Contagion of evacuation decision making on real map

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ABSTRACT
In this paper, we deal with evacuation decision making of people in the disaster area. By threshold model, we discuss about whether all agents decide evacuate or not. It has been confirmed that not all people in the affected area evacuated during the Great East Japan Earthquake. But, many evacuation simulations treat that all people evacuate. In the precious work, on the assumption that all people decide evacuate, we treated about the needed time to evacuate all people if psychological conditions exist at the time of disaster. In this paper, we deal with the condition that not all people evacuate and focus on contagion of evacuation decision making on real map. We found that for contagion of evacuation decision making, local neighborhood is needed and connection of sub network is needed.

Categories and Subject Descriptors
I.6.4 [Computing Methodologies]: Simulation and Modeling-Model Validation and Analysis

General Terms
Human Factors

Keywords
Tsunami, evacuation, multi-agent simulation, Kure city.

1. INTRODUCTION
The Great East Japan Earthquake GEJE was a 9.0 magnitude undersea mega thrust earthquake that occurred on Friday, March 11, 2011. After the earthquake, since there were many people who were unable to effectively evacuate, damage was considered to have spread. In fact, the ratio of victims to the residents in GEJE was lower than that in the Meiji Sanriku Earthquake, which was an 8.2 magnitude undersea mega thrust earthquake that occurred off the Pacific coast of Japan on June 15, 1896. It is believed that various disaster prevention methods take effect [22]. Although according to a questionnaire and interview [4], 30%–40% of the people did not evacuate in Japan. In addition, it has been confirmed that not all people in the affected area evacuated in GEJE [7].

There have been numerous studies on tsunamis, especially in Japan, such as the simulation of tsunami hydrodynamics performed by the Japan Cabinet Office or the Japan Coast Guard. Conversely, simulations such as Ohata [17], Helbing [3], and Mas [13] have focused on crowd behavior of at time of disaster. In the latter simulations, most of researches adopt multi-agent simulation [10]. Furthermore, Katada [11] integrated simulations of tsunami hydrodynamics and evacuations.

Noting psychological conditions and behavioral characteristics at time of disaster are also important [5]. After GEJE, some people successfully brought an elderly person unable evacuate on his own to a shelter from the seaside in Natori city. But, some people failed and were victim of tsunami [14]. In Ishinomaki city, 2,500 people successfully evacuated to shelters. On the other hand, 40,000 people returned to the seaside from the hillside by a car to evacuate family members. Then, the resulting traffic jam brought the streets to a standstill [15].

Drabek [1] shows that families evacuated as units with a strong tendency to go to homes of relatives rather than in public shelters before flood at Denver in 1965. Quaratelli [19] shows that there are three wide-spread but incorrect images of withdrawal which often influence disaster planning and emergency organization responses to disasters. Victims actively participate in extensive patterns of informal mutual and self help. Perry [18] formulates a number of recommendations for building "incentives to evacuate" into warning systems, that utilize normal behavioral tendencies which have been observed in past warning responses. Hirose [4] stated that psychological conditions occur at the time of disaster. However, limited studies utilize a psychology model for evacuation simulation.

Contagion is said to occur if one behavior can spread from a finite set of agents to the whole population. When can behavior that is initially adopted by only an infinite set of agents spread to the whole population? Hasan et al. [2] adopt the threshold model of social contagion process proposed by Watts [23]. And they propose to develop a novel network science model to specifically investigate the social influence process within a community network. And they show that faster propagation of warning is observed in community networks with greater inter-community connections. And they investigate effect of the initial seed on cascade propagation for uniform degree distribution. And they show that the local neighborhood will be relatively smaller than the affected cluster size which makes the cascade to propagate fast.

Newman [16] reviews developments in the field, inspired by empirical studies of networked systems such as the Internet, social networks, and biological networks, researchers have in recent years developed a variety of techniques and models to help us understand or predict the behavior of these systems. The origin of large but rare cascades that are triggered by small initial

BICT 2014, December 01-03, Boston, United States

DOI 10.4108/icst.bict.2014.257887

shocks is a phenomenon that manifests itself as diversely as cultural fads, collective action, the diffusion of norms and innovations, and cascading failures in infrastructure and organizational networks [23]. Watts presents a possible explanation of this phenomenon in terms of a sparse, random network of interacting agents whose decisions are determined by the actions of their neighbors according to a simple threshold rule.

In our former work [9], we also dealt with threshold model [20] and showed that collective behavior is affected in the structure of the social network, the initial collective behavior and diversity. Then, we also dealt with cascade model [23]. We found that collective behavior is affected in the structure of the social network and threshold and collective behavior was stochastic [9]. Moreover, collective behavior is almost same as threshold model, though the decision is not interactive and simultaneously. That is, our results with heterogeneous rules or heterogeneous networks are possible to apply for cascade model.

In our previous work [8], we adopted a multi-agent simulation that focused on psychological conditions at time of disaster. We supposed that all agents evacuate and agents move to shelter. We confirm that it takes more time to complete evacuations if psychological conditions exist at the time of disaster. And we found that evacuation time that all agents finish evacuation shortens when another agent in a hurry to evacuate. There, similar to other evacuation simulations, we set that all people evacuate. In this paper, to deal with the condition that not all people evacuate and we want to combine our former work [9] and our previous work [8] and we deal with contagion of evacuation decision making.

