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Evaluation of PSO Algorithm Considering Obstacle Avoidance in Evacuation Guidance

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Abstract

In recent years, IoT has been expected to provide support during natural disasters, and studies focusing on ant colony optimization (ACO) have been conducted for providing evacuation routes for evacuees. We previously proposed a modified algorithm for ACO that improved on the slow convergence of ACO, but the problem with ACO-based evacuation is the time it takes the evacuees to reach a safe zone.

In this study, we proposed a route suggestion algorithm that improves particle swarm optimization (PSO) to reduce the time required for ACO evacuation, and compared the performance of ACO and the proposed PSO. We also proposed a method that combines ACO and PSO and evaluated its performance.

Key words and phrases: ACO PSO Evacuation guidance Natural disaster

1. Introduction

Wide-area disasters caused by earthquakes can lead to several human casualties in different ways; for example, casualties caused by structural damage and fire in the process of evacuation. In such a situation, it is necessary to evacuate quickly to a safe place. However, due to structural damage or fire caused by an earthquake, evacuation may become difficult because routes that would otherwise have been available are no longer available. Evacuees need to be able to obtain information for such situations.

In recent years, the widespread use of smartphones and other portable communication devices has facilitated and improved information sharing, and disaster preparedness in this new era of information sharing

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has been been widely researched [1] [2]. Therefore, a system that automatically presents evacuation routes via smartphones is effective [3].

Our goal is to reduce the number of steps required to evacuate to a safe location in situations where the original path is restricted due to structural damage or fire caused by an earthquake.

2. Related Work

2.1. Particle Swarm Optimization(PSO)

Particle swarm optimization (PSO)[4] was developed by J. Kennedy and R. Eberhart in 1995. The basic idea is to "share information with the entire flock," which was derived from the behavior of a flock of birds in finding food. The particles that make up the flock do not behave freely, but follow certain rules by combining information specific to the particles that make up the flock with information shared by the entire flock.

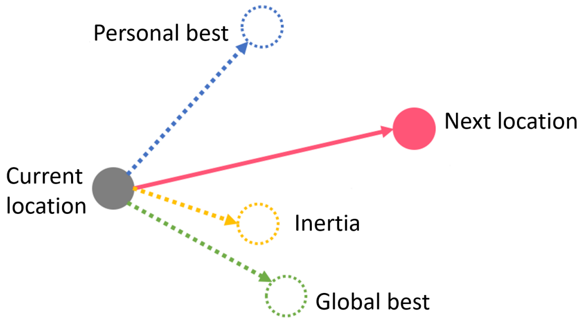

Figure 1: PSO behavior

The method of determining the direction of movement of a PSO is explained (Figure 1). Each particle in the swarm has information about its "position" and "velocity", and the search is performed collectively. The optimal solution is searched for by updating the position and velocity of each particle.

In the tth search, if the velocity of particle i is $V_i(t)$ and the position is $X_i(t)$, the velocity $V_i(t+1)$ and position $X_i(t+1)$ for the $t+1$th search are updated using the following equation.

$$
\begin{aligned}
V_i(t+1) &= wV_i(t) + c_1 r_1 (X_i^{pbest}(t) - X_i(t)) \\
&+ c_2 r_2 (X^{gbest}(t) - X_i(t)) \qquad (1) \\
X_i(t+1) &= X_i(t) + V_i(t+1) \qquad (2)
\end{aligned}
$$

where $X_i^{pbest}(t)$ is the location of the best solution of particle i in the search up to the tth time, and $X^{gbest}(t)$ is the location of the best solution of the particle group.

By subtracting the position $X_i(t)$ of particle i at the tth time from each position, we obtain a vector to its own best solution and a vector to the best solution of the group of particles.

$wV_i(t)$ represents the vector of inertia, w, c_1, and c_2 are the coefficients and weights of each vector, and r_1 and r_2 are random numbers from 0 to 1. These vectors are combined to determine the next direction to go.

The procedure is as follows.

1. Initialize the position and velocity of the particles using random numbers.
2. For each particle, update the position according to equation (2).
3. Based on the information of all particles, update *pbest* and *gbest*.
4. Update the velocity.

Set the number of times to search in advance, and repeat steps 2 to 4 until that number of times is completed.

2.2. Ant Colony Optimization(ACO)

Ant colony pptimization (ACO) [5] is based on ant behavior. Ants use a volatile pheromone to make their movements. An ant that finds food brings the food back to its nest while secreting the pheromone on the ground. Subsequent ants use the pheromone applied to the ground to reach the food, and they themselves overwrite the pheromone in their path. The result is a pathway that many ants take. As a result, pheromones in the pathways that many ants take gradually accumulate and become more concentrated. In contrast, the concentration of pheromones in the pathways that ants do not take gradually decreases due to volatilization.

When there are multiple pathways with different path lengths, ants can form the shortest path. The process of path generation in this case is as follows.

1. Ants without pheromone information will wander randomly and search for food.
2. If the speed of ant progression is constant, ants that choose shorter pathways compared to longer pathways will make more frequent trips to the food and nest.
3. Pathways that many ants have traveled leave a thick pheromone residue, increasing the probability that subsequent ants will choose the same pathway.
4. Pheromones secreted along shorter pathways will increase in concentration over time, whereas pheromones along longer pathways will disappear due to volatilization.

