Validation of Evacuation Decision Model: An Attempt to Reproduce Human Evacuation Behaviors during the Great East Japan Earthquake

Akira Tsurushima
SECOM CO., LTD., Intelligent Systems Laboratory, Tokyo, Japan

Keywords: Evacuation Behavior, Herd Behavior, Decision Making, Video Analysis, Response Threshold Model.

Abstract: The evacuation decision model was developed to represent human herd behavior during disaster evacuations and employed to analyze symmetry breaking phenomena in evacuation exit choices. However, it has yet to be tested on actual human evacuation data. By examining video footage recorded during the Great East Japan Earthquake, we discovered unusual evacuation behaviors previously unreported in the literature. Those being the choice between fleeing and the drop-cover-hold on action. These behaviors formed a unique spatial pattern when observed in a room. In this study, we attempt to reproduce this unique human evacuation behavior via multiagent simulations using the evacuation decision model and demonstrate that simple herd behavior is sufficient to reproduce the spatial pattern of the evacuation decisions.

1 INTRODUCTION

In constructive approaches, model validation is crucial but in this case difficult, due to the limited amount of available objective data since our model domain is human behavior during disasters. The evacuation decision model (Tsurushima, 2019a) was developed to represent human herd behavior during disaster evacuations. It is employed to analyze symmetry breaking phenomena in evacuation exit choices which are typical in disaster evacuation situations (Tsurushima, 2019b; Tsurushima, 2019c). Herd behavior refers to the mentality of individuals that make decisions based on other people's choices or behaviors instead of their own intentions or analysis. Herd behavior is a cognitive bias, a mental tendency yielding erroneous behaviors or irrational decisions resulting in unfavorable outcomes, which can often be observed in disaster evacuations (Cutter and Barnes, 1982; Elliott and Smith, 1993). Symmetry breaking in exit choice is a phenomenon observed when people evacuate from a room with two identical exits, in which the exits are often unequally used and evacuees gather at one of them. These behaviors result in the inefficient use of exits, increasing the total evacuation time. The evacuation decision model has successfully reproduced symmetry breaking phenomena in evacuation exit choices; however, it is yet to be tested using real human evacuation data owing to the difficulty of obtaining those data.

Research on human behaviors during disaster evacuation has primarily been conducted through interviews (Mas et al., 2012; Drury et al., 2015), laboratory experiments using humans (Schmidt and Galea, 2013; Garcimartín et al., 2014), or laboratory experiments using non human animals (Saloma et al., 2003; Altshuler et al., 2005; Ji et al., 2017). However these techniques are limited because of the following:

1. interviews can only be conducted with survivors,
2. it is difficult to reproduce the mental pressure of real evacuations in laboratory experiments, and
3. animal behaviors are not necessarily identical to human behaviors.

None of the above assures that data obtained by those methods refer to real human behaviors in disaster situations.

With the increase in surveillance cameras and smartphones, video images of human behavior during disasters have been recorded; recently, those videos have been analyzed and human evacuation behaviors investigated (Yang et al., 2011; D'Orazio et al., 2014b; Gu et al., 2016; Hori, 2018). Problems such as accessibility and poor video quality have limited the success of these approaches (Shiwakoti and Sarvi, 2013).

Tsurushima, A.
Validation of Evacuation Decision Model: An Attempt to Reproduce Human Evacuation Behaviors during the Great East Japan Earthquake.
DOI: 10.5220/0008874300170027
In *Proceedings of the 12th International Conference on Agents and Artificial Intelligence (ICAART 2020) - Volume 1*, pages 17-27
ISBN: 978-989-758-395-7; ISSN: 2184-433X

A video clip captured in a meeting room in Sendai during the Great East Japan Earthquake of March 11, 2011 (Fig. 1) is exceptionally valuable for the following reasons:

- the earthquake was captured in one continuous scene from the beginning to the end,
- the initial position of the people in the room when the shaking began was clearly recorded, and
- the professionalism of the camera crew rendered it relatively easy to examine the behavior of each individual during the earthquake.

By studying this video, real human behaviors during an earthquake can be analyzed. In this study, by reproducing human evacuation behaviors observed in the video, we attempt to confirm the validity of the evacuation decision model.

The aim of this paper is twofold. First, by analyzing the behavior of the individuals in the video, unusual human behaviors that are yet to be reported in the literature are introduced and examined. Second, for validation, unusual human behaviors are reproduced by multiagent simulations using the evacuation decision model.

2 RELATED WORK

Because real-life experiments of earthquake evacuations are difficult to perform owing to the complexities of such environments, studies on human evacuation behaviors during earthquakes have been conducted through surveys and interviews.

Kimura et al. conducted a study to understand the behavioral and psychological reconstruction processes of victims in the 2004 Mid-Niigata prefecture earthquake through a survey of sample size 543 (Kimura et al., 2006). Mas et al. estimated distributions of departure times of tsunami evacuations through revealed preference and stated preference surveys (Mas et al., 2012). Drury et al. studied the solidarity behaviors of evacuees of the 2010 Chile earthquake by interviewing 1240 people (Drury et al., 2015). Morita et al. interviewed people in Yamada-machi and Ishinomaki-shi to investigate the pre-/post-earthquake evacuation behaviors of the Great East Japan Earthquake (Morita et al., 2015).

Recently, novel approaches using video to analyze human behaviors during earthquake evacuations have emerged.

Yang et al. analyzed the 2008 Wenchuan earthquake videos and discovered that the relationship between arrival time and order of evacuee arrival is linear in evacuation drills but nonlinear in real evacuations (Yang et al., 2011).

D'Orazio et al. discovered several unique evacuation behaviors in earthquakes through video analysis, e.g., people preferred to search for safe positions instead of exits when the shaking was strong; Haiti evacuees attempted to reach for exits but the Japanese adopted drop-cover-hold on procedures and preferred group evacuations; people attempted to maintain social attachments during evacuations; people tended to follow the common behavior; and people stayed at safe and familiar places after the earthquakes (D'Orazio et al., 2014b).

Gu et al. examined school students' evacuation behaviors in videos and stated that the response time was linear in normal conditions but nonlinear in real evacuations, and the cumulative number of evacuees was linear in exercises but nonlinear in real situations (Gu et al., 2016).

