Analysis Methods of Agent Behavior and Its Interpretation in a Case of Rescue Simulations

Tomoichi Takahashi

Meijo University, Tenpaku, Nagoya, 468-8501, Japan
ttaka@ccmfs.meijo-u.ac.jp

Abstract. The agent-based approach has been proved to be useful for the modeling phenomena of traditional social fields. In order to apply agent-based simulation results to practical usages, it is necessary to show potential users the validity of the simulation outputs that arise out of the agents' behaviors. In cases that involve human actions, it is difficult to obtain sufficient amounts of data on real cases or experimental data to validate the simulation results.

In this paper, we review the metrics that have been used to evaluate rescue agents in the Rescue Simulation Agent competition and propose a method to analyze the simulation output by presenting the agent behavior with a probability model. We present that the analysis results of the method are comparable to a human-readable interpretation and with task-dependent knowledge and discuss its applicability to real-world cases.

1 Introduction

Society consists of multi-heterogeneous entities. The simulation of various phenomena in the society involves human behaviors and social structures. By presenting human behaviors as agents, the agent-based approach has enhanced the potential usage of computer simulations as a tool for modeling and analyzing human behaviors from social scientific viewpoints [3]. When disasters threaten human life, we want to use agent-based social simulation (ABSS) to predict the evacuation behavior of person and to estimate damage of disasters. Like a triage system that patients will be sorted according to need when medical conditions are insufficient for all patients to be treated, the emergency centers of local governments will prepare their prevention plans against disasters, so that the damage from the disaster will become the least with their limited rescue resources.

When the ABSS is applied to practical usages, it is necessary to demonstrate the validity of the ABSS's outputs to the potential users. In scientific and engineering fields, the following principle has been repeatedly used to increase the fidelity of simulations: *Guess* → *Compute consequence* → *Compare experiment results with simulation results* [2]. Social phenomena are in contrast to physical phenomena that can be explained using the laws of natural science. The social phenomena are not so much objectively measured but subjectively interpreted

L. Iocchi et al. (Eds.): RoboCup 2008, LNAI 5399, pp. 331–342, 2009.

by humans [6]. It makes difficult to systematically analyze the social phenomena and to evaluate the performances of agents. In most cases, it is difficult to obtain data on real cases or conduct experiments to verify the results of ABSS and the analysis results.

Earthquake disasters and rescue simulations are composed of disaster simulators and human-behavior simulations. While the components of disaster simulators, such as fire and building collapse, have been programmed on the basis of models developed in civil engineering fields, agent technology that is used to simulate human behaviors with these disaster simulations does not have such theoretical background. This makes it difficult to compare the results with the real data and follow the principles, because we cannot conduct physical experiments on disasters on a real scale, involve humans in the experiments, and the results of agent-based approach simulation have emergent properties.

In this paper, considering the disaster and rescue simulation system as an example of ABSS, we propose a method to analyze the simulation outputs without any metrics related with the application domain and show the interpretation of the analysis results. In section 2, the background of this study and related studies are described. Section 3 discusses the performance metric that has been used in RoboCup Rescue Agent Competition. Section 4 shows the agent behavior presentation based on a probability model and experiment results. The discussion on future research topics and a summary are presented in section 5.

2 Background and Related Studies

There are several human behaviors that lead to life-threatening situations. One example is the crowd behavior induced by panic. Studies have been conducted for simulating models of collective behaviors of pedestrians. For, example, D. Helbing et al. demonstrated an optimal strategy for escaping from a smoke-filled room by modeling pedestrians as Newton particles and the interaction among them as a generalized force model [1]. The methods are macro level simulations and the wills of individuals, for example some people stop not to push others in crowded places, are not presented with the force model. It is a future issue to implement the wills of agents and to observe how human behavior will change when announcing proper indications to the crowds are given in the panic.