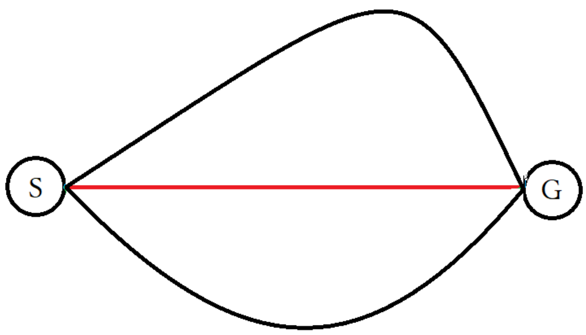

Figure 2: Route selection

The process of creating a path is explained in Figure 2.

Let the starting point be S and the target point be G. There are three paths between S and G with different distances. Three ants for each of the three paths start working simultaneously and in parallel. If the ants are moving at the same speed, the ant that chooses the red path in the center will be the one that reaches the target point. When the ants return to the starting point, they head for the target point G again, referring to the pheromone applied to the path. Since pheromones are weakened by volatilization, pheromones other than the central pathway are gradually not selected. Since ants prefer pathways with dense pheromones, they can select the shortest pathway, which is the pathway that is applied more often.

2.3. Information-sharing under disaster using Mobile Ad Hoc Network

In the event of a disaster, evacuees need to move quickly to a safe place, and information on the location of the safe place and the route to it is essential for evacuation. However, safe routes change when fires or collapses occur. Furthermore, base stations may collapse due to earthquakes or other disasters, which may cause communication infrastructure equipment to stop functioning. In such a situation, evacuees will not know where the safe place is, and they will not know where to turn. In such a situation where the infrastructure is no longer available, there is research on the use of MANET to exchange information among evacuees.

Ota et al. [6] used a mobile ad hoc Network (MANET) during the evacuation to share information on safe and dangerous areas using several methods.

2.4. Evacuation guidance system based on ACO

Ohta et al. used ACO to construct an evacuation route. Goto et al.[7] extended ACO to prioritize avoidance of dangerous locations. In the study by Goto et al., deodorant pheromones were given to ACO for evacuation route search. Deodorant pheromones have two functions: counteracting and attenuating. The counteracting function reduces the amount of pheromone in areas judged to be dangerous. As a result, the approach to the dangerous area can be reduced. The attenuation function is nearly the same as the diffusion function of the deodorizing pheromone. By attenuating the amount of pheromone around the route leading to the dangerous area, it prevents people from moving to the route leading to the dangerous area.

In addition, Ohta and Goto et al. [8] found that the number of steps required for evacuation is shorter when ACO is used to simulate evacuees than when they move randomly. The algorithm used in the ACO-based evacuation system used in Goto et al.'s study to determine pheromone updates and movement directions is shown below. Normal pheromone is a pheromone applied to the evacuation route. It is the updated equation for normal pheromone when the evacuee has reached a safe place (Equation 3). The pheromone value $\tau_{ij}(t+1)$ on (i,j) coordinates at time $t+1$ is as follows.

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k \in G_t} \Delta\tau_{ij}^k \tag{3}$$

G_t is the evacuee who has reached a safe location at time t, and the pheromone $\tau_{ij}(t)$ decreases based on the volatility rate ρ at each step. Once the evacuee k has reached a safe location, $\tau_{ij}(t)$ increases by $\Delta\tau_{ij}^k$. $\Delta\tau_{ij}^k$ is determined by equation (4). The α is the amount of pheromone to be applied and T_k is the set of coordinates (i,j) that the evacuee k passed when he/she reached a safe place, i.e., the evacuation route.

$$\Delta\tau_{ij}^k = \begin{cases} \alpha & if(i,j) \in T_k \\ 0 & (otherwise) \end{cases} \tag{4}$$

Set an upper limit τ_{max} and a lower limit τ_{min} with respect to the pheromone value $\tau_{ij}(t)$ (Equation 5).

$$0 < \tau_{min} \leq \tau_{ij}(t) \leq \tau_{max} \tag{5}$$

This method of pheromone application is referred to as normal ACO (nACO) in this paper.

Deodorant pheromone $\tau_{ij}(t)' < 0$ decreases normal pheromone $\tau_{ij}(t)$. The pheromone information considering deodorant pheromone on (i,j) coordinates is as follows (Equation 6).

$$\tau_{ij}(t)'' = \tau_{ij}(t)' + \tau_{ij}(t) \tag{6}$$

Once the deodorant pheromone has been applied in the vicinity, the pheromone in the vicinity is reduced as follows (Equation 7).

$$\tau_{ij}(t+1) = (1 - \sigma^{n_{ij}^k(t)+1})\tau_{ij}(t) \tag{7}$$

σ is the deodorant rate and $n_{ij}^k(t)+1$ is the distance from the coordinate (i,j) where evacuee k found the danger zone. This causes the deodorant pheromone to spread over a certain area. The ACO algorithm, which adds the definition of deodorant pheromone to nACO, is the ACO algorithm used in this paper.

At each step, the evacuee moves from the current location to one of the eight surrounding squares. The direction of movement is determined probabilistically.

$$p_{xy}(t) = \frac{\tau_{ij}(t)}{\sum_{(i,j)\in X^k(t)} \tau_{ij}(t)} \tag{8}$$

$P_{xy}(t)$ denotes the probability of moving to the (x, y) coordinates at time t, and $X^k(t)$ denotes the location where evacuee k is available for movement. Equation (8) shows the probability of moving from the eight surrounding squares to the square with the highest relative pheromone value.