Hori analyzed videotapes and estimated the walking speed of individuals during earthquake evacuations (Hori, 2018).

Bernardini et al. studied whether evacuees followed the recommended evacuation actions during and after earthquakes using a video database. They compared the response of people in New Zealand, Italy, and Japan (Bernardini et al., 2019).

Several attempts have been made to build earthquake evacuation simulations and subsequently propose human behavior models for evacuations. Li et al. developed a method for predicting the number of casualties in earthquake evacuations using a cellular-automaton-based evacuation behavioral model in conjunction with a finite-element-based environment model. The evacuation behavioral model was verified by a real-life video recording of classroom evacuation of Mingshan high school (Li et al., 2018).

Many researchers have adopted agent-based models to represent human evacuation behaviors. Delcea et al. developed an agent-based model for classroom evacuation behaviors using NetLogo (Wilensky, 1999) to analyze the differences in evacuation processes between collaborative classrooms and traditional classrooms. The model was verified against data acquired from evacuation experiments with 18 participants (Delcea et al., 2020).

Osaragi et al. constructed an agent model incorporating a procedure concerning typical evacuation behaviors such as initial reactions, searching for routes, methods of evacuation, walking in a crowd, and activities while waiting. The model was employed to develop efficient disaster prevention planning (Osaragi et al., 2012).

Mas et al. developed a tsunami evacuation simulation model based on the Great East Japan Earthquake to evaluate evacuation feasibility and shelter demand analysis. The agent model consists of four layers: evacuation decisions, shelter selections, route findings, and speed adjustments (Mas et al., 2012).(Mas et al., 2012).

D'Orazio et al. identified numerous unique evacuation behaviors (rules) through video analysis. They then combined these rules into behavioral flowcharts which were incorporated into the conduct of the agents in their simulation models. Agent behaviors were based on the intentional model, which represents interactions among agents and between an agent and the environment, and the social force model, which represents the internal factors motivating the agents (D'Orazio et al., 2014a; D'Orazio et al., 2014b; Bernardini et al., 2014).

Most studies focused on fleeing behaviors during evacuations, and a few studies mentioned the drop-cover-hold on action (D'Orazio et al., 2014b; Bernardini et al., 2019). In this study, by analyzing videos captured during the Great East Japan Earthquake, we investigated evacuees' choice of decision between performing the drop-cover-hold on action or fleeing from a room.

3 VIDEO ANALYSIS

The video frame as shown in Fig. 1 was captured in a hotel meeting room in Miyagino-ku, Sendai-shi, Miyagi Prefecture, Japan, at 14:46 JST on Friday, March 11, 2011 [1]. The behavior of 48 people in the room was recorded during the Great East Japan Earthquake, an earthquake off the coast of Japan with a magnitude of 9.0. We carefully traced and summarized the behavior of each person shown in Fig. 1b-d.

Fig. 2 depicts the initial positions of all 48 people when the earthquake started. The room is square with only one exit in the lower right corner. Initially, all 48 people were sitting at tables in a square, with everyone facing inwards. After the shaking from the earthquake started, the following three behaviors were observed in the video:

1. Stand and remain at their current position (Stand)
2. Exit and flee from the room (Flee)
3. Hide under the table, also known as "drop, cover, and hold on" (Drop)

Fig. 1d depicts the temporal behavioral changes for each of the 48 people for 99 s after the shaking started. Although the entire video lasted 139 s, the final 40 s of the video was dark owing to a power outage; hence, analysis was difficult. In the chart, the gray, white, and black circles indicate stand, flee, and drop behaviors, respectively, while $\times$ indicates behavior unidentifiable from the video. Fig. 1c depicts the number of times that people changed their behaviors. For example, a person changing his/her behavior from sitting to fleeing is indicated by a white circle at the time the behavior changed. Fig. 1b shows a cumulative curve of the number of behavioral changes in Fig. 1c. The dotted, dashed, and solid lines indicate drop, flee, and the sum of both behaviors, respectively. Figure 1a depicts the acceleration generated by the earthquake in the North-South, East-West, and up-down directions[2]. Two vertical dashed lines at 28 and 68 s indicate the two peaks of shaking intensity.

Fig. 1d indicates the time when each person changed their behavior. At 4 s, person 46 was the first to take action (flee). Person 29 remained in his/her chair for 75 s, and then changed his/her behavior to stand. As shown in Fig. 1b, the cumulative number of people who displayed evacuation behaviors in real disasters follows a convex curve, as compared with the linear trend exhibited in evacuation drills (Gu et al., 2016).

The final behavior of all 48 people at 99 s is shown in Fig. 3. A white circle with a black number denotes an evacuee who selected the flee behavior, and a black circle with a white number denotes an evacuee who selected the drop behavior. A gray number is an evacuee whose behavior is unknown. In summary, 26 evacuees selected flee and 12 evacuees selected drop.

Fig. 3 illustrates that most people close to the exit selected flee, while those farther from the exit selected drop, which is an intriguing behavior never reported previously. The boundary between flee and drop crosses the room diagonally, as if people within a certain distance from the exit selected flee and the others selected drop, thus leading to the following hypothesis.

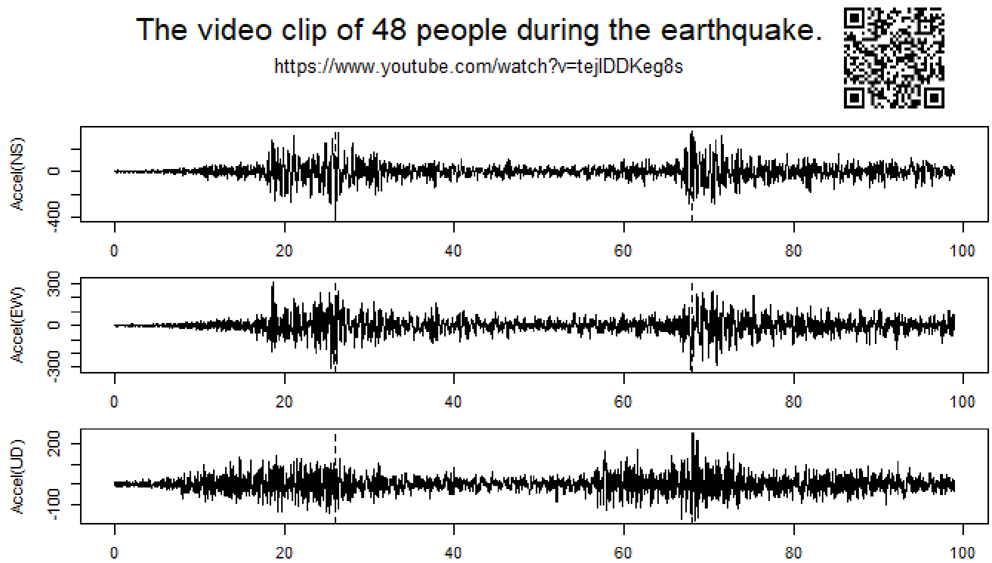
Hypothesis 1. *The evacuation decision between flee or drop is based on the distance from the exit.*