The other example is rescue and evacuation movements during natural disasters. When disasters take place, the collapse of buildings will hurt civilians and block roads with debris. Fires burn houses, and smoke from these burning houses impedes the activities of firefighters. Kitano et al. proposed the RoboCup Rescue simulation (RCRS) that integrates various disaster simulation results and agent actions [5]. The wills of agent are implemented to represent the behaviors of civilians, firefighters, the human rescuers etc. Their microscopic behaviors are summed to the output of RCRS such as the number of living civilians, the area of houses that are not burnt, the recovery rate of blocked road and so on. They are metrics used in disaster related documents.

With these metrics, some attempts have been done to apply RCRS to practical applications. Schurr et al. applied the RCRS to train human rescue officers [8]. In their system, the human officers command the rescue agents in the RCRS as they would do to real rescuers. How many damages are decreased at the end of simulations by their commands is used to estimate how well the officers direct them at the disaster situations. We showed that simulation results of the RCRS have a good correlation with data in the fire department report and also reported comments from local governments when they were questioned about the possibility of using the RCRS as their tools [9]. The comments are as follows:

– There are no precedents that ABSS is used to design the prevetion plans and no theoretical backgrounds for the models.
– The simulation size is quite different from a real one; for example, the number of agents is smaller than that in a real world situation.

These comments indicate that the validity of the ABSS is required to persuade users who have the will to use the ABSS as their tools. The requirement is not limited to only the RCRS but is also to the cases when the ABSS is applied to fields such as

– real-life data which could validate the results of simulations are often nonexistent or difficult to obtain,
– domains are too dynamic or complex to make models.

3 Studies on Evaluation of Agents' Performance from the Past Competitions

Given initial disaster conditions, RCRS simulates disaster and rescue situations. The rescue agents save people or extinguish fires, and their behaviors change the disaster situations. RCRS outputs the number of casualties, the amount of damage from fires, and other metrics. The metrics are intricately linked with each other, and sometimes conflict each other. For example, the decision of rescue headquarters to save victims may increase the damage from fires because they have limited rescue resources. It is difficult to set a multi-attribute metric that measures the behaviors of rescue agent properly.

Ranking index: The RCRS has been used the following formula to rank the performance of teams since 2001 competition.

$$V = (P + \frac{H}{Hint}) \times \sqrt{\frac{B}{Bmax}}$$

where P is the number of living civilian agents, H denotes the health point values (i.e., how much stamina the agents have after rescue operations) of all agents, and B is the area of houses that are not burnt. Hint and Bmax are values at start; the score decreases as the disasters spread. Teams with higher scores have been evaluated to perform better rescue performance.

Table 1. Changes in metrics for two sensing conditions

sensing C.	metrics	initial V.	Team X	Team Y	Team Z
Base	P	120	79	98	90
	H	1200	574	606	582
	B	14270	14213	14176	13707
	V	12100	78.9	97.7	88.2
Half-vision	P	120	79	64	65
	H	1200	565	464	600
	B	14270	14213	4434	13681
	V	12100	78.9	35.7	83.3

Robustness to changes: Robustness is another property of the performance of agents. Robust agents will perform little more than before when the conditions to the agents become worse. In RoboCup 2004, they had a challenge session to test the robustness of agents [7]. A team that was consisted of 13 fire brigades, 6 ambulances and 12 police agents performed rescue operations under varying sensing conditions in the same situations of disaster. The relative variations of metrics, such as $|V_{Base} - V_{Half-vision}|/V_{Base}$, are used to estimate the robustness of agents' performances. Table 1 shows the results of three teams for two sensing conditions, Base and Half-vision. Agents could see objects that are within 100m from them in Base sensing condition and the radius of visibility is set to 50m in Half-vision case. From Table 1,

- Team X is the most robust one. Although the performance on H decreases a little at Half-vision case, the scores of V are practically equal.
- In the Base case, teams Y and Z saved more lives than team X, while more houses were burnt down.
- The decreases in P and B of team Y were significant compared to the others. Especially, the decrease of B in Half Vision case leads that team Y was not robust.