Goto's research identified reducing the number of steps required to evacuate to a safe place in the simulation as a future work. In ACO, when there are no pheromones around, evacuees move randomly. Therefore, the number of steps increases.

In this study we aim to reduce the number of steps by using location-based evacuation.

3. Proposal method

3.1. Overview

In this study, we propose evacuation guidance using PSO to reduce the number of steps. In addition, PSO is extended with a vector that considers the avoidance of obstacles.

The proposed method runs on a simulator, and in this study, a multi-agent simulator was created using java. The agents correspond to evacuees. The operational procedure of the simulation is shown (Figure 3). A loop in which all evacuees perform an action is defined as one step.

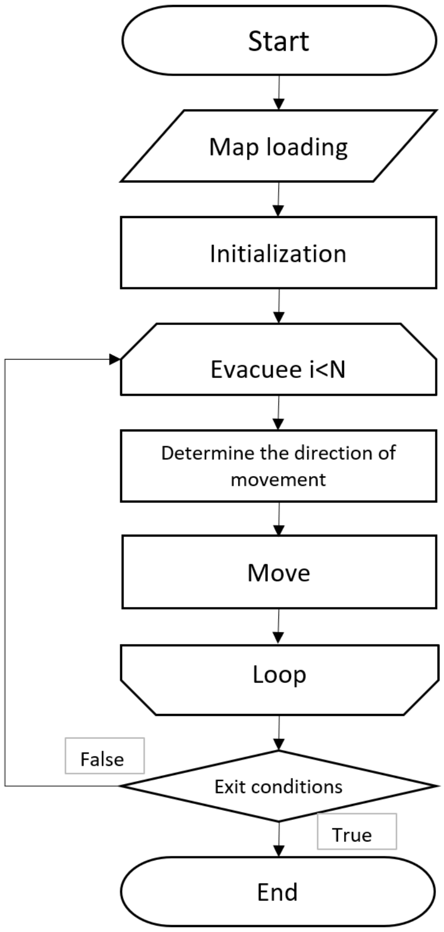

Figure 3: Simulator flowchart

3.2. MAP loading

This time the simulator reads a text file of a specific size as a map. Enter the following items in the text file.

1. Road (passable) (Figure 4 white)
2. Wall (Impassable)(Figure 4 Black)
3. Hazardous areas due to fire or collapse (impassable) (Figure 4 red)
4. Safe Place (Figure 4 Green)

Here is an example of inputting a map samplemap.txt of size 4×4 (Figure 4).

samplemap.txt

```
1 1 4 4
3 1 4 4
3 1 1 1
2 2 2 2
```

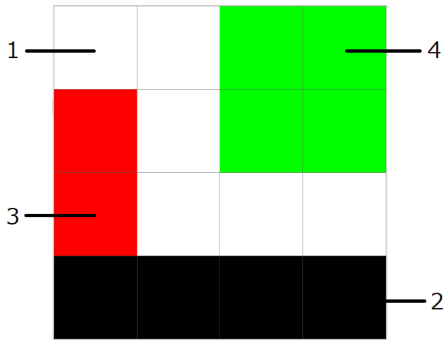

Figure 4: Map loaded with samplemap.txt

3.3. Initialization

Set various parameters in the initial setup.

- Number of evacuees
- Refugee Generation Location
- Parameters related to vector
- Conditions for termination

3.4. Determining the direction of movement

The evacuees with PSO consists of a vector of inertia ($\overrightarrow{b_1}$), a vector toward its own best solution ($\overrightarrow{b_2}$) and a vector toward the best solution of the particle swarm ($\overrightarrow{b_3}$).

As an extension, we added an obstacle avoidance vector ($\overrightarrow{b_4}$).

This vector is a vector in a random direction different from the direction of the obstacle in which the evacuee is proceeding to avoid a collision. Set $\overrightarrow{b_1}$-$\overrightarrow{b_4}$ as follows.

$\overrightarrow{b_1}$: Inertia vector of evacuees

$\overrightarrow{b_2}$: Vector of evacuees toward the dense area

$\overrightarrow{b_3}$: Vector toward safe place

$\overrightarrow{b_4}$: Vector of repulsion emitted from obstacles

Let the weight of $\overrightarrow{b_1}$ be w and the weights of $\overrightarrow{b_2}$-$\overrightarrow{b_4}$ be r_2-r_4 respectively, and the direction of movement is as follows (Equation 9) (Figure 5).

$$\text{Direction of movement} = w\overrightarrow{b_1} + r_2\overrightarrow{b_2} + r_3\overrightarrow{b_3} + r_4\overrightarrow{b_4} \tag{9}$$

r_2 to r_4 are random numbers of numbers within a certain range for each step.

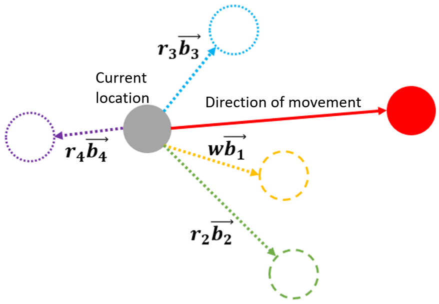

Figure 5: Determining the direction of movement

The scalar values for each vector were as follows (Equation 10)-(Equation 13), respectively.

$$|\overrightarrow{b_1}| = 0.1 \tag{10}$$

$$|\overrightarrow{b_2}| = \frac{1}{\sqrt{X^{pbest} - X_i}} \tag{11}$$

$$|\overrightarrow{b_3}| = \frac{1}{\sqrt{X^{gbest} - X_i}} \tag{12}$$

$$|\overrightarrow{b_4}| = \frac{1}{2x} \tag{13}$$

The X^{pbest} represents the location where the evacuees are crowded, X^{gbest} represents the location of the safe place, and X_i represents the location of the ith evacuee. The x represents the distance between the evacuee and the obstacle, and the closer the distance, the greater the repulsion.