2. SIMULATION MODEL

2.1 Kure City

We reproduced the Ohata' model [17] on multi-agent simulator Artisoc [24]. We supposed that the Nankai Trough Earthquake occurred in the day-time on Sunday when the majority of the residents of Kure city were at home. It is estimated that the magnitude of the earthquake was 6+ and the resulting tsunami with waves of up to 4 m in height reached the city 161 min after the earthquake. We deal with the area forecasted to be flooded [6], especially in the lower altitude areas of less than 10 m. In our model, we adopted 10 towns in the city and 30 shelters [8] as shown in Table 1. In this paper, we reproduce the contagion of evacuation model.

According to the basic resident register of March 31, 2013 [12], the residents per household averaged 1.937. We set an agent as two people, which is the average population of a household, as shown in Table 1. According to former papers [1][21], many people evacuated by family unit. Agent is generated on an intersection node for each town at the first time step. Because number of agents are 10,088 and number of intersection node are 213, some agents are located on an intersection node. As shown in Table 1, there are many agents lives in from town 5 to 9, where are located in right hand side of Figure 1.

2.2 Decision of Agent

The simulation model consists of two stages. The first stage builds a social network on the city, which represent neighbors. The second stage applies the threshold model of social contagion on the social network.

Table 1. Town identification (ID), population, number of resident agents, and shelter ID

Town ID	Population	Number of agents	Shelter ID
0	67	33	0
1	2,292	1,146	1, 2, 3
2	64	32	4, 5
3	2,430	1,215	6, 7, 8, 9
4	987	493	10, 11, 12, 13
5	2,960	1,480	14
6	4,375	2,187	16, 17, 18, 19, 20, 21, 22, 23
7	1,506	753	24, 25
8	4,323	2,161	26, 27
9	1,173	586	28, 29
Sum	20,177	10,088	30

2.2.1.1 *Social network*

We set the radius *R* of neighbors for all agents. Each agent can interact with the agents within the circle of radius *R*. According to the position of agent, each agent has links with neighbor agents. Here, we set radius *R* as 60 (115m), 90 (173m) and 120 (230m) as shown in Figure 1.

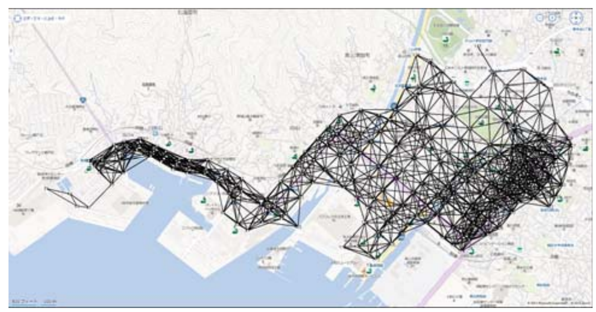


Figure 1. Network of neighbor agents when *R* is 120.

2.2.1.2 *Threshold model*

1. Each agent is given a fixed threshold value, *theta* as 0, 0.05 and 0.1, monotonously.

2. There are two possible states 0 (Not evacuated) and 1 (Decided to evacuate) for each agent. Proportion of neighbors who have evacuated at time step *t*: $p_i(t)$ *updates* the agent's state at next time step *t+1*. At each time step, each agent observes the proportion of its neighbors in state 1. Then, the agent switches to 1 if the proportion $p_i(t)$ exceeds its threshold *theta*.

If $p_i(t) \geq theta$: Agent *i* chooses 1

The case with value of *theta* is 0 means that the agent always changes the state to 1. And the case with value of *theta* is 0.1 means that agent changes the state to 1 only when proportions of the neighbors who have evacuated at previous time step are greater equal than 0.1. In this simulation, we deal with whether agent decides evacuate or not. To simplify, we set agent stays at the intersection node and doesn't move at all. In the future work, we will make agent move to the shelters.

In traditional cascade model, randomly chosen an agent decide a time step. In former work [9], we set the timing of decision as simultaneously, that is, all agents can decide each time step to save the resources of simulation.

2.3 Condition and Evaluation

We compared nine patterns by the combination of radius *R* (60, 90 and 120) and threshold *theta* (0.0, 0.05 and 0.1). We evaluated simulation results by collective behavior. We define collective behavior *p(t)* that the proportion of agents having chosen 1 (Decided to evacuated) in whole population at time *t*. We set initial collective behavior *p*(0) as 0.01, where agents randomly are state 1. We set the end of simulation as 100 time step and investigate the final collective behavior *p**.

3. SIMULATION RESULTS

3.1 Transition of collective behavior

Figure 2 shows a simulation result when radius *R* is 60 and threshold *theta* is 0.05. In the population, there are only one percent of agents are in state 1 at first time step. That is, only few agents decide to evacuate. Then, agent decides each time step and collective behavior, the proportion of agent who chosen 1, is gradually increasing. Collective behavior sometimes converges to 0.1 in 30 time step and sometimes converges 0.7 in 50 time steps.