However, a different hypothesis for the phenomenon can be constructed. That is, although people make arbitrary decisions between flee and drop, herd behavior is the basic mechanism forming this diagonal spatial pattern, as it is often observed in collective evacuations.

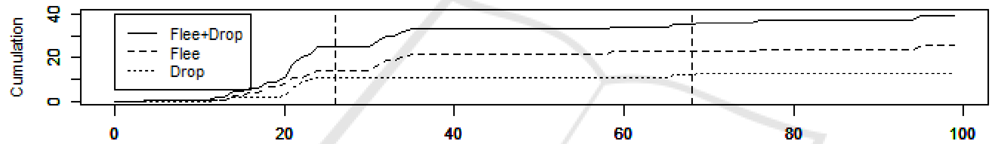
Hypothesis 2. *The herd behavior among people causes the diagonal spatial pattern, even if each individual randomly chooses to flee or drop.*

[1] https://www.youtube.com/watch?v=tejlDDKeg8s

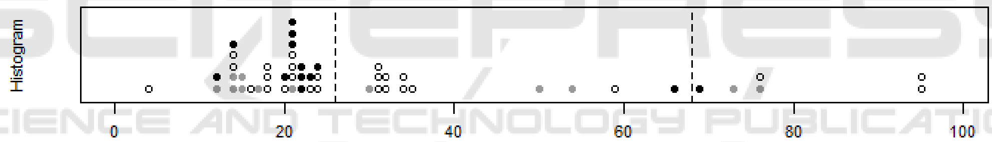
[2] https://www.data.jma.go.jp/svd/eqev/data/kyoshin/jishin/110311_tohokuchiho-taiheiyouoki/index.html (Observation Point: Sendai-shi, Miyagino-ku, Gorin).



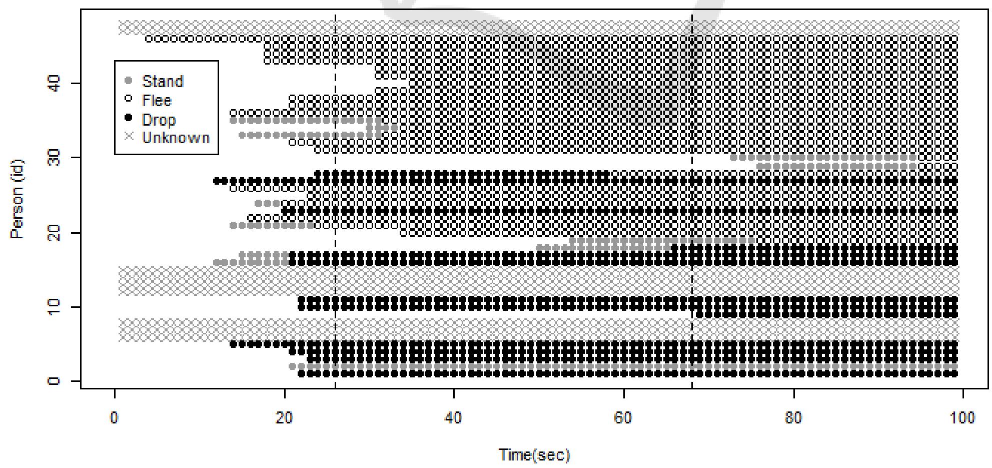
(a) Earthquake accelerations.



(b) Cumulative person behavioral changes.



(c) Behavorial change histogram.



(d) Per person behavioral history.

Figure 1: Temporal behavioral changes in 99 s, of 48 people in the video.

It is obvious that Hypothesis 1 can generate the diagonal spatial pattern. However, this hypothesis requires higher level cognitive processes such as rules, scenarios, or procedures to estimate the distance to the exit and to judge whether this distance is above a certain threshold. By contrast, Hypothesis 2 requires only

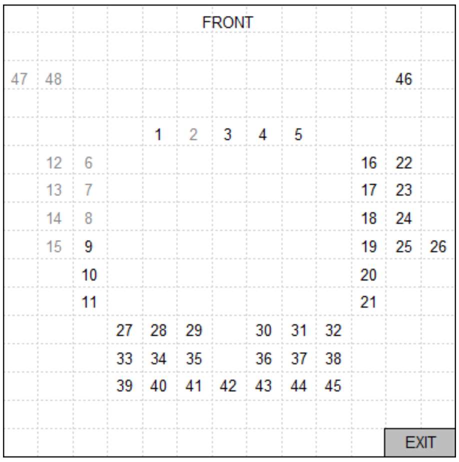


Figure 2: Initial location of the people in the video.

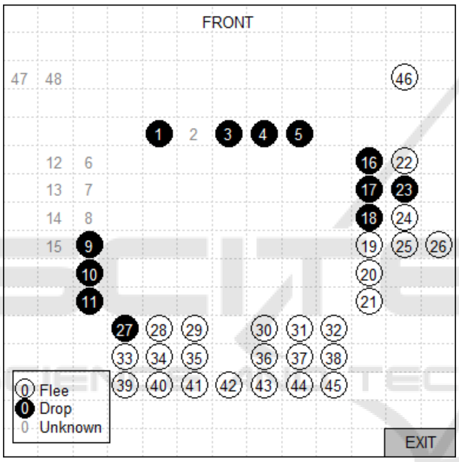


Figure 3: Selection of drop and flee at the end of the video.

lower-level cognitive processes, i.e., the herd behavior, which is typical in many organisms.

