

Reproducing Symmetry Breaking in Exit Choice under Emergency Evacuation Situation using Response Threshold Model

Akira Tsurushima

SECOM CO., LTD., Intelligent Systems Laboratory,
8-10-16 Shimorenjaku, Mitaka, Tokyo, Japan

Keywords: Response Threshold Model, Exit Choice, Evacuation, Herd Behavior.

Abstract: When people evacuate from a room with two identical exits, it is known that these exits are often unequally used, with evacuees gathering at one of them. This inappropriate and irrational behavior sometimes results in serious loss of life. In this paper, this symmetry breaking in exit choice is discussed from the viewpoint of herding, a cognitive bias in humans during disaster evacuations. The aim of this paper is to show that the origin of symmetry breaking in exit choice is simple herd behavior, whereas many models in the literature consider the exit choice decisions either as panic or rational behavior. The evacuation decision model, based on the response threshold model in biology, is presented to reproduce human herd behavior. Simulation with the evacuation decision model shows that almost all agents gather at one exit at some frequency, despite individual agents choosing the exit randomly.

1 INTRODUCTION

The choice of exits is a crucial factor in emergency evacuations. The wrong choice will cause inefficient evacuations which are possible to result in serious loss of life. Much work have been done investigating human exit choice in evacuations. Some of these works point to symmetry breaking in exit choice (Elliott and Smith, 1993; Helbing et al., 2002).

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. This inefficient use of exits is not necessarily limited to panic situations. It was observed that, even in an evacuation drill conducted at the New National Theater in Tokyo (Onishi et al., 2015), with incorrect routing of the people at the front, all subsequent people followed, resulted in inappropriate evacuation.

Many researchers consider herd behavior, one of the most representative and important cognitive biases in disaster evacuations, to be an underlying mechanism of symmetry breaking in exit choice (Helbing et al., 2000; Altshuler et al., 2005; Pan, 2006; Lovreglio et al., 2014b). Herd behavior, which is caused by the mental tendency to decide one's behav-

ior based on the behavior of others, has been observed in many evacuations including the Three Mile Island nuclear power plant accident (Cutter and Barnes, 1982) and football stadium disasters in the United Kingdom (Elliott and Smith, 1993). It has been studied extensively in numerous fields and is also known as crowd behavior, conformity bias, peer effect, bandwagon effect and majority syncing bias (Henrich and Boyd, 1998; Dyer et al., 2008; Raafat et al., 2009).

Numerous models have been proposed to represent exit choice in evacuations. However, many of these models consider the major cause of symmetry breaking in exit choice to be either panic (Helbing et al., 2000) or rational behaviors (Lovreglio et al., 2016b). The aim of this paper is to show that symmetry breaking in exit choice can be reproduced by simple herd behaviors. A method is proposed to reproduce symmetry breaking in evacuation through two exits with the use of the evacuation decision model which represents herd behavior in humans (Tsurushima, 2018a). The evacuation decision model is based on the response threshold model in biology. Furthermore, the model does not incorporate predefined rules or scenarios nor assumes the ratio of individualistic and herd behaviors in advance.

The remainder of this paper is organized as follows. Section 2 shows the models of exit choice in the literature. Section 3 discusses herd behavior from

the viewpoint of leaders and followers. Section 4 introduces the response threshold model and Section 5 presents the evacuation decision model. The simulation model of exit choice is stated in Section 6 and the simulation results are analyzed in Section 7. The discussion and the conclusion are given in Section 8 and Section 9, respectively.

2 RELATED WORKS

Numerous studies for exit choice in evacuations have been conducted since Helbing et al. (2000). Evacuation experiments with human subjects were conducted to investigate several features of human exit choice behaviors (Kobes et al., 2010; Fridolf et al., 2013) and a database containing evacuation data including exit choice was developed (Shi et al., 2009). It was also reported that symmetry breaking in emergencies occurs not only in humans but also in ants (Altshuler et al., 2005; Ji et al., 2017) and mice (Saloma et al., 2003).

Multi-agent simulations and cell automaton models have been used to study efficient evacuations in disaster situations. Many models to reproduce human exit choice in evacuations have been proposed by several authors and these models can be categorized into the following five classes.

Rule based Model

Agents in this class have predefined rules, scenarios, or sequences of actions, and their choice of exits is made by these rules. One example of such a rule is “if an agent detects two exits and its uncertainty level is high, then the agent pursues the exit that has the most crowds” (Pan et al., 2005). These rules are built by surveys conducted at target sites and some literature (Augustijn-Beckers et al., 2010), or based on theories such as Cialdini’s social proof theory (Pan, 2006), the OCC (Ortony, Clore and Collins) model (Sharpan-skykh and Treur, 2010; Zia et al., 2011), etc. The choice of rules are arbitrary made by designers though there is no widely accepted general way of choosing these rules.

Cell Automaton Model

The cell automaton (CA) model represents collective behaviors of evacuees using a two dimensional matrix with simple rules. This model can efficiently reproduce dynamics of self-organization phenomena such as jamming, clogging, oscillation and so on. The relation between evacuation time and exit width or door

separation was studied using the CA model (Perez et al., 2002). The floor field model was also used to analyze herd behaviors by varying the length between two exits (Kirchner and Schadschneider, 2002) and in environments with multiple exits and obstacles (Huang and Guo, 2008). One of the strengths of the CA model is its high computational efficiency since the model itself is simple and abstract. However, none of the above was able to reproduce the symmetry breaking in exit choice.

