. As well, the ants carrying the food along the pheromone also put pheromone on the same ground, strengthening the effectiveness of attraction. The strengthening of pheromone results in some routes between the nest and the food. Conversely, pheromone on the ground unused by the ants gradually decreases the density of pheromone by evaporation. Thus, the accumulation of pheromone along restricted routs causes positive feedback, so that ants can find the shortest route among multiple routes with different lengths. If pheromone information were not available, ants would forage by moving at random.

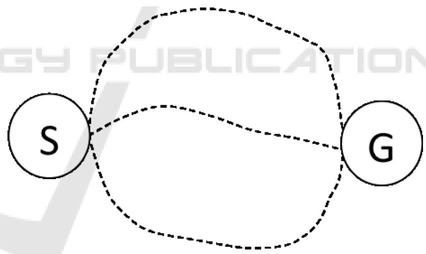

Figure 1: Route generation by the ACO. S and G denote the starting point and destination point, respectively.

Figure 1 illustrates a route established by foraging ants. Consider that three ants explore on three routes with different distances between a starting point S and a destination point G. First, the ants simultaneously explore from S to G. Once the ants reach a branch, they select their own directions randomly. If all the ants select the middle route, they will arrive at the destination at the same time. After that, in the process where the ants return to S, they deposit their pheromone. If they return to G again, they can use the previously deposited pheromone as guidance. Notice here that the ants preferentially select the middle route, because the density of the pheromone on the other routes is decreased by evaporation. In this way, the ACO finds the shortest route. Summarizing the steps of ACO, they are as follows:

1. Ants seek a route between the starting point (Start) and destination point (Goal).
2. Ants locally explore a branch along the route.
3. Ants secrete pheromone on the ground while they travel their routes.
4. Pheromone evaporates at a constant rate.
5. The above steps are repeated through the specified number of iterations.

3.2 Extended Pheromone Behaviors

Assume that we simply search evacuation routes based on the algorithm of Section 3.1 in the event of a disaster. In this case, even if the suggested evacuation route is the approximately shortest route, it may include or touch danger zones. In order to avoid danger zones, we have introduced deodorant pheromone that decreases the pheromone laid around danger zones. Deodorant pheromone erases the traces of previously deposited pheromone and attenuates the pheromone in surrounding regions, and imparts new information about danger zones.

In our ACO, normal pheromone contributes to constructing shorter evacuation routes, and deodorant pheromone contributes to adjusting the evacuation routes to avoid danger zones. Thus, the two kinds of pheromone cooperatively construct safe evacuation routes for evacuees.

3.2.1 Normal Pheromone

The normal pheromone is applied along the passable evacuation route. Once an evacuee arrives at a safe area, the normal pheromone is updated by Eq. (1), where $\tau_{ij}(t)$ is the pheromone value at coordinates (i, j) at time t, and G_t denotes the evacuees who arrived at the safe area in time t.

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k \in G_t} \Delta\tau_{ij}^k \tag{1}$$

$\tau_{ij}(t)$ is decreased by an evaporation rate ρ, and is increased by $\Delta\tau_{ij}^k$ for evacuee k that has reached the safe area, step by step.

$\Delta\tau_{ij}^k$ is determined by α and T_k, where α is the amount of pheromone applied at coordinates (i, j), and T_k denotes the traffic when the evacuee k has reached the safe area as follows:

$$\Delta\tau_{ij}^k(t) = \begin{cases} \alpha & if\ (i,j) \in T_k \\ 0 & otherwise \end{cases} \tag{2}$$

$\tau_{ij}(t)$ is limited by upper and lower bounds, τ_{max} and τ_{min} well as traditional ACOs based on MAX-MIN ant system (Sttzle and Hoos, 2000). The upper bound prevents solutions from being trapped in local minimums, which is one of characteristics of local neighborhood searching. The lower bound permits searching of any solutions.

$$0 < \tau_{min} < \tau_{ij}(t) \le \tau_{max} \tag{3}$$

In the case where the normal pheromone is only used, our ACO works in the same way as traditional ACOs. We call it normal ACO (nACO).

3.2.2 Deodorant Pheromone

The deodorant pheromone, which exerts a repulsive force on evacuees, causes normal pheromone to be updated whenever an evacuee encounters a danger zone. At this time, the density of the normal pheromone is decreased.