In this study, we show that the evacuation decision model can represent human evacuations in a real disaster situation by demonstrating that Hypothesis 2 holds using multiagent simulations, i.e., the simple herd behavior is sufficient to produce the diagonal spatial pattern generated by the flee and drop decisions.

4 EVACUATION DECISION MODEL

In this study, we adopted the evacuation decision model (Tsurushima, 2019a; Tsurushima, 2019b) to represent the herd behavior among evacuees during an earthquake. The evacuation decision model is based on the response threshold model in biology, which represents the division of labor in eusocial organisms (Bonabeau et al., 1996; Bonabeau et al., 1998). The evacuation decision model has been used to reproduce cognitive aggregation (Tsurushima, 2019a) and symmetry breaking in exit selection (Tsurushima, 2019b; Tsurushima, 2019c) during evacuations.

In the evacuation decision model, the environment has an objective risk value r, which refers to the severity of disaster threats. An agent i in the environment acts as either a leader or a follower, depending on his/her internal mental state X. The agent will act as a leader if $X = 1$, allowing him/her to select his/her behavior, while a follower's ($X = 0$) behavior is selected by the behaviors of others. The value of X changes with some probability during evacuations. Thus, an agent sometimes acts as a leader and at other times a follower.

The agent has a parameter θ_i, called the response threshold, which determines the degree to which the agent participates in the evacuation. The values of θ vary by agent. The probability P that an agent becomes a leader per unit time is

$$P_i(X = 0 \to X = 1) \quad = \quad \frac{s_i^2}{s_i^2 + \theta_i^2}, \tag{1}$$

where s_i is the local estimation in the stimulus of the environment associated with agent i.

The probability that an agent becomes a follower per unit time is

$$P_i(X = 1 \to X = 0) \quad = \quad \varepsilon, \tag{2}$$

where ε is a constant probability that agents become followers, given as a simulation parameter. The estimation of the stimulus of agent i per unit time is given by the following difference equation

$$s_i(t+1) = max\{s_i(t) + \hat{\delta} - \alpha(1-R)F,\ 0\}, \tag{3}$$

where $\hat{\delta}$ is an increase of the stimulus per unit time

$$\hat{\delta} = \begin{cases} \delta & \text{if } r > 0 \\ 0 & \text{otherwise,} \end{cases} \tag{4}$$

and α is a scale factor of the stimulus. R is the risk perception function which is a function of the objective risk r:

$$R(r) \quad = \quad \frac{1}{1 + exp(-g(r - \mu_i))}, \tag{5}$$

where g is the activation gain which determines the shape of the sigmoid function. μ_i is the risk perception of agent i, which represents an individual's sensitivity to risk. The evacuation progress function i.e., the local estimation of the evacuation progress of agent i is

$$F(n) = \begin{cases} 1 - n/N_{max} & n < N_{max} \\ 0 & \text{otherwise,} \end{cases} \tag{6}$$

where n is the number of agents in the vicinity, and N_{max} is the maximum possible number of agents in the vicinity.

5 EARTHQUAKE EVACUATION SIMULATION

This section presents the earthquake evacuation simulation in detail. The simulation configuration is similar but not identical to the video depicted in Figure 1. The aims of this simulation are to reproduce the convex curve of cumulative evacuees from Fig. 1b and the diagonal spatial pattern of Fig. 3. To represent herd behavior, the evacuation decision model is incorporated into the agents; however, the agents have no higher-level cognitive processes to determine whether the distance to the exit exceeds a threshold. The simulation model was implemented using NetLogo 6.0.2 (Wilensky, 1999).

5.1 Configuration

In this study, 500 agents, $A = \{a_1, a_2, \ldots, a_{500}\}$, were randomly distributed in a square room (40×40 units), with the lower left corner as the origin and the exit at the lower right corner. Assuming simulation time $t = 1, \ldots, T$, an agent $a_i \in A$ has coordinates $x_i(t), y_i(t) \in \mathbb{R}$, a local estimation of the stimulus $s_i(t) \in \mathbb{R}$, a mental state $X_i(t) \in \{1, 0\}$, and an action $\pi_i(t) \in \{\textit{undecided, flee, drop}\}$, where *undecided* indicates that the agent has not determined an action yet, *flee* implies that the agent has selected Flee, and *drop* means that the agent has selected drop. Furthermore, an agent has two parameters; the response threshold θ_i and the risk sensitivity μ_i. Let $x_i(1), y_i(1) \sim U(3, 38)$, $s_i(1) = 0, X_i(1) = 0, \pi_i(1) = \textit{undecided}, \theta_i \sim U(0, 100)$, and $\mu_i \sim U(0, 100)$ be the initial values of the simulation, with the simulation terminated at $T = 270$.

The vicinity of a_i is defined as $V_i = \{a_j \in A \mid \nu(a_j, a_i)\}$, where $\nu : A^2 \to \{\textit{true, false}\}$, and ν refers to the range of five units and 120° towards the direction of motion of a_i.

It is noteworthy that n in Equation 6 will be $n = |\{a_j \in V_i \mid \pi_j(t) = \textit{undecided}\}|$, because both flee and drop are considered as evacuation behaviors in our simulation.

At each time step, an agent with $\pi_i(t) = \textit{flee}$ moves toward the exit (G_x, G_y) by Δx, Δy, as determined by solving Problem 1.

Algorithm 1: Leader.

if $\pi_i(t) = \textit{undecided}$ **then**
  $\tau \sim U(0, 1)$
  if $\tau \leq 0.5$ **then**
    $\pi_i(t) \Leftarrow \textit{drop}$
  else
    $\pi_i(t) \Leftarrow \textit{flee}$
  end if
end if
if $\pi_i(t) = \textit{flee}$ **then**
  Solve Problem 1 and determine Δx, Δy
  $x_i(t) \Leftarrow x_i(t) + \Delta x$; $y_i(t) \Leftarrow y_i(t) + \Delta y$
end if

Algorithm 2: Follower.