Social Force Model

Helbing et al. (2000) introduced the phenomenon of inefficient use of alternative exits in evacuations. They conducted simulations of evacuation from a room with multiple exits filled with smoke using the social force model (Helbing et al., 2000; Helbing et al., 2002). They showed that some mixture of individualistic and herd behaviors is more efficient than purely individualistic or herd behaviors. However, in their simulations, the relation between exit choice and evacuation efficiency is unclear. What they have shown is the efficiency of *finding* unknown exits in invisible environments, not the evacuation efficiency of *choosing* alternative exits. The agents in their model do not choose exits in any meaningful way since, in the social force model, the desired direction of an agent is predetermined via input to the model.

Game Theory based Model

Some models assume the existence of a utility function in an agent, with the agent behaving to maximize its utility. In the game theory based model, agents interact with each other and try to achieve Nash equilibrium for the game in order to maximize mutual utilities. In (Lo et al., 2006) the choice of exits was formulated as a non-cooperative game, and the mixed strategy solution of the game was analyzed. In exit choice experiments using ants, the number of ants escaping from different exits was found to be equal to the ratio between the widths of the exits; and this finding was analyzed from the viewpoint of Nash equilibrium (Ji et al., 2017).

Discrete Choice Model

The discrete choice model assumes that agents make exit choices decisions based on a finite set of attributes associated with the exit alternatives. The utility function of an agent consists of two terms: the first part is the expected value of the perceived utility derived from the attributes, and the second term is its random

residual from the real value. A mixed logit model or multinomial logit model is often used to formulate the utility function, and data collected from human subjects are applied to estimate its coefficients. For example, Lovreglio et al. uses the following factors to formulate the utility function (Lovreglio et al., 2016a).

- Number of evacuees close to the exits
- Flow of evacuees through the exits
- Number of evacuees close to the decision maker towards one of the exits
- Smoke near the exits
- Evacuation lights above the exits
- Distance of the decision maker from the exit

The relation between evacuation time and exit choice strategies (e.g. least distance, least travel time, hive, vision field) was studied using multinomial logit models and an internet survey (Duives and Mahmasani, 2012). Paper-based surveys and face-to-face interviews have been conducted using the SP-off-RP method to formulate the exit choice behaviors using multinomial logit models and mixed logit models (Haghani et al., 2014). The difference between behavioral features of emergency and non-emergency egress was analyzed using a mixed logit model and face-to-face interviews (Haghani and Sarvi, 2016). Online surveys using video simulations were conducted to formulate a mixed logit model (Lovreglio et al., 2014a; Lovreglio et al., 2014b). In (Lovreglio et al., 2016a) the effect of the presence of smoke and emergency lighting was analyzed using online surveys with virtual reality and a mixed logit model.

Utility-based models (e.g. game theory-based models and discrete choice models) consider the exit choice decisions as rational behaviors, whereas other models consider them as the result of panic or irrational behaviors (Lovreglio et al., 2016b). The major limitation of utility based approaches is the assumption that decisions in emergency evacuations can be obtained through surveys and interviews. This is because it is difficult to reproduce the imminent situation of real evacuations, and subjects are only able to respond to questionnaires based on conscious decisions.

In this paper, we propose a novel approach to reproduce the symmetry breakage in exit choice. Our approach, which is able to reproduce herd behaviors in evacuations, is based on the response threshold model in biology. It shows that symmetry breaking in exit choice can be reproduced without assuming any decision making process including rules, scenarios, or

utilities. In this approach, the symmetry breaking in exit choice emerges as the result of herd behaviors, even though agents choose the exit randomly.

3 LEADERS AND FOLLOWERS IN HERDING

Raafat et al. (Raafat et al., 2009) defined herding as “the alignment of thoughts or behaviors of individuals in a group (herd) through local interactions rather than centralized coordination.” According to this definition, each individual is affected by other individuals in some way when determining its own behavior. However, there must at least be one individual that behaves through its own intentions and affects the others, otherwise no one would be able to act.

Thus it is reasonable to assume that a herd consists of leaders and followers, where the leaders determine their behaviors through their own intentions and the followers determine their behaviors through the behavior of other leaders or followers. In addition, no individual shall affect or be affected by all the members of the group.

This leads to several questions. How is a leader or follower determined? Is there an appropriate ratio of leaders to followers? Are the roles of the leaders and followers fixed, or do they change dynamically? If they change, what rules affect those changes? The answers to these questions are not obvious, especially if a privileged and centralized control mechanism does not exist. This can be called the leader and follower problem.

If the leader and follower problem is focused on evacuation, where a room with a single exit is filled with randomly distributed agents, the goal would be to evacuate all the agents from the room. A leader will be intent on leaving the room and be able to adjust its behaviors accordingly, so clearly it is able to leave the room. On the other hand, a follower determines its own behavior through the behavior of others, regardless of its own intention. In this case, a follower will move toward the exit if many agents move, but will stay put if they do not. Thus it is unclear whether a follower will be able to leave the room.

Two simulation experiments¹ were conducted to investigate the nature of the leader and follower problem. The aim of these experiments is to show that simple rules of assigning the role of leaders and followers are inadequate to reproduce evacuation behaviors. In these experiments, 200 agents are distributed

¹NetLogo 6.0.2 (Wilensky, 1999) is used to implement the models presented in this paper.