Time change of rescue: The factor of time change is important, when rescue rates are taken into consideration from the viewpoint that the initial actions are important for rescue. Figure 1 shows Team Y's time sequence changes of the metric for two simulations. The vertical axis is the relative values to the initial and the horizontal axis shows time steps. The left figure shows the rate of P is constant in the Base condition, while it decreases as time proceeds in the Half-vision condition (right figure).

Attributes such as P, H and B are typical metrics that are present in disaster reports. These evaluation using P, H, B and V are helpful to estimate the overall results of the simulations, however the macro-level properties are complex collective outputs that arise out of agent behaviors and their interactions. They do not have the resolution to analyze what behaviors of agents cause the differences of these metrics and do not give a clue to explain why the performance of one agent team is better than the others.

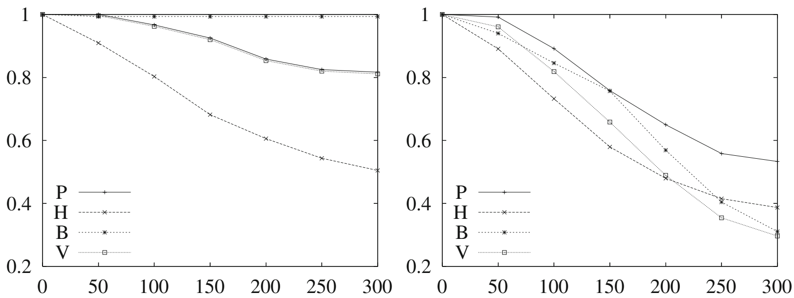


Fig. 1. Changes of Team Y's metrics during simulation steps (Left:Base condition, Right:Half vision condition)

4 Analysis of Agents Behaviors Based on Probability Model

It is necessary to interpret objectively the behaviors of the specific agents from the simulation results. We propose a method to analyze the agents' behaviors.

4.1 Problem Formulation and Behavior Presentation

Multi agent system (MAS) is simply formalized as follows [10].

$$action : S^* \to A, \quad env : S \times A \to \mathcal{P}(S),$$

where $A = \{a_1, a_2, \ldots, a_l\}$ is a set of agent actions, $S = \{s_1, s_2, \ldots, s_m\}$ is a set of environment states and $\mathcal{P}(S)$ is the power set of S. An agent at s_i plans possible actions and executes an action, a_i, according to their knowledge and data that they have gained. The action changes the situations of the environment. The interaction between an agent i and the environment leads to the next state. It is represented as a history h_i:

$$h_i : s_0 \xrightarrow{a_0} s_1 \xrightarrow{a_1} s_2 \xrightarrow{a_2} s_3 \cdots .$$

The set of all agents' histories, $\mathcal{H} = \{h_1, \ldots, h_n\}$ where n is the number of agents, is the information displayed on a screen.

The users of MAS [1] are not necessarily aware of the agents' states, s_i, and their will that causes actions, a_i. The users set the parameters of simulations and check the visual changes in $\mathcal{H}$ that are assumed to display the changes in the states of agents, s_i^o. The observable changes are not equal to the changes of agents' states, s_i, that are not displayed on the screen. The users observe how

[1] In this section, the "user" of MAS are referred to people at rescue centers of local governments. They are not programmers, so they are not familiar with the programs and only observe the output of ABSS.

the situations change on monitors, create gradually their own models of agent behaviors, and understand how the ABSS mirrors the social behaviors.

Our idea is to implement the process of the users by extracting the features of agent behavior from $\mathcal{H}$ based on the probability models. Behaviors of agents with the same aim will select similar situations to achieve their goals. However, agents do not necessarily act in the same way because their internal states, the history of their actions, and prior information are different. The behaviors of agents at state i are presented as a set $\{p_{ij}\}$ where p_{ij} is the probability that the agents at state i will take an action that causes it will be at state j at the next time. The probability describes rescue agent behavior by assuming the following:

Assumption 1. Agents select their actions to attain their goal efficiently and promptly.
Assumption 2. States that agents visit more often are more important for the agents than other states.
Assumption 3. Differences between actions with good and bad performances are represented as differences in the history of actions.