3.5. Movement

When moving, the evacuee is allowed to move one square of eight squares around themself for each step. In other words, the moving speed of the evacuee is constant. As a result of the calculation of the movement direction selection, they move forward to one of the 8 squares around them according to the angle of their movement. If the direction of movement is impassable by a wall or a hazardous area, the evacuee proceeds probabilistically in the direction in which they can move.

3.6. Conditions for Termination

The simulation ends when the number of evacuees who have achieved a safe location plus the number of evacuees who cannot reach their destination matches the default number of evacuees.

4. Evacuation performance of the proposed PSO

In this section, we show the usefulness of PSO considering obstacle avoidance as described in the section on the proposed method. We also compare evacuation movements with and without obstacle avoidance.

Using the map in Figure 6, an experiment was conducted in which evacuees were randomly assigned to move toward a safe location. The information on the map is summarized in Table 1.

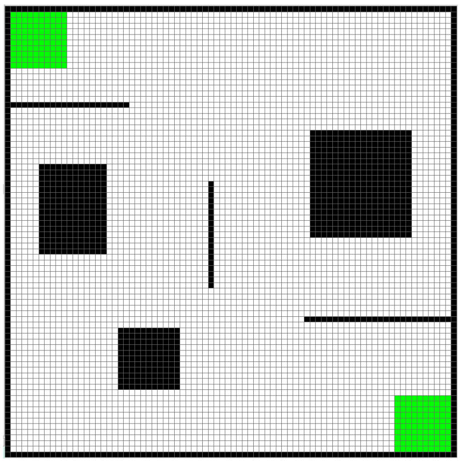

Figure 6: Map used in the preliminary experiment

Table 1: Map information

Color	information
White	Road(passable)
Black	Wall(impossible to pass)
Green	Safe place(destination)
Yellow	Evacuee

The parameters of the experiment are shown in Table 2.

Table 2: Parameters of PSO

Parameter	Value
Evacuees	100
MAP Size	80×80
w	0.7
r_2	0.79 - 0.97
r_3	0 - 0.17

4.1. PSO algorithm not considering obstacle avoidance

Simulations were performed using PSO without considering obstacle avoidance (Figure 7).

To make it visible what route the evacuees took, pink was applied to the paths they took. The darker the color, the more people passed through. In the experiment, some evacuees were unable to evacuate because the walls on their way to a safe place became an obstacle.

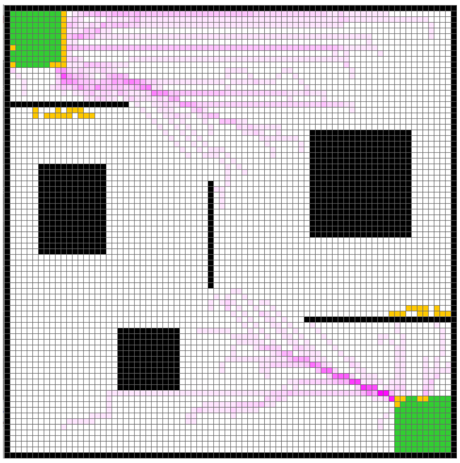

Figure 7: Execution result without considering obstacle avoidance

4.2. PSO algorithm considering obstacle avoidance

Simulation experiments were conducted with a similar map using PSO with extended vectors considering obstacles (Figure 8).

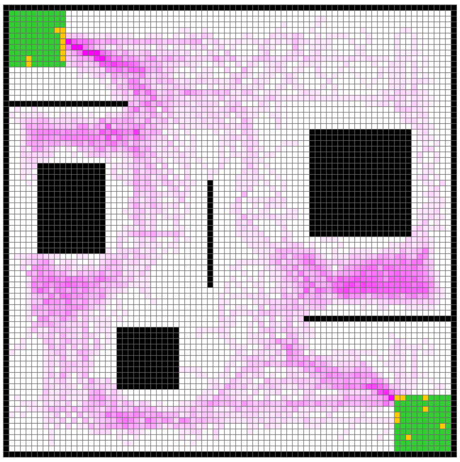

Figure 8: Execution result considering obstacle avoidance

Experiments were conducted to obtain paths that allowed evacuees to avoid obstacles and move to a safe location.

4.3. Comparison results

The number of people who completed the evacuation was compared according to the number of steps in Figures 7 and 8 (Figure 9). The number of evacuees was assumed to be 100.

The number of people who completed the evacuation was higher when obstacle avoidance was considered.

This experiment was conducted to demonstrate the superiority of PSO considering obstacle avoidance as described in the proposed method. The results show that the number of evacuees did not increase from a certain value when obstacle avoidance was not taken into account. This is because of the collision with the obstacles on the way to the safe place. When obstacle avoidance was taken into account, all evacuees were able to evacuate to a safe location. Therefore, it can be said that it is better to use a vector that takes obstacles into account in order for evacuees to reach a safe place.