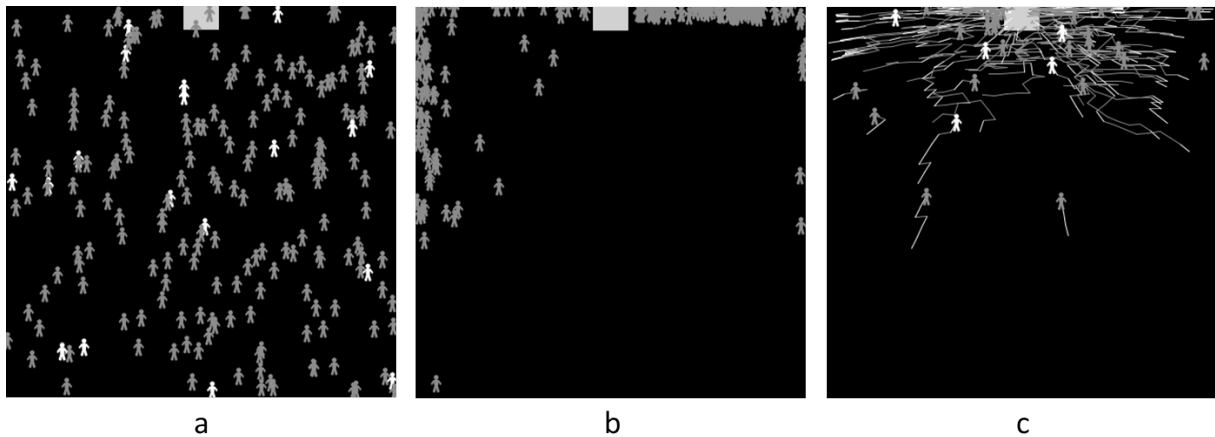


Figure 1: The leader and follower simulations. a) Experiment 1 or 2 - Initial state, b) Experiment 1 - Terminal state, c) Experiment 2 - State near the end of the experiment (Thin lines following agents indicate their trails).

in a room (33×33 units) with an exit (Figure 1a). A leader agent (white) moves toward the exit but a follower agent (gray) randomly chooses an agent in its vicinity and mimics its movement.

Experiment 1

In experiment 1, 10% of the agents are randomly selected as the leaders and the remaining agents are followers. The roles of the leader and follower are fixed during simulation.

Figure 1b shows the terminal state of experiment 1. All leaders and some followers have evacuated but most of the followers are still in the room. Since they are all followers, they cannot move through their own intention, and thus all of them are unable to move. This is because most followers choose to follow other followers, but only some follow leaders. Chains of followers who do not have a leader will not be able to exit under these conditions. Only followers following a leader will be able to exit.

It is obvious that the assumptions of experiment 1 are not suitable as a solution to the leader and follower problem.

Experiment 2

In experiment 2, 10% of agents are chosen as leaders as in experiment 1, but the roles of the leaders and followers dynamically change during the simulation. Therefore, an agent acts as a leader at certain moments, but acts as a follower at other times. Only the ratio of the leaders and followers is constant.

At the end of the simulation, all agents have left the room. Thus experiment 2 may be a candidate solution of the leader and follower problem. However,

as shown in Figure 1c, some unnatural and wasteful movements (e.g. oscillating back and forth between the two walls) of the followers are observed just before the end of the simulation. Such unnatural movements can be avoided by increasing the ratio of leaders, but it is not obvious what ratio is appropriate. Also, the assumption that the ratio of the leaders and followers is always constant is unrealistic.

Derek Sivers pointed out the importance of the first follower in his famous talk at TED2010 and said “the first follower is what transforms a lone nut into a leader”². This implies that there is no leader without any follower, and vice versa. Therefore, leader and follower is a mutual dependence relation since the existence of one can only be supported by the existence of the other.

From the above, we conclude that

- the roles of leaders and followers should change over time
- the assumption that the ratio of leaders to followers is constant is unrealistic.
- leaders and followers is a mutual dependence relation

Hasegawa et al. (2016) showed a similar kind of mutual relation between hardworking ants and lazy ants using the response threshold model. There was a negative correlation between hardworking and lazy workers. Lazy workers automatically replaced hardworking but resting workers in processing tasks when the number of hardworking workers decreased (Hasegawa et al., 2016). Therefore, the existence of inactive workers is only supported by the existence of

²https://www.ted.com/talks/derek_sivers_how_to_start_a_movement

active workers, and vice versa. To take these points into account, the response threshold model, which is an ideal model to represent this kind of mutual relationship, is adopted as a model for human herd behaviors in evacuation situations.

4 THE RESPONSE THRESHOLD MODEL

The response threshold model (Bonabeau et al., 1996) is well known in biology and ecology as a model for division of labor in eusocial organisms. It is also known as an efficient distributed algorithm to solve task allocation problems (Bonabeau et al., 1997) and has a variety of applications in engineering including the coordination of multiple robots (Castello et al., 2016; Krieger et al., 2000), efficient coverage of distributed mobile sensor networks (Low et al., 2004), and distributed allocation of multi-agent systems (Agassounon and Martinoli, 2002).