A stochastic matrix $\mathbb{P} = \{p_{ij}\}$, where p_{ij} is the probability that the agents at state i will be at state j after one time step, has the following conditions $p_{ij} \geq 0$ and $\sum_i p_{ij} = 1$ for all j. The transition probability can be approximated by taking the ensemble average of how many times agents change states from i to j from the ABSS output. When applying a stochastic matrix directly to interpret agent behaviors, there are the following problems:

- Let m be the size of states, the size of $\mathbb{P}$ is $m \times m$. Knowing m itself indicates that the states of the agents are known before analyzing their behaviors.
- $\sum_i p_{ij} = 1$ for all j implies that transitions to any state can occur. In simulations, there may be some states that do not appear. In such states, $\sum_i p_{ij}$ is zero.

We use a frequency matrix, $\mathbb{F} = \{f_{ij}\}$ instead of $\mathbb{P}$. $\mathbb{F}$ is a variant of $\mathbb{P}$ where p_{ij} are normalized as $\sum_{ij} f_{ij} = 1$. The following properties are indicated by considering $\mathbb{F}$ as a directed graph with f_{ij} s associated with the correspondent edges.

Property 1. $\mathbb{F}$ indicates the behavior of corresponding agents. The rank of $\mathbb{F}$ is proportional to the range of agent motions.
Property 2. Large elements of dominant eigenvectors correspond to states that are important in social simulations.
Property 3. When agents behave two patterns, the eigenvectors corresponding to the patters are independent each other.

4.2 Exemplifications of Matrix Representation

Two illustrative cases are shown to explain the matrix presentation of agents' behavior.

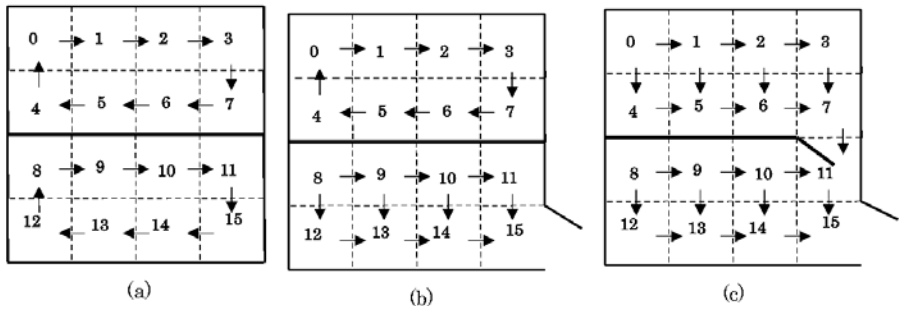


Fig. 2. Three cases of human movements; the room is divided into 4×4 cells and 16 cells correspond to the visual states

Crowds evacuation behavior: Figure 2 shows human movements when they escape from a smoke-filled room. The room is divided into two parts and the figures correspond to the following cases.

(a) Unfortunately, people are unfamiliar with the room and move around in circles to find an exit.
(b) People in the lower part know there is an exit. When persons come at cell 15, they notice the exit and exit.
(c) People in the upper room know that there is a door between two parts. When people come at cell 7, they notice there is the door and move to the lower part through it.

Their behaviors are observed as the time sequence of their locations. The latter part of a 16 × 16 matrix for case (b) is shown below. It show the elements of a sub matrix from 8th to 11th row and 8th to 15th column when the agent at cell 8 moves to whether cell 9 or cell 12 with probability 0.5 for both.

$$\begin{array}{c c}
 & \begin{array}{cccccccc} 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 \end{array} \\
\begin{array}{c} 8 \\ 9 \\ 10 \\ 11 \end{array} & \begin{pmatrix} & 0.5 & & & 0.5 & & & \\ & & 0.5 & & & 0.5 & & \\ & & & 0.5 & & & 0.5 & \\ & & & & & & & 1 \end{pmatrix}
\end{array}$$

The rank of the matrix corresponding to case (a), (b) and (c) are 16, 14, and 12, respectively, and the components of eigenvectors are separated according to the patterns of the movements.