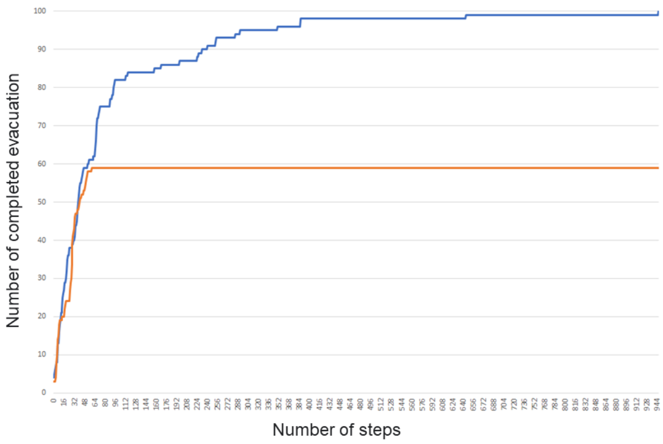

Figure 9: Comparison of the number of people who have completed evacuation

5. Evaluation experiments of the proposed PSO and ACO

In this section, we describe the evaluation experiments for PSO and ACO conducted using our evacuation guidance simulations. Two types of maps are used to evaluate the rate of fulfillment of evacuation termination conditions (evacuation completion rate) and the number of steps it takes to fulfill them during a disaster event and a non-disaster event, respectively. The ACO described in a related study is used as a comparison for the PSO.

Information on the MAP used in this experiment is shown in Table 3.

Table 3: Map information

Parameter name	value
Evacuees	100
MAP size	80×80
Color	information
White	Road(passable)
Black	Wall(impossible to pass)
Red	Fire(impossible to pass)
Green	Safe place(destination)
Yellow	Evacuee

The experiment is terminated when 60000 steps are reached and when all evacuees have completed their actions up to that point.

The two conditions under which each evacuee completes the action are as follows.

- Evacuees have been moved to a safe place.
- The evacuee was caught in a fire or collapse and was unable to act.

The evacuation is terminated when 6,000 steps are reached because of the time limit set for the evacuation.

5.1. Experiment 1

Simulations were conducted using a map that assumes a situation where the road is narrow and there are multiple paths to a safe place (Figure 10).

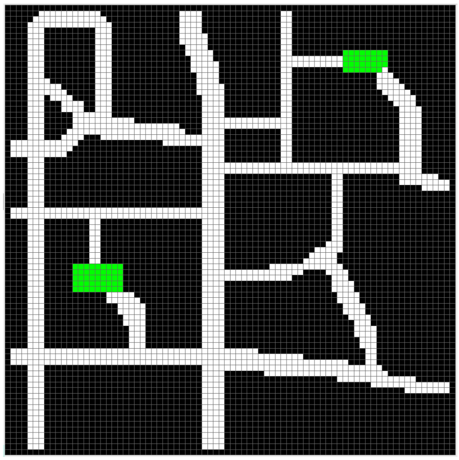

Figure 10: Map used in Experiment 1

5.1.1. No fire and no collapse simulation

To consider a fire or collapse situation, evacuation must be possible in an unconsidered situation. We tested whether it is possible to evacuate to a safe place in each of these situations. The parameters set in the experiment are summarized respectively (Table 4) (Table 5).

Table 4: ACO parameters

Pheromone parameter name	value
Volatilization rate(ρ)	0.0002
Coating value(α)	1.1
Upper limit(τ_{max})	50.0
Lower limit(τ_{min})	1.0
Deodorant value(τ')	-50.0

Table 5: PSO parameters

Parameter name	value
Inertial weight(w)	0.53
Weight towards a crowded place(r_2)	0.79 - 0.97
Weight towards a safe place(r_3)	0 - 0.17
Repulsive weight(r_4)	0 - 0.03

Each method was performed 500 times, and the average number of steps taken to meet the termination condition and the evacuation completion rate are summarized in Table 6.

Results show that both have an evacuation completion rate of 1.0. This indicates that all 500 evacuations were completed. The average step is less for PSO.

5.1.2. Simulation with fire and collapse

In the previous section, an experiment was conducted to move to a safe location without considering fire or collapse. The evacuation completion rate results show that both ACO and PSO completed the evacuation. However, when evacuating in the event of an actual disaster, it is necessary to take into account the possibility of unexpected impassable areas appearing. Therefore, an impassable area was established on the outdoor map (Figure 10) that expands by one square for every 200 steps, up to 1000 steps (Figure 11).