$n_d \Leftarrow |\{a_j \in V_i \mid \pi_j(t) = \textit{drop}\}|$
$n_e \Leftarrow |\{a_j \in V_i \mid \pi_j(t) = \textit{flee}\}|$
$n_u \Leftarrow |\{a_j \in V_i \mid \pi_j(t) = \textit{undecided}\}|$
if $n_d > n_e$ **and** $n_d > n_u$ **then**
  $\pi_i(t) \Leftarrow \textit{drop}$
else if $n_e > n_d$ **and** $n_e > n_u$ **then**
  $\pi_i(t) \Leftarrow \textit{flee}$
end if
if $\pi_i(t) = \textit{flee}$ **then**
  Solve Problem 1 and determine Δx, Δy
  $x_i(t) \Leftarrow x_i(t) + \Delta x$; $y_i(t) \Leftarrow y_i(t) + \Delta y$
end if

Problem 1.

$$min \quad (x_i(t) + \Delta x - G_x)^2 + (y_i(t) + \Delta y - G_y)^2 \tag{7}$$

$$s.t. \quad \Delta x^2 + \Delta y^2 = 1 \tag{8}$$

An agent with $\pi_i(t) \neq \textit{flee}$ remains in the same position, i.e., $\Delta x = 0$ and $\Delta y = 0$.

When $X = 1$, a_i acts as a leader by executing Algorithm 1 and executes Algorithm 2 as a follower if $X = 0$. The followers only mimic the most popular behavior in their vicinity. Only the leaders intentionally determine their behaviors, albeit a random choice between flee and drop.

The room has an objective risk that starts at $r(1) = 0$ and increments by one for each time step up to the maximum value of $r(t) = 100$. The local estimation of the stimulus of a_i starts at $s_i(1) = 0$ and increments by δ at each time step as $F \approx 0$ in the initial stages of the simulation. Thus, $P_i(X = 0 \to X = 1)$ increases gradually depending on θ_i, thus resulting in the emergence of leader agents. Subsequently, followers appear and herding spreads among the agents.

Finally, the overall simulation procedure is shown in Algorithm 3. The following parameters were used: $\alpha = 1.2$, $\delta = 0.5$, $\varepsilon = 0.2$, $g = 1.0$, and $N_{max} = 10$.

Algorithm 3: Simulation.

Initialization
for $t = 1$ to T **do**
  $r \Leftarrow min\{r+1,\ 100\}$
  for all $a_i \in A$ **do**
    Calculate R {Equation 5}
    Calculate F {Equation 6}
    Calculate s_i {Equation 3}
    $\tau \sim U(0,1)$
    if $\tau < P(X=1 \to X=0)$ **then**
      $X_i \Leftarrow 0$
    else
      $\tau \sim U(0,1)$
      if $\tau < P(X=0 \to X=1)$ **then**
        $X_i \Leftarrow 1$
      end if
    end if
    if $X_i = 0$ **then**
      Execute Algorithm 2 {Follower}
    else if $X_i = 1$ **then**
      Execute Algorithm 1 {Leader}
    end if
    if $(x_i(t) - G_x)^2 + (y_i(t) - G_y)^2 < 1$ **then**
      $A \Leftarrow A \setminus a_i$
    end if
  end for
end for

5.2 Result 1

In this section, results of the simulation described in Section 5.1 are presented.

Fig. 4 depicts the cumulative curves of evacuees who performed evacuation actions per simulation time. The solid line in the chart is obtained by the function $\varphi(t)$:

$$\varphi(t) \quad = \quad \varphi(t-1) + \sum_{a_i \in A} \gamma_i(t), \tag{9}$$

where

$$\gamma_i(t) \quad = \quad \begin{cases} 1 & t = min\{z \mid \pi_i(z) \neq undecided\} \\ 0 & \text{otherwise}, \end{cases} \tag{10}$$

and $\varphi(0) = 0$.

The function $\varphi(t)$ illustrates the temporal change in the cumulative number of evacuees who performed either the flee or drop action. Similar to Fig. 1b, the cumulative curves in Fig. 4 are convex, which is typical for actual disaster evacuations (Gu et al., 2016).

Fig. 5 illustrates the location of the remaining agents in the room at $t = T$. A total of 211 agents remained in the room, and all of them were with $\pi_i(T) = drop$. Interestingly, all of the remaining agents were located in the far side of the room from the exit, in a triangular shape with a diagonal boundary across the room. As the side close to the exit was empty, it could be inferred that the agents farther from the exit performed the drop action and those closer performed the flee action. This result is consistent with the observation of Fig. 3.

If we divide the room into two spaces with a diagonal line $y = x$, and let the number of agents in the upper left space be $N_u = |\{a_i \mid y_i(T) \geq x_i(T)\}|$ and the lower right space be $N_l = |\{a_i \mid y_i(T) < x_i(T)\}|$, we have $N_u = 183$ and $N_l = 28$, and the difference $N_d = N_u - N_l = 155$.

Here, we adopted entropy to evaluate the simulation results quantitatively (Crociani et al., 2016). Fig. 6 depicts each agent's action at the end of the simulation at their initial location $t = 1$. The black and white circles represent $\pi_i(T) = drop$ and $\pi_i(T) = flee$, respectively. As shown in Fig. 6, with a few exceptions, most agents initially located in the upper left space selected drop and those in the lower right space selected flee. To evaluate whether the decision between flee and drop is divided by the diagonal line $y = x$, entropy H is introduced.

$$H \quad = \quad -r_g\, log_2(r_g) - r_b\, log_2(r_b), \tag{11}$$

where

$$r_g = L_g/(L_g + L_b) \tag{12}$$

$$r_b = L_b/(L_g + L_b), \tag{13}$$

and

$$L_g = \sum_{\{a_i | y_i(1) \geq x_i(1) \wedge \pi_i(T) = drop\}} l_i + \tag{14}$$

$$\sum_{\{a_j | y_j(1) < x_j(1) \wedge \pi_j(T) = flee\}} l_j \tag{15}$$

$$L_b = \sum_{\{a_i | y_i(1) \leq x_i(1) \wedge \pi_i(T) = drop\}} l_i + \tag{16}$$

$$\sum_{\{a_j | y_j(1) > x_j(1) \wedge \pi_j(T) = flee\}} l_j, \tag{17}$$

where

$$l_i = \sqrt{2\left(\frac{x_i(1) - y_i(1)}{2}\right)^2} \tag{18}$$

and l_j is the minimum distance between the initial position of a_i and the diagonal $y = x$. L_g is the sum l_i of the shortest distances to the diagonal from the initial position of a_i in the upper left space with $\pi_i(T) = drop$ and an agent in the lower right space with $\pi_i(T) = flee$. Conversely, L_b is the sum of l_i