The response threshold model consists of agents with response thresholds θ and an environment with task-related stimuli s . An agent responds to the stimuli and engages in a task if s exceeds its θ . The intensity of s will increase if the task is not performed sufficiently and will decrease if a sufficient number of agents are engaged in the task. An agent i has a random variable X representing its mental state. The agent is active if $X = 1$, and inactive if $X = 0$. The probability P_i that an agent will be active per unit time is:

$$P_i(X = 0 \rightarrow X = 1) = \frac{s^2}{s^2 + \theta_i^2}, \quad (1)$$

and inactive per unit time is:

$$P_i(X = 1 \rightarrow X = 0) = \varepsilon, \quad (2)$$

where ε is a constant probability with which an active agent gives up task performance. The intensity of s per unit time is given by:

$$s(t+1) = s(t) + \delta - \alpha \frac{c}{C}, \quad (3)$$

where δ is the increase of the stimulus per unit time, α is a scale factor of the efficiency of task performance, c is the number of agents engaging in the task, and C is the total number of agents.

5 THE EVACUATION DECISION MODEL

In this paper, the evacuation decision model (Tsurushima, 2018a), based on the response threshold

model, which reproduced the evacuation behaviors observed at the Great East Japan Earthquake (Tsurushima, 2018b), is adopted to study symmetry breaking in exit choice in evacuations.

By designating the task to be performed as removing all agents from the room, the evacuation decision model can be applied for solving the leader and follower problem in order to represent human herd behaviors. The environment (the room) has a risk value r which represents the level of objective risks in the environment, and an agent has risk perception parameter μ which represents an individual's risk sensitivity.

In contrast to the model (equation 3) discussed in Section 4, each agent in this model has its own stimulus s_i which is the local estimate of the stimulus s instead of the global stimulus of the environment. The stimulus of the agent i is defined as:

$$s_i(t+1) = \max\{s_i(t) + \hat{\delta} - \alpha(1-R)F, 0\}, \quad (4)$$

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

$$\hat{\delta} = \begin{cases} \delta & \text{if } r > 0 \\ 0 & \text{otherwise,} \end{cases} \quad (5)$$

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

$$R(r) = \frac{1}{1 + e^{-g(r-\mu_i)}}, \quad (6)$$

where g is the activation gain which determines the slope of the sigmoid function. F is the task progress function, the local estimate of task performance:

$$F(n) = \begin{cases} 1 - n/N_{max} & n < N_{max} \\ 0 & \text{otherwise,} \end{cases} \quad (7)$$

where n is the number of agents in the vicinity, and N_{max} is the maximum number of agents in the vicinity. Each agent has a visibility of 120 degrees and a sight distance of five units toward the west direction. This range is considered the vicinity of an agent.

6 THE EXIT CHOICE SIMULATION

We assumed a rectangular room (40×128 units) with four walls in the directions north, east, south, and west clockwise from the top, with two exits at the west end of the room, where the north and south exits are located at the top left and bottom left, respectively (Figure 2). As shown in Figure 2, there are 600 agents initially distributed in the middle of the room in a rectangular shape (14×96 units) and start moving to the west according to the risk level r .

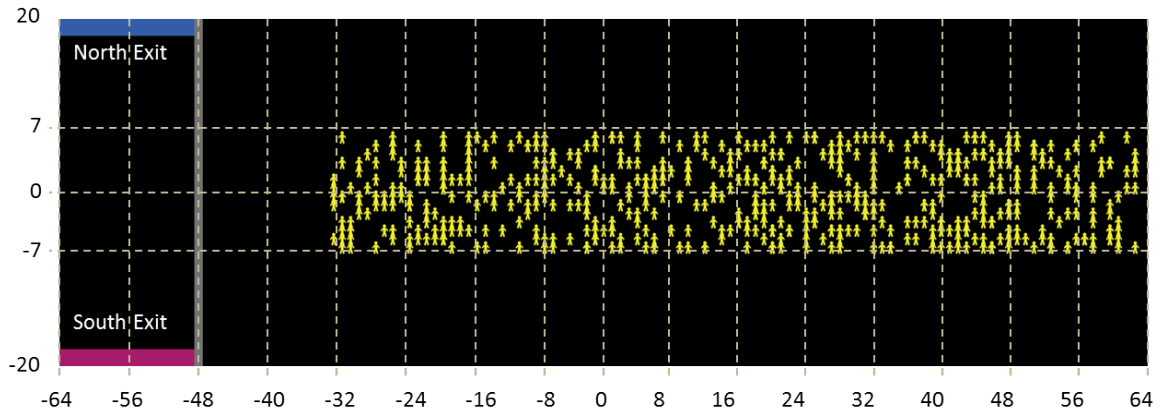


Figure 2: The initial screen of the simulation.

Algorithm 1: Follower's action ($X = 0$).

```

 $V \leftarrow$  the set of agents in the vicinity
 $v_0 \leftarrow$  the number of agents not moving in  $V$ 
 $v_1 \leftarrow$  the number of agents moving in  $V$ 
if  $v_1 > v_0$  then
   $M \leftarrow$  a set of the moving agents in the vicinity
   $e_N \leftarrow$  the number of agents with  $d = north$  in  $M$ 
   $e_S \leftarrow$  the number of agents with  $d = south$  in  $M$ 
   $e_W \leftarrow$  the number of agents with  $d = undecided$  in  $M$ 
  if  $e_N$  is the maximum then
     $d \leftarrow north$ 
    face to the north exit
  else if  $e_S$  is the maximum then
     $d \leftarrow south$ 
    face to the south exit
  else if  $e_W$  is the maximum then
     $d \leftarrow undecided$ 
    face to the west
  end if
  take one step forward
else
  do nothing
end if

```

The northern and southern sections of the room are initially left empty at the beginning of the simulation because each agent will choose either *north* or *south* direction later (the initial choice of the direction is set to *undecided*). The gray vertical line at -48 (G-line) indicates the position where an agent must decide to go to the northern or southern exit, if its direction is not determined by herd behavior ($X = 0$). This decision is only made if the mental state of the agent is a leader ($X = 1$); and the choice of north or south is made at random (choose north with probability 0.5). Assuming $d = undecided$ and $X = 0$ as initial settings, an agent will perform Algorithm 1 if it is a



Figure 3: The exit choice simulation.