Table 6: Experiment 1 Results without fire or collapse

	Steps	Evacuation completion rate
ACO	10408	1.0
PSO	537	1.0

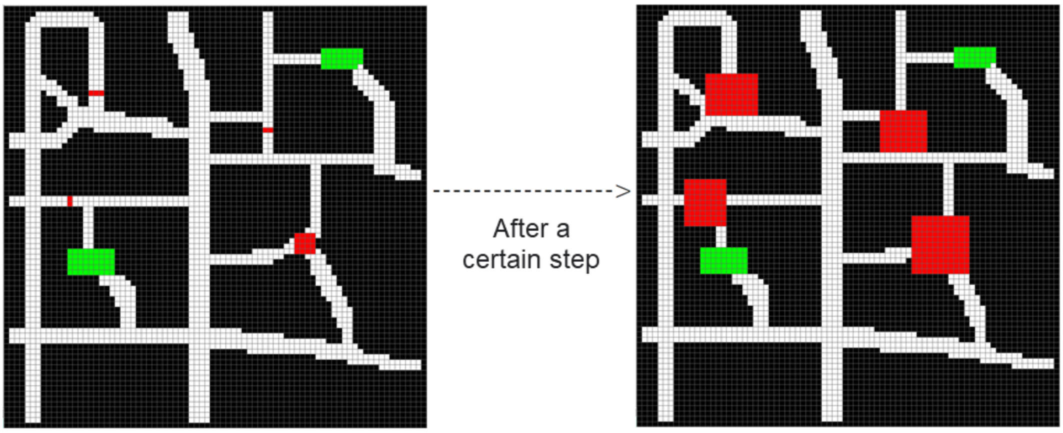

Figure 11: Map of Experiment 1 assuming an impassable place

Each method was performed 500 times. The average number of steps taken to meet the termination condition and the evacuation completion rate are shown in Table 7. The results show that the ACO has an

Table 7: Experiment 1 Results of fire and collapse

	Steps	Evacuation completion rate
ACO	14183	1.000
PSO	1409	0.976

evacuation completion rate of 1.0, while the PSO has a lower rate of 0.976. The average step is less for PSO.

5.2. Experiment 2

Compared to Experiment 1, the evacuation route is thicker and single track. In addition, a situation with an obstacle (depression) on the way was assumed (Figure 12).

5.2.1. No fire and no collapse simulation

The parameters set in the experiment are shown in Tables 8 and 9.

Each method was performed 500 times. The average number of steps taken to meet the termination condition and the evacuation completion rate are shown in Table 10. The results show that both evacuations are completed as the evacuation completion rate is 1.0. The average step is less for PSO.

5.2.2. Simulation with fire and collapse

The outdoor map (Figure 13) has an impassable area that expands by one square for every 200 steps, up to 1000 steps. Each method was performed 500 times. The average number of steps taken to meet the termination condition and the evacuation completion rate are shown in Table 11.

The results show that PSO has an evacuation completion rate of 1.0, while ACO has 0.93, which is less. The average step is less for PSO.

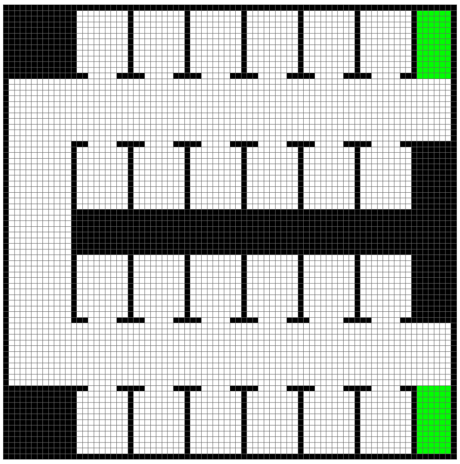

Figure 12: Map used in Experiment 2

Table 8: ACO parameters

Pheromone parameter name	value
Volatilization rate(ρ)	0.0001
Coating value(α)	1.5
Upper limit(τ_{max})	50.0
Lower limit(τ_{min})	1.0
Deodorant value(τ')	-50.0

6. Discussion

6.1. Experiment 1

Under the fire and collapse scenario, PSO had an evacuation completion rate of 0.976. This indicates that some people did not complete the evacuation even though the simulation met the termination conditions. The average number of steps required to complete an evacuation was reduced compared to the ACO, but the percentage of completed evacuations was lower. Therefore, although PSO can be expected to reduce the number of steps, PSO is not superior to ACO in terms of the evacuation completion rate.

We summarize why PSO, with an average step count of 1654 steps, can lead to a situation where the process is not completed within 6,000 steps. When the simulator was run with PSO, several evacuees were observed to approach the fire in an attempt to get to a safe location, unable to take into account the impassability caused by unexpected fires or collapses (Figure 14).

The PSO thought that the number of times they were approaching the fire would be greater than the ACO, and as a result, the evacuation would not be completed.

Therefore, we made a new comparison of the number of times the fire was approached (Table 12).

Table 9: PSO parameters

Parameter name	value
Inertial weight(w)	0.35
Weight towards a crowded place(r_2)	0.027 - 0.2
Weight towards a safe place(r_3)	0.11 - 0.23
Repulsive weight(r_4)	0.3 - 0.76

Table 10: Experiment 2 Results without fire or collapse

	Steps	Evacuation completion rate
ACO	17965	1.0
PSO	2235	1.0

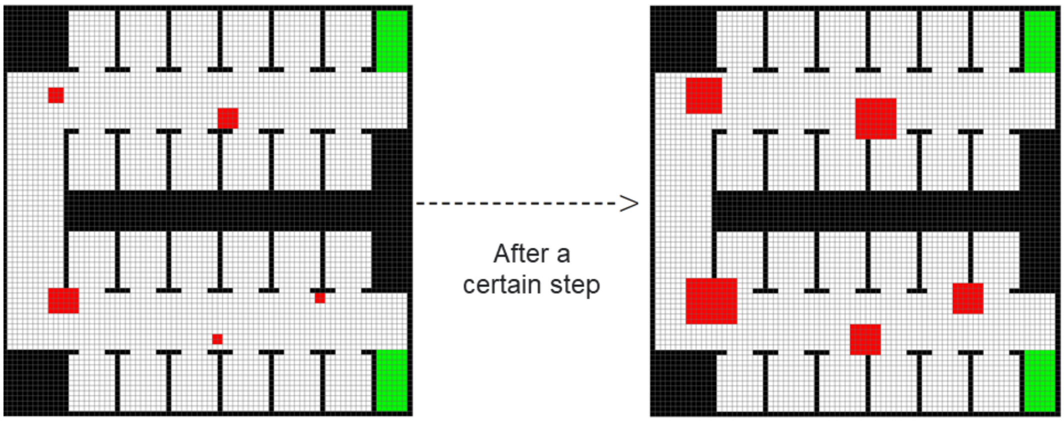

Figure 13: Map of Experiment 2 assuming an impassable place

The results show that the ACO has a higher number of approaches. However, since the number of steps is different, a new "Fire proximity ratio" was added to the table.