Also, the deodorant pheromone decreases the density of the pheromone not only at the center of the danger zone but also at the surrounding area. The update of normal pheromone in a certain range including a danger zone is performed based on the following equation:

$$\tau_{ij}(t+1) = (1 - \sigma^{n_{ij}^k(t)+1})\tau_{ij}(t) \tag{4}$$

Where σ is the rate of the deodorant, and $n_{ij}^k(t)$ is the distance from the coordinate (i, j) marked as a danger zone by evacuee k. Under Eq. (4), the deodorant pheromone spreads only within a certain range.

In the simulation, we limit the spread of the deodorant pheromone as $n_{ij}^k(t) \le N$.

We call our ACO that includes both normal and deodorant pheromones the extended ACO (eACO).

4 SIMULATION MODEL

4.1 Disaster Scenario

This section shows the scenario that we assume in our simulation. The scenario is based on the situation of the city of Rikuzentakata, which was extensively damaged in the 2011 Great East Japan Earthquake. The peak inundation and evacuation locations in Rikuzentakata have been published in the Rikuzentakata Earthquake Verification Report (Rikuzentakata, 2014). In addition, the onset times of the earthquake and tsunami as well as the peak time of the inundation have been summarized in chronological order (Ushiyama and Yokomaku, 2012). From these references, we have determined the time allowed for evacuation is approximately 45 minutes after the earthquake occurs. Then the flooding gets to be maximized. Table 1 shows the time schedule of each event.

Table 1: Timing of each event.

Time	Event
14:46	Earthquake occurs
15:24	Inundation start
15:29	Inundation peak

Figure 2 chronologically shows the situations of tsunami. By using the information and assumptions, we have succeeded in reproducing the flood situations of tsunami induced by the earthquake in the city of Rikuzentakata. However, refugees must have also encountered fire and collapse of rubble as secondary disasters at several locations during their evacuation, though the details of them were not recorded. We simply assume those secondary disasters occur randomly.

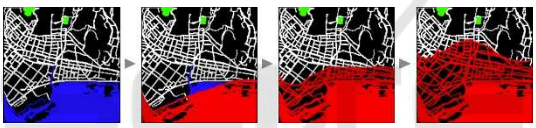

Figure 2: Chronological order of the tsunami damage situation.

As mentioned in Section 4.1, we assume that the evacuation time is restricted to the period from the earthquake outbreak to arrival of the tsunami. The start and end of the simulations are depicted in Figures 3 and 4, respectively. Evacuation activities are simulated by a multi-agent simulator in which the agents correspond to people. In the simulation, the city of Rikuzentakata is mapped onto a 200 200 grid (Figure 3). Each grid cell denotes a passable area, an impassable area, a safe area or a danger zone. Once the simulation starts and the earthquake breaks out, the simulator generates evacuees randomly in the passable areas on the map. After that, evacuees determine their evacuation routes based on local information along ACO based guidance.

4.2 Simulator Overview

Each evacuee obtains pheromone information from the eight cells surrounding the cell he or she resides, determining his or her next move along the guidance of the pheromone information.

In each simulation step, the evacuees move from their current cells to one of the eight surrounding the

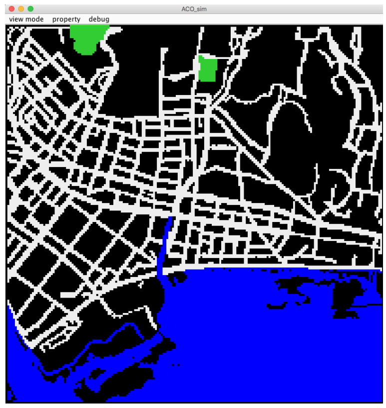

Figure 3: Start of the simulation.

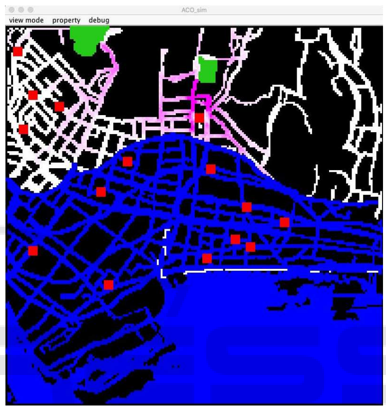

Figure 4: End of the simulation. Red squares mark danger zones.

cells. At this time, the direction where to move is stochastically determined by the pheromone information described in Section 3.2. The probability $p_{xy}(t)$ of an evacuee's moving to (x,y) at time t is given by the following equation:

$$p_{xy}(t) = \frac{\tau_{xy}(t)}{\sum_{(i,j)\in X^k(t)} \tau_{ij}(t)} \tag{5}$$

Where $X^k(t)$ indicates the movable locations surrounding the evacuee k. Equation (5) probabilistically promotes the movement toward neighbor cells with relatively high pheromone values.