Algorithm 2: Leader's action ($X = 1$).

```

 $cx \leftarrow$  the X-coordinate of the current position
 $gx \leftarrow$  the X-coordinate of G-line
if  $cx \leq gx$  and  $d = undecided$  then
   $randValue \leftarrow$  randomly select a value  $\in [0, 1]$ 
  if  $randValue < 0.5$  then
     $d \leftarrow north$ 
    face to the north exit
  else
     $d \leftarrow south$ 
    face to the south exit
  end if
else
  face to the west
end if
  take one step forward

```

follower ($X = 0$) or Algorithm 2 if it is a leader ($X = 1$). An agent executes Algorithm 1 or Algorithm 2 every unit of time.

Thus the follower may determine its direction even though it has not yet crossed G-line. The parameters of the evacuation decision model are assumed to be $\epsilon = 0.8$, $\delta = 0.5$, $\alpha = 1.2$, $N_{max} = 10$, and $g = 1.0$.

7 RESULTS AND ANALYSIS

As shown in Figure 3, in many cases, the agents are equally divided between north and south exits. De-

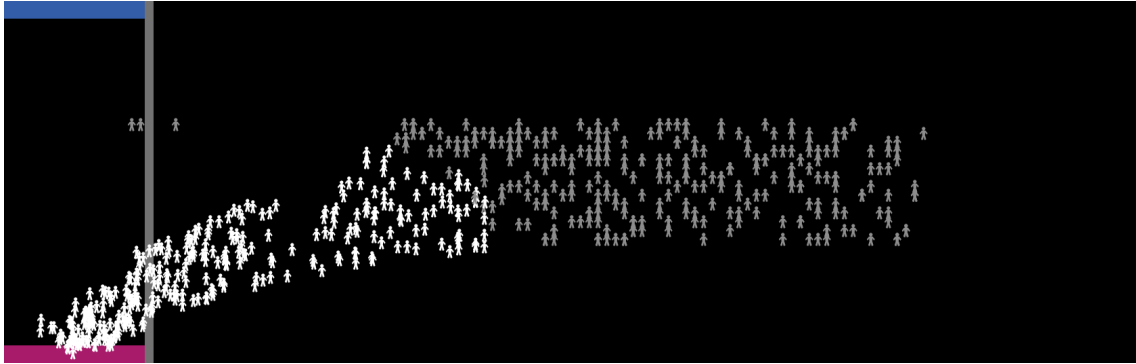


Figure 4: Symmetry breaking in the exit choice simulation. Notice the arc when agents choose the same exit.

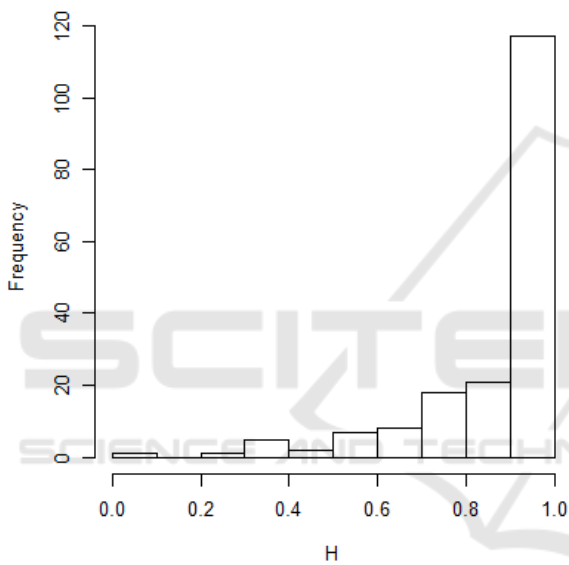


Figure 5: The frequency of H .

spite the fact that each agent randomly chooses north or south, most agents will automatically head toward the closer exit.

Sometimes almost all agents happen to choose the same direction and gather at one exit (Figure 4). In this figure, the decisions of the white agents, which move to the south direction, propagate far to the east from G-line (the arc in the figure). This kind of behavior is commonly observed when many agents choose the same direction.

The entropy of the agents that select north or south can be expressed by the following equation:

$$H = -r_n \log(r_n) - r_s \log(r_s), \quad (8)$$

where r_n is the ratio of the agents heading north and r_s is the ratio of the agents heading south at the end of the simulation. The range of H is $H \in [0.0, 1.0]$. The ratios of the agents moving north and south are

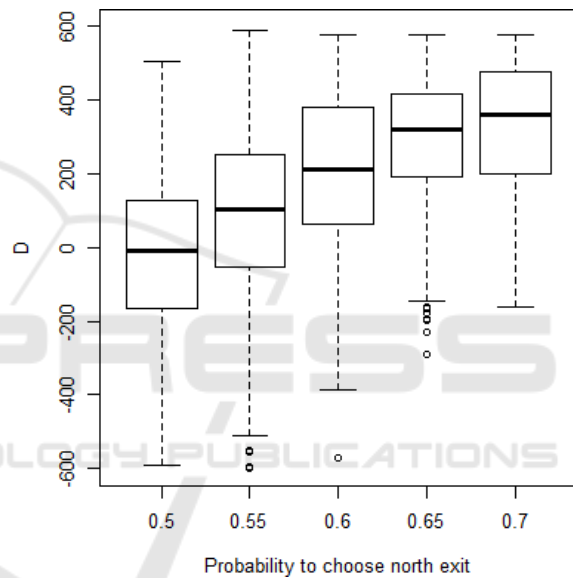


Figure 6: The distribution of D with different probabilities.

equal if $H = 1.0$, and all the agents moving toward the same direction if $H = 0.0$. The frequency of H over 180 simulations is shown in Figure 5. Although the frequency is small, the phenomenon where most of the agents gathered at a single exit was observed.