$$\text{Fire proximity ratio} = \text{Fire proximities} \,/\, \text{Steps} \tag{14}$$

The fire proximity ratio represents the probability that any one of the evacuees in the evacuation will touch the fire location per step. In PSO, the number of steps increased due to the proximity to the impassable location and the evacuation was not completed in situations where an unexpected fire completely blocked the path to safety. Therefore, in situations such as Experiment 1, it is necessary to prevent not only the number of steps but also the proximity to the fire.

6.2. Experiment 2

The map for Experiment 2 has more actionable locations than Experiment 1, and thus, the number of steps has increased for both ACO and PSO. The evacuation completion rate for ACO is 0.93. This is because there are more actionable locations than in Experiment 1, so the number of steps it takes to reach a safe location increased, and the evacuation could not be completed even after 6,000 steps. When fire is considered, as in Experiment 2, the PSO is superior to the ACO in both evacuation completion rate and average number of steps.

In Experiment 2, unlike Experiment 1, PSO performed better in both evacuation completion rate and average number of steps in the simulation considering fire. The reason lies in the extended fire (Figure 15). In the case of Experiment 2, which considered fire, the spreading fire did not completely block the path to

Table 11: Experiment 2 Results of fire and collapse

	Steps	Evacuation completion rate
ACO	28638	0.93
PSO	11880	1.0

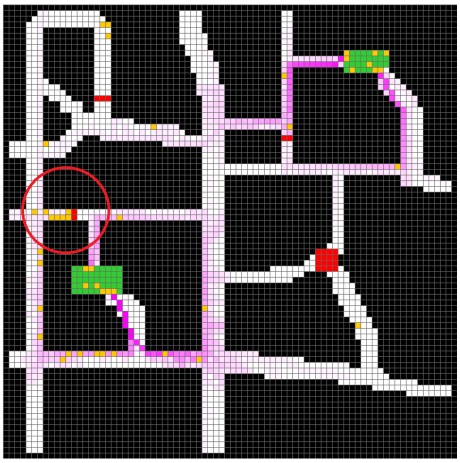

Figure 14: Simulation using PSO of Experiment 1

Table 12: Fire approaches

	Steps	Evacuation completion rate	Fire approaches	Fire proximity ratio
ACO	14183	1.0	1045	0.073
PSO	1409	0.976	450	0.248

safety. If the unanticipated impassable did not seem to completely block the path to the safe location, then better results than the ACO could have been obtained because the path to the safe location could have been avoided.

6.3. Additional experiment

Experiments were conducted with an algorithm that merges PSO and ACO. This was done to avoid approaching the fire to complete the evacuation and also to reduce the number of steps. The following equation is used to determine the direction of movement.

$$\text{Movement direction} = \alpha(\text{PSO movement direction}) + (1-\alpha)(\text{ACO movement direction}) \tag{15}$$

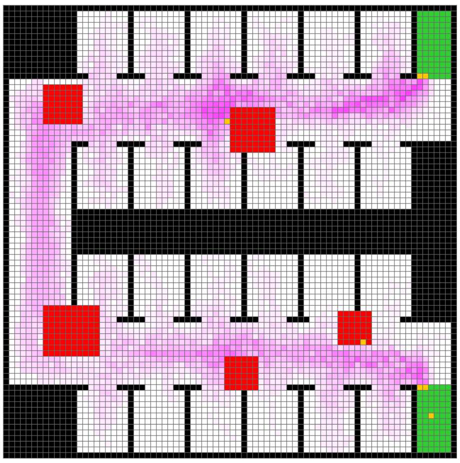

Figure 15: Simulation using PSO of Experiment 2

The α represents the weights; the higher the α value, the more priority is given to the direction of movement of the PSO, and the lower the value, the more priority is given to the direction of movement of the ACO.

The value of α was increased by 0.1 from 0 to 1, and each was simulated on the map from Experiment 1. The number of steps, the approach rate, and the evacuation achievement rate for each are summarized (Figure 16, 17, 18).