Sometimes, the guidance may give undesirable suggestion such as going towards a danger zone. In such cases, the evacuee stop moving at that time, and then, deposits the deodorant pheromone to mark it for other evacuees. Once the evacuee reaches a safe area, pheromone information put along his trace is reset.

Table 2: Simulation parameters.

Parameter	Value
Number of evacuees	1000
Evaporation rate ρ	0.0005
Amount of pheromone adding α	1.0
Upper bound of pheromone τ_{max}	30.0
Lower bound of pheromone τ_{min}	1.0
Constant of deodorant pheromone τ'	-50.0
Influence range of deodorant pheromone N	2
Deodorant rate σ	0.5

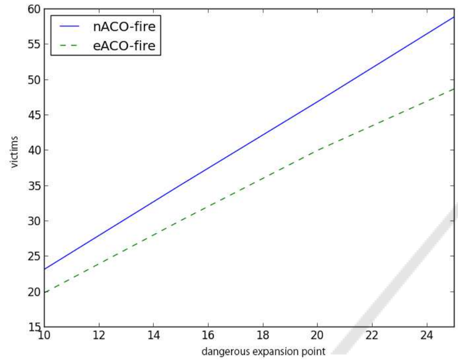

Figure 5: The number of evacuees caught in danger zones versus the number of victims.

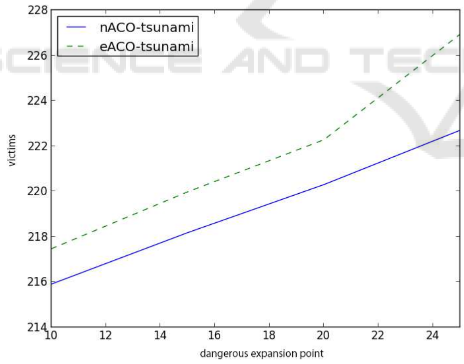

Figure 6: The number of evacuees involved in the tsunami versus the number of victims.

5 EXPERIMENTAL RESULTS

This section compares the simulation results of the cases using nACO and eACO.

The simulation used the settings listed in Table 2, and randomly located 10 to 25 danger zones (incremented by five). Each experiment was run 500 times, and the mean values are plotted. In the following figures, the solid and dashed lines indicate the results of the cases using nACO and eACO, respectively.

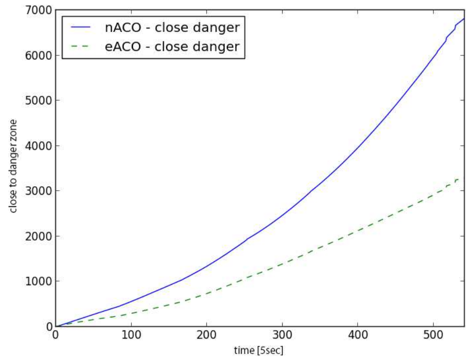

Figure 7: The number of approaches of evacuees to danger zones, as a function of simulation time.

5.1 Results

Figure 5 shows the relationship between the number of danger zones and the number of victims encountering danger zones. We have observed that more evacuees are entrapped in the case for nACO than eACO.

Figure 6 shows the relationship between the number of danger zones and the number of victims encountering tsunami. In this case, the number of endangered evacuees is higher in the case for eACO than nACO.

Figure 7 plots the cumulative number of times that evacuees approach the danger zones. Overall, using the eACO decreases the number of evacuees approaching the danger zones.

5.2 Discussion

Although the number of at-risk evacuees increases as the number of danger zones increases in both algorithms, we can observe that the number of those in the case for eACO smaller than nACO. This reflects the effect of the deodorant pheromone that repels agents from danger zones and their vicinities. However, this benefit was partially offset by the increased number of evacuees affected by the tsunami (Figure 6). The deodorant pheromone in eACO enforces a detour-like evacuation activity on evacuees and have them exposure to the tsunami risk.

We therefore investigate how much duration time the evacuees need to escape the tsunami through safe routes while avoiding dangerous area by using eACO in the next experiment.

6 ADDITIONAL SCENARIO

We have already experienced another devastating tsunami in 2004 that followed an earthquake off the coast of Sumatra, which was recorded as magnitude 9.1. In this disaster, there was a relatively long lapse of time between the outbreak of the earthquake and the arrival of the tsunami. Given the pattern of the earthquake, we can vary the timing of the tsunami attack. In this experiment, we have changed the lapses of time between the outbreak of the earthquake and arrivals of the tsunami whereas the other parameters is left unchanged.