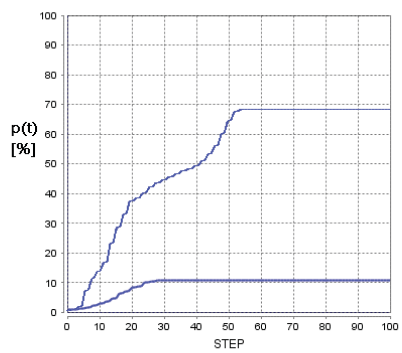
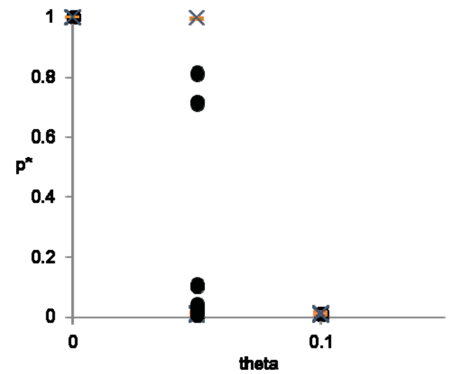


Figure 2. Typical cases of transition of collective behavior.

3.2 Results of collective behavior

We simulate until 100 time step, we call this as a trial and repeat 100 trials for each pattern. Figure 3 show the simulation result. When radius *R* is 60, final collective behavior becomes 1.0 and all agents decide to evacuate when *theta* is 0.0. On the other hand, when *theta* is 0.1, final collective behavior becomes 0.01 and only initially agents remain to evacuate. And when *theta* is 0.05, final collective behavior can be various values with depending on the trials. When radius *R* is 90 and 120, final collective behavior becomes 1.0 and all agents decide to evacuate when *theta* is 0.0. On the other hand, when *theta* is 0.1, final collective behavior becomes 0.01 and only initially agents remain to evacuate. And when *theta* is 0.05, final collective behavior becomes 0.01 or 1.0 with depending on the trials.

Table 2 shows the histogram of the final proportion *p** of agents who decide to evacuate when *theta* is 0.05. Final collective behavior can be 1.0 or high value. But, we found that it is rarely. When radius *R* is 60, final collective behavior becomes to 0.1 eleven times, becomes 0.7 three times and becomes 0.8 twice of 100 trials. When radius *R* is 90, final collective behavior becomes to 1.0 eighteen times of 100 trials. When radius *R* is 120, final collective behavior becomes to 1.0 nine times of 100 trials.



●: R =60, −: R=90, ×: R=120

Figure 3. Result of collective behavior.

when theta is 0.05		*R*		
		60	90	120
*p**	0-0.05	84	82	91
	0.05-0.15	11	0	0
	0.15-0.25	0	0	0
	0.25-0.35	0	0	0
	0.35-0.45	0	0	0
	0.45-0.55	0	0	0
	0.55-0.65	0	0	0
	0.65-0.75	3	0	0
	0.75-0.85	2	0	0
	0.85-0.95	0	0	0
	0.95-1.0	0	18	9

Table 2. The histogram of final collective behavior.

4. DISCUSSION

From Table 2, we found that when radius *R* is 90 or 120 and *theta* is 0.05, collective behavior tends to go to extreme, that is final collective behavior become 0.01 or 1.0. And when radius *R* is 60 and *theta* is 0.05, collective behavior can be moderate. Then, if agent can observe far agents, contagion of evacuation depends on trials, but it is rarely that all agents evacuate. Otherwise, agent can observe only near agents, contagion of evacuation tends to occur, but it is difficult to evacuate all agents. We focus on this point. When radius *R* is 60, all agents don't connect each other and there are some isolated sub networks. We found that disconnection of network makes contagion of evacuation decision making inefficiently. Therefore, if sub networks are connected each other, evacuation decision making can propagate in whole population. Hasan et al. [2] show that for faster propagation of warning, inter-community connections is needed. We deal with contagion of evacuation decision making, their result apply to our results. For contagion of evacuation decision making, connection of sub network is needed.

On the other hands, narrow neighborhood promotes evacuation. In this model, there are one percent of agents decides to evacuate at first. When neighbors are small, the proportion of decided agent to evacuate can be greater than threshold. Then, when agent can observe the narrow neighbors, contagion of evacuation is possible.

Additionally, it is needed the sub networks are connected each other to more large contagion. Hasan et al. [2] show that for faster propagation of warning, local neighborhood is needed be relatively smaller than the affected cluster size. We deal with contagion of evacuation decision making, their result apply to our results. For contagion of evacuation decision making, local neighborhood is needed.

5. CONCLUSION

In this paper, we dealt with evacuation decision making of people in the disaster area. By threshold model, we discussed about whether all agents decide evacuate or not. In this paper, we dealt with the condition that not all people evacuate and focus on contagion of evacuation decision making on real map. We found that for contagion of evacuation decision making, local neighborhood is needed and connection of sub network is needed.

In the future works, we will extend of the result to former study [8]. And we will adopt that people decide to evacuate by TV news, communication media and so on.

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