Figure 6 shows how the difference between the number of agents choosing north and south (D) varies with the probability to choose the north exit. For example, $D = 600$ means all agents evacuated from the north and $D = -600$ means all agents evacuated from the south. The figure shows that most agents may happen to gather at the opposite (south) exit even though leaders chose the north exit with a probability greater than 0.5. For instance, there was a case where the leaders chose north with probability 0.6, but 586 agents (97.7%) gathered at the south exit.

The value of ϵ and the position of G-line are major factors that affect the value of H . Figure 7 shows the

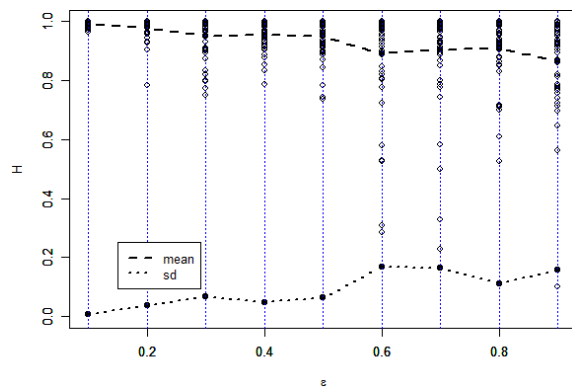


Figure 7: Relationship between ϵ and H over 50 simulations.

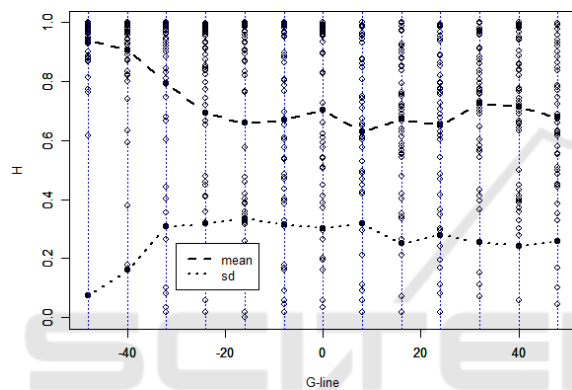


Figure 8: Relationship between position of G-line and H over 50 simulations.

results of simulations varying the value of ϵ from 0.1 to 0.9. The values of H in each simulation are shown in Figure 7 (small circles on dotted lines). The means of 50 simulations with different ϵ are shown by the broken line and the standard deviations are shown by the dotted line. In Figure 7, the symmetry breakings are only observed when ϵ is greater than 0.5 and the means of H tends to decrease as the values of ϵ increase. This implies that the greater chances of herd behavior results in the symmetry breakings.

Figure 8 shows the results of simulations where the position of G-line was moved from -48 to +48.

In Figure 8, the X-axis shows the position of G-line. The G-lines in Figure 3 and Figure 4 are located at -48, and the center of the room is at 0. The values of H in each simulation are shown in Figure 8 (small circles on dotted lines). The means of 50 simulations with different G-line positions are shown by the broken line and the standard deviations are shown by the dotted line. This clearly shows that the mean of H tends to decrease as the position of G-line shifts to east, meaning that an earlier decision results in the uneven use of two exits. An earlier decision implies that

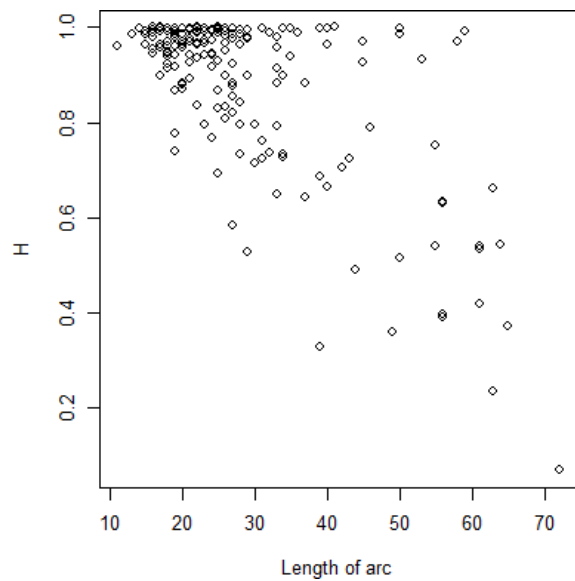


Figure 9: Correlation of arc length of agents and H .

the agents have more chances to be affected by others because all agents move in the same direction and the traveling time of an agent moving along with others who have already chosen their direction increases.

The long arc of white agents in Figure 4 shows that when symmetry breaking happens, many agents have already made decisions well before G-line. The results of 180 simulations in which the position of G-line is set to -48 are given in Figure 9. This shows the correlation of the values of H and the maximum distances between G-line and the positions of decisions made by the agents (X-axis). The correlation coefficient of -0.6715 suggests that a longer arc will result in a smaller H .