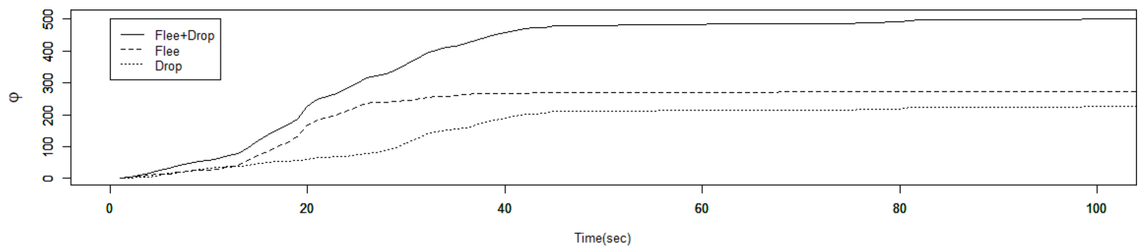


Figure 4: Cumulative number of evacuees over the simulation time.

Figure 5: Distribution of remaining agents in the room at the end of the simulation.

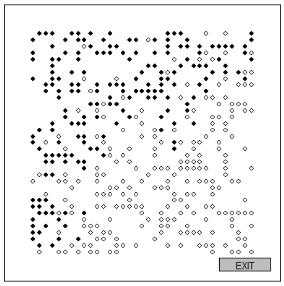


Figure 6: Initial locations and the decisions between flee and drop. Black circles refers to $\pi_i(T) = drop$, and white circles refers to $\pi_i(T) = flee$.

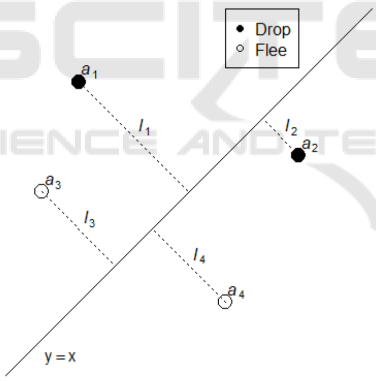


Figure 7: Calculations of L_g and L_b. In this case, $L_g = l_1 + l_4$ and $L_b = l_2 + l_3$.

of the shortest distance to the diagonal from the initial position of agent a_i in the upper left space with $\pi_i(T) = flee$ and an agent in the lower right space with $\pi_i(T) = drop$. For example, in the case of Fig. 7, $L_g = l_1 + l_4$ and $L_b = l_2 + l_3$.

With a smaller H, flee and drop behavior are delineated by the $y = x$ diagonal, whereas the behavior becomes intermingled if H is close to 1.0. The entropy in Fig. 6 is $H = 0.48$.

5.3 Result 2

A total of 150 simulations were conducted and the results are presented in this section. Fig. 8 shows the mean value, $\Phi(t) = \overline{\varphi(t)}$, of the cumulative number of evacuees over 150 simulations. The curves in Fig. 8 are convex and smoother than those in Fig. 4.

The histograms of N_d and H are shown in Fig. 9 and Fig. 10, respectively. N_d is the difference in the number of agents in the spaces, separated by the diagonal $y = x$ and H is the entropy of the evacuation decisions. The mean, standard deviation (σ), and minimum and maximum values of N_d and H are summarized in Table 1.

Table 1: Statistics of N_d and H over 150 simulations.

	min	mean	σ	max
N_d	-89.0	95.2	48.8	177
H	0.35	0.63	0.13	1.00

The kernel density distribution given by coordinates $x_i(T)$, $y_i(T)$ of the agents remaining in the room at $t = T$ over 150 simulations is shown in Fig. 11. Locations farther from the exit exhibit a higher kernel density, yielding a correlation between the distance from the exit and the number of the remaining agents.

6 ANALYSIS

In this section, we analyze the relationship between the final agent decisions and the agent parameters using logistic regression analysis. The objective variable is the final decision $\pi_i(T)$ by assuming $drop = 1$ and $flee = 0$, and the explanatory variables are the distance between the initial agent location and the exit

$$L_i = \sqrt{(x_i(1) - G_x)^2 + (y_i(1) - G_y)^2}, \qquad (19)$$

response threshold θ_i, and risk sensitivity μ_i.

A total of 200 and 500 training and test samples, respectively, were randomly selected from 75,000 samples (500 agents $\times$ 150 simulations). Large amounts of training data reduce both the p-value and

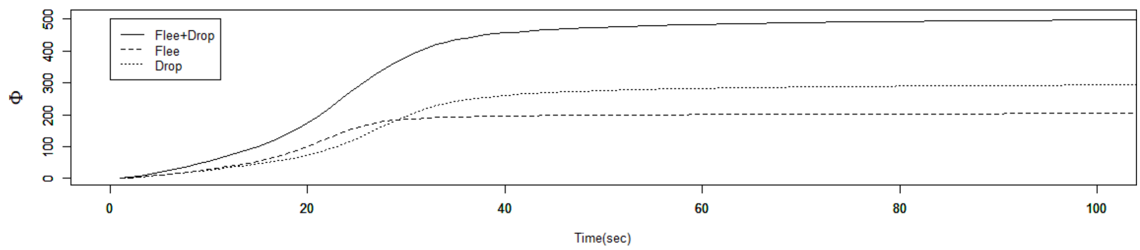


Figure 8: Mean values of $\varphi(t)$, $\Phi(t)$, over 150 simulations.

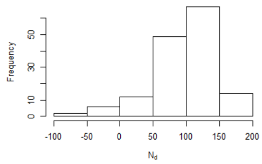


Figure 9: Histogram of N_d.

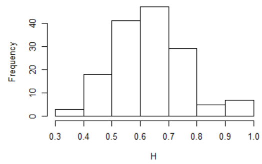


Figure 10: Histogram of H.