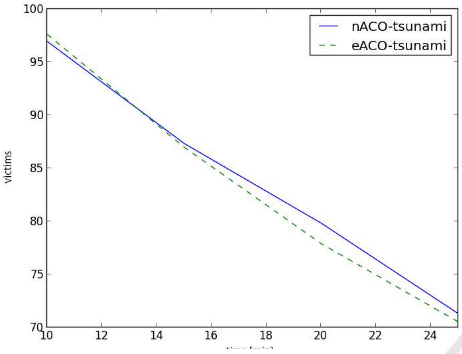

Figure 8: The number of evacuees involved in the tsunami, versus delay time of the tsunami.

6.1 Results

Figure 8 plots the number of evacuees involved in the tsunami, versus the delay time of the tsunami. If there is a time lapse of approximately 20 minutes, the number of tsunami victims became smaller in the case for eACO than nACO.

6.2 Discussion

Our eACO algorithm is beneficial when there is sufficient duration time for escape between the outbreak of an earthquake and the following tsunami. However, neither ACO is effective in a case that immediate evacuation is needed, because considerable time is required to construct safe evacuation routes. On the other hand, the eACO is applicable to many real scenarios in which evacuees can flee dangerous situations, such as building collapses and fire, before a tsunami strikes.

7 CONCLUSIONS

This paper proposes an evacuation support system and analyzes its effectiveness by simulation experiments of a case of the wide-scale disaster area in the city of Rikuzentakata. The city was extensively damaged by the 2011 tsunami.

The proposed evacuation system that implements our approach extends the ant colony optimization method (ACO), which allows agents to share their routing information after reaching safe areas. In the model, evacuees take the routes traveled in previous evacuation activities while they avoid dangerous area by using the information given by preceding evacuees.

Comparing with the normal ACO, our ACO model decreases the numbers of evacuees caught in danger zones. The result indicates that our approach assists to construct safe evacuation routes that bypass dangerous zones. However, it increases the number of evacuees who were caught in the tsunami. We can observe that our method is beneficial when there is sufficient time lapse between the outbreak of the earthquake and the arrival of the tsunami. In that case, the additional deodorant pheromone repels evacuees from danger zones, while guiding them away from the inundation of the tsunami.

As a future work, we plan to evaluate and generalize the various experimental parameters. We also need to investigate how to disperse the escape routes for mitigating the traffic congestion of the evacuees. It is necessary because in actual evacuation scenes people may concentrate on a particular path toward safe areas and hinder the evacuation activities. The present evacuation guidance system focuses on the direction of movement. To simulate precise evacuation behavior, the agents must undertake more human-like intelligent actions.

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REFERENCES

Asakura, K., Fukaya, K., and Watanabe, T. (2013a). Construction of navigational maps for evacuees in disaster areas based on ant colony systems. *International Journal of Knowledge and Web Intelligence*, 4:300–313.

Asakura, K., Fukaya, K., and Watanabe, T. (2013b). A map construction system for disaster areas based on ant colony systems. *Procedia Computer Science*, 22:494–501. 17th International Conference in Knowledge Based and Intelligent Information and Engineering Systems.

Avilés, A., Takimoto, M., and Kambayashi, Y. (2014). Distributed evacuation route planning using mobile agents. In *Transactions on Computational Collective Intelligence XVII*, volume 8790, pages 128–144.

Dorigo, M., Maniezzo, V., and Colorni, A. (1996). Ant system: optimization by a colony of cooperating agents. *IEEE Transactions on Systems*, 26(1):29–41.

Mas, E., Suppasri, A., Imamura, F., and Koshimura, S. (2012). Agent-based simulation of the 2011 great east japan earthquake/tsunami evacuation: An integrated model of tsunami inundation and evacuation. *Journal of Natural Disaster Science*, 34(1):41–57.

Ohta, A., Goto, H., Matsuzawa, T., Takimoto, M., Kambayashi, Y., and Takeda, M. (2016). An improved evacuation guidance system based on ant colony optimization. In *Intelligent and Evolutionary Systems*, volume 5 of *Proceedings in Adaptation, Learning and Optimization*, pages 15–27.

Rikuzentakata (2014). The city of rikuzentakata the great east japan earthquake verification report: Rikuzentakatashi higashi nihon daishinsai kenshou houkoku sho (in japanese).

Sttzle, T. and Hoos, H. H. (2000). Maxmin ant system. *Future Generation Computer Systems*, 16(8):889–914.

Ushiyama, M. and Yokomaku, S. (2012). Estimation of situation in rikuzentakata city just before tsunami atack based on time stamp data. *Japan Society for natural disaster science*, 31(1):47–58.