In Figure 9, a few samples with long arcs and large H values are observed, whereas no samples with short arcs and small H value is observed. This suggest that the long arc of agents may be an important factor in symmetry breaking in the exit choice problem.

8 DISCUSSION

Lovreglio et al. (2016b) stated that the evacuation decision of choosing the most crowded exit can be the result of a rational decision making process instead of an “irrational-panic” decision (Lovreglio et al., 2016b). In our exit choice simulation, the evacuation decision model shows that even though an agent selects exits randomly, with some frequency we can observe almost all agents gathering at one exit. This shows that symmetry breaking in exit choice during evacuation can be the result of simple herd behavior,

disregarding any rational decision making processes. The fact that the same phenomenon can be observed in experiments using organisms without intelligence such as ants and mice (Altshuler et al., 2005; Ji et al., 2017; Saloma et al., 2003) also supports our result. Furthermore, our results also show that herd behavior is a major factor of this phenomenon and that the arc length of agents, indicating early decision making, especially affects the occurrence of symmetry breaking in the exit choice.

The evacuation decision model only deals with cognitive or psychological factors such as decision, perception, and bias; physical factors such as collision, clogging, and disturbance are not considered at all. An agent can simply pass through other agents, even though they are positioned in front of it. It is worth noting that the symmetry breaking in evacuation occurs despite disregarding physical factors.

The evacuation decision model is a bio-inspired distributed task allocation algorithm based on the response threshold model. The model itself is simple, simply switching between two mental states, $X = 0$ and $X = 1$, in some probabilistic manner. What to do in these states is not stated and is open to the user, giving broad generality to the model. In the case of the exit choice simulation, we chose Algorithm 1 and Algorithm 2 for $X = 0$ and $X = 1$, respectively. The evacuation decision model only represents the cognitive bias in evacuation, but for actual evacuation scenarios, the consideration of physical factors is necessary; and, especially in the case of human evacuation, higher cognitive functions such as choosing the shortest route are also very important to consider.

The generality of the evacuation decision model allows these factors to be easily incorporated. The higher cognitive model can be incorporated in the state $X = 1$, which shows intentional decision making. By assuming the output as a movement vector, the evacuation decision model can be employed easily in conjunction with a physical pedestrian dynamics model such as Helbing's social force model. The evacuation decision model can be viewed as a platform that separates a higher cognitive function and a physical model, and then naturally connects these two by introducing the layer of cognitive bias.

9 CONCLUSION

The evacuation decision model, based on the response threshold model in biology, represents human herd behavior in evacuation situations. The exit choice simulation with the evacuation decision model shows that almost all evacuees gather at one exit at a non-

negligible frequency even though they choose exits randomly. The results show that exit choice decision can be the result of simple herd behaviors disregarding any rational decision. The simulation also showed the relation between these inappropriate uses of exits and earlier decision making.

ACKNOWLEDGEMENTS

The author is grateful to Robert Ramirez, Yoshikazu Shinoda, and Kei Marukawa for their helpful comments and suggestions.

REFERENCES

- Agassounon, W. and Martinoli, A. (2002). Efficiency and robustness of threshold-based distributed allocation algorithms in multi-agent systems. In *Proceedings of the first international joint conference on Autonomous agents and multiagent systems AAMAS '02*, volume 3, pages 1090–1097.
- Altshuler, E., Ramos, O., Nuñez, Y., Fernández, J., Batista-Leyva, A. J., and Noda, C. (2005). Symmetry breaking in escaping ants. *The American Naturalist*, 166(6):643–649.
- Augustijn-Beckers, E.-W., Flacke, J., and Retsios, B. (2010). Investigating the effect of different pre-evacuation behavior and exit choice strategies using agent-based modeling. *Procedia Engineering*, 3:23–35.
- Bonabeau, E., Sobkowski, A., Theraulaz, G., and Deneubourg, J.-L. (1997). Adaptive task allocation inspired by a model of division of labor in social insects. In *Proceeding of Biocomputing and Emergent Computation*, pages 36–45.
- 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.
- Castello, E., Yamamoto, T., Libera, F. D., Liu, W., Winfield, A. F., Nakamura, Y., and Ishiguro, H. (2016). Adaptive foraging for simulated and real robotic swarms: the dynamical response threshold approach. *Swarm Intelligence*, 10(1):1–31.
- Cutter, S. and Barnes, K. (1982). Evacuation behavior and Three Mile island. *Disasters*, 6(2):116–124.
- Duives, D. C. and Mahmassani, H. S. (2012). Exit choice decisions during pedestrian evacuations of buildings. *Transportation Research Record: Journal of the Transportation Research Board*, 2316:84–94.
- Dyer, J. R. G., Ioannou, C. C., Morrell, L. J., Croft, D. P., Couzin, I. D., Waters, D. A., and Krause, J. a. (2008). Consensus decision making in human crowds. *Animal Behavior*, 75:461–470.