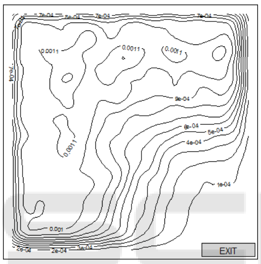


Figure 11: Kernel density of $x_i(T)$ and $y_i(T)$ over the room.

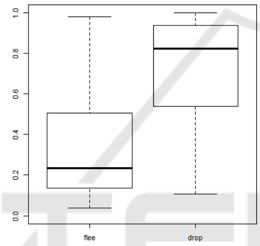


Figure 12: Logit model discriminating between drop and flee.

Table 2: Results of the logistic analysis. Coefficients and P-values.

	Intercept	L_i	θ_i	μ_i
coeff	-3.4486	0.0033	0.0115	0.0055
P-values	0.0	0.0	0.0796	0.3532

the reliability of the analysis; therefore, we set the amount of training data to 200 samples. The results of the logistic regression analysis in terms of the coefficients and p-values are shown in Table 2.

From Table 2, the primary factor in the drop/flee decision is the distance to the exit ($p < 0.01$). This implies that the response threshold θ_i may have some effect ($p < 0.1$), while the risk sensitivity μ_i may not have an effect on the decision ($p > 1$).

The box plot in Fig. 12 shows the discrimination results of 500 test data samples by the logit model from Table 2 developed from the logistic regression analysis. It indicates that the logit model can discriminate between drop and flee decisions for unknown data.

7 DISCUSSION AND CONCLUSION

By analyzing a video captured during the Great East Japan Earthquake, we discovered that the decision between drop and flee was influenced by the distance to the exit, a finding that was not reported previously. Subsequently, we constructed two hypotheses for the origin of this behavior and demonstrated that the spatial pattern of the decisions could be reproduced. Furthermore, Hypothesis 2 holds based on simulations using the evacuation decision model, which represents human herd behavior during evacuations.

Our simulation results in Figs. 5 and 6 show that the decision between drop and flee is determined by the distance from the exit. However, Figs. 9 and 10 indicate that the results from the simulation vary, i.e., the results described in Section 5.2 are not always obtained. Contrary to our expectations, some simulations had $N_d = -89$, signifying that more agents remained in the area closer to the exit, and some simulations resulted in $H \approx 1.00$, which implies a combination of drop and flee behaviors.

Although we concede that exceptional cases like these occur, it is clear that the evacuation decision model is sufficient to produce results that are similar to our findings from the video analysis of the Great East Japan Earthquake, albeit at a slightly lower frequency. The kernel density of the results in Fig. 11 agrees well with the statement above. Furthermore, the results of the logistic regression analysis revealed that the primary factor of deciding between drop and flee for individual agents was the distance between their initial location and the exit. Nonetheless, Hypothesis 2 suggests that each individual does not have to consider this distance to determine his/her behavior; a simple herd behavior is sufficient to produce the diagonal spatial pattern.

The most remarkable aspect of this analysis was that the results were produced by agents who have no higher-level cognitive processes. The agents in our model performed only either imitations or random selections, both of which are unintelligent behaviors.

Neither distance estimation nor thresholds are necessary to reproduce the behaviors in the video. From the discussion thus far, we conclude that Hypothesis 2 holds.

The fact that Figs. 4 and 8 are consistent with Fig. 1b and that the cumulative curve of evacuees is convex in real evacuation situations (Gu et al., 2016) provides additional support that our simulations using the evacuation decision model can yield realistic results.

We do not deny Hypothesis 1; rather, we consider it natural for people close to the exit to select the flee action intentionally. In reality, we believe that both Hypothesis 1 and Hypothesis 2 hold simultaneously. A real evacuation process will be the complex combination of higher-level cognitive processes such as decision making and lower-level cognitive processes such as herd behavior. Some researchers have also pointed out the importance of individuals' emotional responses in crowd evacuation processes (Kefalas and Sakellariou, 2017).

This study demonstrated that the evacuation decision model could reproduce real human evacuation behaviors that were recorded in the video of the Great East Japan Earthquake and could be used to analyze human herd behaviors during earthquakes. Tsurushima (Tsurushima, 2019b; Tsurushima, 2019c) demonstrated that a simple herd behavior could reproduce symmetry breaking in exit selection using the evacuation decision model. Furthermore, the analysis presented herein revealed the significance of herd behavior in collective evacuations. Hence, the evacuation decision model is advantageous for the quantitative analysis of herd behavior effects in human evacuations.

Finally, some potential methodological weaknesses should be considered. First, the video clip analyzed in this study is the only instance where we can find the specific evacuation behavior discussed in this paper. We do not know the universality of this behavior in other evacuation scenarios. There is also some possibility of errors occurring in the video analysis phase as it was controlled manually. Second, most of the parameters adopted in the simulation model were either experimentally or arbitrarily selected. Sensitivity analysis of these parameters is desirable to ensure more accurate future results. Third, the simulation was not configured identically with the actual events captured in the video. It would be interesting to experiment with a more realistic design. However, such considerations are reserved for future work.

ACKNOWLEDGEMENTS

We gratefully acknowledge the help and constructive comments provided by Yoshikazu Shinoda and Kei Marukawa. We would like to thank Editage (www.editage.com) for English language editing.

REFERENCES

Altshuler, E., Ramos, O., Nuñez, Y., Fernańdez, J., Batista-Leyva, A. J., and Noda, C. (2005). Symmetry breaking in escaping ants. *The American Naturalist*, 166(6):643–649.

Bernardini, G., D'Orazio, M., Quagliarini, E., and Spalazzi, L. (2014). An agent-based model for earthquake pedestrians' evacuation simulation in urban scenarios. *Transportation Research Procedia*, 2:255 – 263. The Conference on Pedestrian and Evacuation Dynamics 2014 (PED 2014), 22-24 October 2014, Delft, The Netherlands.

Bernardini, G., Lovreglio, R., and Quagliarini, E. (2019). Proposing behavior-oriented strategies for earthquake emergency evacuation: A behavioral data analysis from new zealand, italy and japan. *Safety Science*, 116:295 – 309.