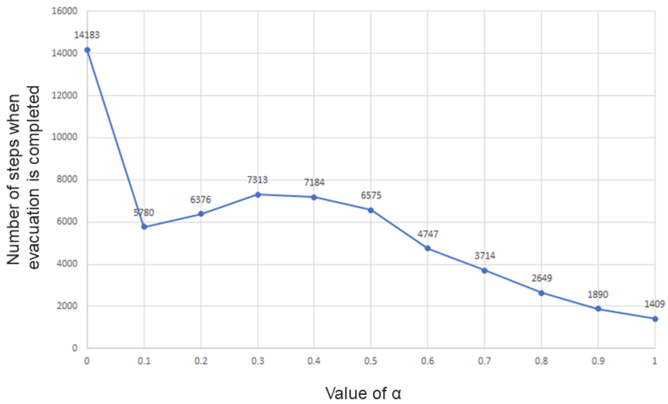

Figure 16: Change in the number of steps according to the value of α

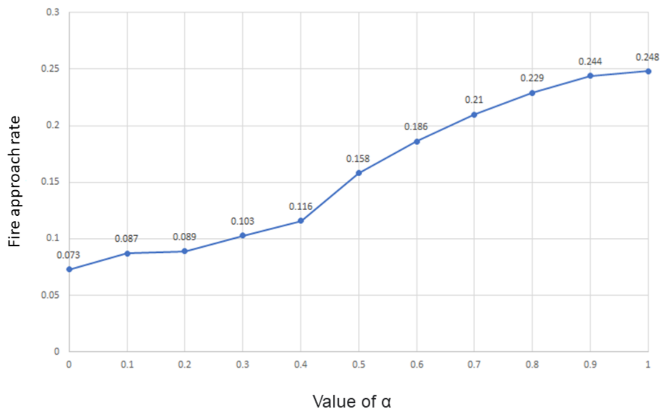

Figure 17: Change in approach rate according to the value of α

Experimental results show that higher values of α lead to better step counts and lower values to better approach rates. Therefore, a correlation was obtained between the number of steps and the approach rate depending on the value of α. To use this algorithm, it is necessary to adjust the value of α according to the situation. In the situation of Experiment 1, when the value of α is 0.9, the number of steps is low and evacuation can be performed with a high evacuation completion rate.

In this study, experiments were conducted in a situation where fire was not anticipated, in a situation where the passage was completely blocked by fire, and in a situation where fire occurred but the passage was not blocked. In all situations, the number of steps resulted in fewer PSO. In other words, in situations where location information can be shared, PSO using location information can provide faster evacuation. The high evacuation completion rate in Experiment 1 indicates that ACO can avoid unexpected disasters by using deodorant pheromones and can evacuate to a safe place without fail. By conducting comparative experiments, we were able to obtain the strengths of each.

The number of steps and the evacuation completion rate can be improved by combining the strengths of each, such as by giving stronger weight to PSO in situations where the first priority is quick damage, and giving stronger weight to ACO in situations where the first priority is avoidance of hazardous locations.

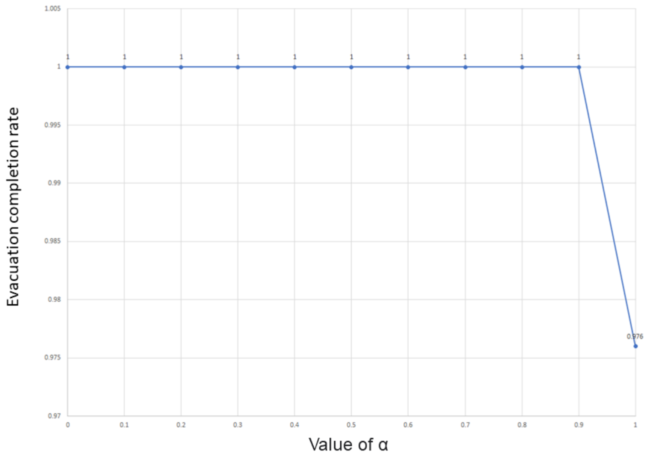

Figure 18: Change in evacuation achievement rate according to the value of α

6.4. Future work

Future work is listed below.

- Intelligence of evacuee behavior in simulators
- Simulation of various situations
- Application of PSO algorithm considering obstacle avoidance to other tasks

This study was only an experiment on simulation, and human evacuation movements were performed at the same speed every step in the direction obtained by a simple vector calculation. However, there may be other factors involved in actual evacuation. For example, evacuation movements are expected to change due to various factors, such as changes in evacuation speed according to the health and mobility of the evacuees, and changes in evacuation routes according to the people who are acting together. Therefore, further improvement is needed in the behavior of agents assuming evacuees to perform the simulation. In addition, although two types of maps were used for evacuation in this study, it is desirable to further optimize the system by adapting it to other evacuation scenarios.

The ACO or PSO algorithm in this study is an algorithm that forms a route based on evacuee information. Since we have been studying the use of deep learning to determine the danger of a location based on camera images from unmanned vehicles such as drones [9], we would like to investigate methods for forming evacuation routes based on information from unmanned vehicles such as drones and balloons in the future.

7. Conclusion

The objective of this study was to reduce the number of steps it takes to evacuate to a safe location. Simulations were created and experiments were conducted as an adaptation of the proposed method. The results showed a reduction in the number of steps compared to the ACO. It was also found that in situations where the path to a safe place was completely blocked, the number of steps required to avoid the situation was greater than that of the ACO. Combining ACO with PSO solved that problem as well. Future work includes intelligence of evacuee behavior in the simulator, adjustment of various parameters, and evacuation for disasters other than earthquakes.

Some natural disasters, such as tsunamis, require immediate evacuation routes to safe higher ground, even through some hazardous areas, while other disasters require evacuation routes through safe detours to avoid collapsing buildings. In this study, we have described the performance of PSO and ACO, and the performance of route suggestion by combining them. We would like to work in the future to construct an evacuation guidance system that combines all types of algorithms for evacuation route suggestion in a well-balanced manner according to the purpose.

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