- 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.
- Fridolf, K., Ronchi, E., Nilsson, D., and Frantzich, H. (2013). Movement speed and exit choice in smoke-filled rail tunnels. *Fire Safety Journal*, 59:8–21.
- Haghani, M., Ejtemai, O., Sarvi, M., Sobhani, A., Burd, M., and Aghabayk, K. (2014). Random utility models of pedestrian crowd exit selection based on SP-off-RP experiments. *Transaction Research Procedia*, 2:524–532.
- Haghani, M. and Sarvi, M. (2016). Human exit choice in crowd built environments: investigating underlying behavioural differences between normal egress and emergency evacuations. *Fire Safety Journal*, 85:1–9.
- Hasegawa, E., Ishii, Y., Tada, K., Kobayashi, K., and Yoshimura, J. (2016). Lazy workers are necessary for long-term sustainability in insect societies. *Scientific Report*, 6(20846).
- Helbing, D., Farkas, I., and Vicsek, T. (2000). Simulating dynamical features of escape panic. *Nature*, 407(28):487–490.
- Helbing, D., Farkas, I. J., Molnar, P., and Vicsek, T. (2002). Simulation of pedestrian crowds in normal and evacuation situations. *Pedestrian and Evacuation Dynamics*, 21(2):21–58.
- Henrich, J. and Boyd, R. (1998). The evolution of conformist transmission and the emergence of between-group differences. *Evolution and Human Behavior*, 19:215–241.
- Huang, H.-J. and Guo, R.-Y. (2008). Static floor field and exit choice for pedestrian evacuation in rooms with internal obstacles and multiple exits. *Physical Review E*, 78:021131.
- 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*.
- Kirchner, A. and Schadschneider, A. (2002). Simulation of evacuation processes using a bionics-inspired cellular automaton model for pedestrian dynamics. *Physica A*, 312:260–276.
- Kobes, M., Helsloot, I., Vries, B. d., and Post, J. (2010). Exit choice, (pre-)movement time and (pre-)evacuation behavior in hotel fire evacuation - Behavioural analysis and validation of the use of serious gaming in experimental research. *Procedia Engineering*, 3:37–51.
- Krieger, M. J. B., Billeter, J.-B., and Keller, L. (2000). Ant-like task allocation and recruitment in cooperative robots. *Nature*, 406:992–995.
- Lo, S., Huang, H., Wang, P., and Yuen, K. (2006). A game theory based exit selection model for evacuation. *Fire Safety Journal*, 41:364–369.
- Lovreglio, R., Borri, D., dell’Olio, L., and Ibeas, A. (2014a). A discrete choice model based on random utilities for exit choice in emergency evacuations. *Safety Science*, 62:418–426.
- Lovreglio, R., Fonzone, A., and dell’Olio, L. (2016a). A mixed logit model for predicting exit choice during building evacuations. *Transportation Research Part A: Policy and Practice*, 92:59–75.
- Lovreglio, R., Fonzone, A., dell’Olio, L., and Borri, D. (2016b). A study of herding behaviour in exit choice during emergencies based on random utility theory. *Safety Science*, 82:421–431.
- Lovreglio, R., Fonzone, A., dell’Olio, L., and Ibeas, A. (2014b). The role of herding behaviour in exit choice during evacuation. *Procedia - Social and Behavioral Sciences*, 160:390–399.
- Low, K. H., Leow, W. K., and Ang, Jr., M. H. (2004). Task allocation via self-organizing swarm coalitions in distributed mobile sensor network. In *AAAI ’04 Proceedings of the 19th national conference on artificial intelligence*, pages 28–33.
- Onishi, M., Yamashita, T., Hoshikawa, T., and Sato, K. (2015). Transmission of knowledge for evacuation drill using pedestrian tracking and simulation - example of opera concert with evacuation drill in new national theater, Tokyo -. *Handouts in SIGCONF 2015, The Japanese Society for Artificial Intelligence*, SIG-KST-026-06.
- Pan, X. (2006). *Computational modeling of human and social behaviour for emergency egress analysis*. PhD thesis, Stanford University.
- Pan, X., Han, C. S., and Law, K. H. (2005). A multi-agent based simulation framework for the study of human and social behaviour in egress analysis. In *International Conference on Computing in Civil Engineering 2005*, pages 1–12.
- Perez, G. J., Tapang, G., Lim, M., and Saloma, C. (2002). Streaming, disruptive interference and power-law behavior in the exit dynamics of confined pedestrians. *Physica A*, 312:609–618.
- Raafat, R. M., Chater, N., and Frith, C. (2009). Herding in humans. *Trends in Cognitive Sciences*, 13(10):420–428.
- 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.
- Sharpanskykh, A. and Treur, J. (2010). Adaptive modeling of social decision making by agents integrating simulated behaviour and perception chains. *Computational Collective Intelligence. Technologies and Applications. ICCCI 2010. Lecture Notes in Computer Science*, 6421:284–295.
- Shi, L., Xie, Q., Cheng, X., Chen, L., Zhou, Y., and Zhang, R. (2009). Developing a database for emergency evacuation model. *Building and Environment*, 44:1724–1729.
- Tsurushima, A. (2018a). Modeling herd behavior caused by evacuation decision making using response threshold. In *Pre-proceedings of the 19th International Workshop on Multi-Agent-Based Simulation (MABS2018) - A FAIM workshop*, Stockholm, Sweden.
- Tsurushima, A. (2018b). Simulating earthquake evacuation decisions based on herd behavior. In *Proceedings of*

the 35th Annual Meeting of the Japanese Cognitive Science Society.

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

Zia, K., Riener, A., Ferscha, A., and Sharpanskykh, A. (2011). Evacuation simulation based on cognitive decision making model in a socio-technical system. In *15th IEEE/ACM International Symposium on Distributed Simulation and Real Time Applications*, pages 98–107.