Bonabeau, E., Theraulaz, G., and Deneubourg, J.-L. (1996). Quantitative study of the fixed threshold model for the regulation of division of labour in insect societies. *Proceedings of The Royal Society B*, 263(1376):1565–1569.

Bonabeau, E., Theraulaz, G., and Deneubourg, J.-L. (1998). Fixed response thresholds and the regulation of division of labor in insect societies. *Bulletin of Mathematical Biology*, 60:753–807.

Crociani, L., Vizzari, G., Yanagisawa, D., Nishinari, K., and Bandini, S. (2016). Route choice in pedestrian simulation: Design and evaluation of a model based on empirical observations. *Intelligenza Artificiale*, 10:163–182.

Cutter, S. and Barnes, K. (1982). Evacuation behavior and Three Mile island. *Disasters*, 6(2):116–124.

Delcea, C., Cotfas, L.-A., Craciun, L., and Molanescu, A. G. (2020). An agent-based modeling approach to collaborative classrooms evacuation process. *Safety Science*, 121:414 – 429.

D'Orazio, M., Quagliarini, E., Bernardini, G., and Spalazzi, L. (2014a). EPES - earthquake pedestrians' evacuation simulator: A tool for predicting earthquake pedestrians' evacuation in urban outdoor scenarios. *International Journal of Disaster Risk Reduction*, 10:153 – 177.

D'Orazio, M., Spalazzi, L., Quagliarini, E., and Bernardini, G. (2014b). Agent-based model for earthquake pedestrians' evacuation in urban outdoor scenarios: Behavioural patterns definition and evacuation paths choice. *Safety Science*, 62:450 – 465.

Drury, J., Brown, R., González, R., and Miranda, D. (2015). Emergent social identity and observing social support predict social support provided by survivors in a disaster: Solidarity in the 2010 chile earthquake. *European Journal of Social Psychology*, 46(2):209–223.

Elliott, D. and Smith, D. (1993). Football stadia disasters in the United Kingdom: learning from tragedy? *Industrial and Environmental Crisis Quarterly*, 7(3):205–229.

Garcimartín, A., Zuriguel, I., Pastor, J., Martín-Gómez, C., and Parisi, D. (2014). Experimental evidence of the “faster is slower” effect. *Transportation Research Procedia*, 2:760 – 767. The Conference on Pedestrian and Evacuation Dynamics 2014 (PED 2014), 22-24 October 2014, Delft, The Netherlands.

Gu, Z., Liu, Z., Shiwakoti, N., and Yang, M. (2016). Video-based analysis of school students’ emergency evacuation behavior in earthquakes. *International Journal of Disaster Risk Reduction*, 18:1 – 11.

Hori, M. (2018). *Introduction to Computational Earthquake Engineering*. WORLD SCIENTIFIC (EUROPE), 3rd edition.

Ji, Q., Xin, C., Tang, S., and Huang, J. (2017). Symmetry associated with symmetry break: revisiting ants and humans escaping from multiple-exit rooms. *Physica A*.

Kefalas, P. and Sakellariou, I. (2017). The invalidity of validating emotional multi-agent systems simulations. In *Proceedings of the 8th Balkan Conference in Informatics*, BCI ’17, pages 8:1–8:8, New York, NY, USA. ACM.

Kimura, R., Hayashi, H., Tatsuki, S., and Tamura, K. (2006). Behavioural and psychological reconstruction process of victims in the 2004 mid-niigata prefecture earthquake. In *Proceedings of the 8th US National Conference on Earthquake Engineering*, pages 1–9.

Li, S., Yu, X., Zhang, Y., and Zhai, C. (2018). A numerical simulation strategy on occupant evacuation behaviors and casualty prediction in a building during earthquakes. *Physica A: Statistical Mechanics and its Applications*, 490:1238 – 1250.

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.

Morita, T., Tsukada, S., and Yuzawa, A. (2015). Analysis of evacuation behaviors in different areas before and after the great east japan earthquake. In *Fifth International Conference on Geotechnique, Construction Materials and Environment*.

Osaragi, T., Morisawa, T., and Oki, T. (2012). Simulation model of evacuation behavior following a large-scale earthquake that takes into account various attributes of residents and transient occupants. In Weidmann, U., Kirsch, U., and Schreckenberg, M., editors, *Pedestrian and Evacuation Dynamics*, pages 469–484. Springer.

Saloma, C., Perez, G. J., Tapang, G., Lim, M., and Palmes-Saloma, C. (2003). Self-organized queuing and scale-free behavior in real escape panic. *PNAS*, 100(21):11947–11952.

Schmidt, S. and Galea, E., editors (2013). *Behaviour - Security - Cluture (BeSeCu): Human behaviour in emergencies and disasters: A cross-cultural investigation*. Pabst Science Publishers.

Shiwakoti, N. and Sarvi, M. (2013). Understanding pedestrian crowd panic: a review on model organisms approach. *Journal of Transport Geography*, 26:12 – 17.

Tsurushima, A. (2019a). Modeling herd behavior caused by evacuation decision making using response threshold. In Davidsson, P. and Verhagen, H., editors, *Multi-Agent-Based Simulation XIX. MABS2018. Lecture Notes in Computer Science, vol 11463*, pages 138–152. Springer.

Tsurushima, A. (2019b). Reproducing symmetry breaking in exit choice under emergency evacuation situation using response threshold model. In *Proceedings of the 11th International Conference on Agents and Artificial Intelligence - Volume 1: ICAART,*, pages 31–41. INSTICC, SciTePress.

Tsurushima, A. (2019c). Symmetry breaking in evacuation exit choice: Impacts of cognitive bias and physical factor on evacuation decision. In van den Herik, J., Rocha, A. P., and Steels, L., editors, *Agents and Artificial intelligence 11th International Conference. ICAART2019. LNAI 11978*, pages 293–316. Springer.

Wilensky, U. (1999). NetLogo. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.

Yang, X., Wu, Z., and Li, Y. (2011). Difference between real-life escape panic and mimic exercises in simulated situation with implications to the statistical physics models of emergency evacuation: The 2008 wenchuan earthquake. *Physica A: Statistical Mechanics and its Applications*, 390(12):2375 – 2380.