Rescue agents' behavior: Figure 3 illustrates a situation where a rescue agent comes from n_0 and extinguishes the fires. The agent knows that there are two fires near n_2 and n_3. At crossing n_1, the agent determines which fire to extinguish and selects whether it will go forward, turn right or perform some other actions. The rescue agent behavior at n_1 is presented as $P_1 = \{p_{10}, p_{11}, p_{12}, p_{13}, p_{14}, p_{15}\}$. p_{1j} is the probability that the agents will be at n_j at the next simulation step.

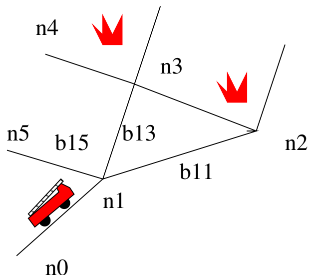


Fig. 3. Illustration of rescue agent behavior model at n_1

Table 2. Metrics of behavior of fire brigade agents in stochastic matrix presentation

Sensing Condition	Team X Size /Rank	Team X ratio of E.V.s 2/1	Team X ratio of E.V.s 3/1	Team Y Size /Rank	Team Y ratio of E.V.s 2/1	Team Y ratio of E.V.s 3/1	Team Z Size /Rank	Team Z ratio of E.V.s 2/1	Team Z ratio of E.V.s 3/1
Base	770/632	0.87	0.67	583/520	0.85	0.39	434/390	0.61	0.22
Half vision	840/767	0.37	0.25	338/250	0.30	0.30	404/364	0.46	0.16

2/1 (3/1): the ratio of 2nd (3rd) eigen value to the dominant one.

n_j covers all nodes in the map, because the agents can pass one or more nodes in one simulation step.

4.3 Analysis of Rescue Simulation Results and Interpretation

The observed states, $\{s^o\}$, are properties that are recognized visually. Assuming the positions of agents represent their states, p_{ij}s are calculated from how frequent the agents visit to the places.

Analysis from static properties of the matrix: Table 1 at Section 3 shows the results of 2004 Challenge sessions that were performed on a virtual city map (Figure 4). The map has 1065 roads, 1015 nodes, and 953 buildings. They correspond to the states of environments. Table 2 shows the size, rank, and eigenvalues of $\mathbb{F}$ for the behaviors of fire brigades.

Table 2 shows interesting features that cannot be obtained from Table 1. The size of $\mathbb{F}$ is the number of points traversed by the fire brigades. Under the Base sensing condition, the fire brigades of teams X and Y visited 770 and 583 points, respectively. The difference shows that the fire brigades of two teams move differently. At the Half-vision sensing condition, the agents of team X move a larger area than the Base condition, although the metrics of team X in Table 1 are similar values, 78.9, for two different sensing condition cases. The agents of team Y and Z move across smaller areas than the Base condition. This shows team X's behavior is different from the others.

The sizes of the eigenvalues correspond to the importance of the places that the agents visited. When there are two major places, the values of the corresponding

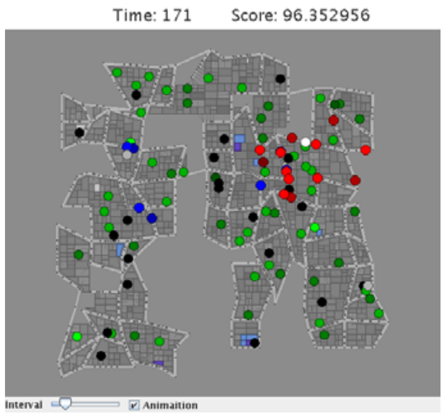


Fig. 4. Map used in 2004 Challenge Game

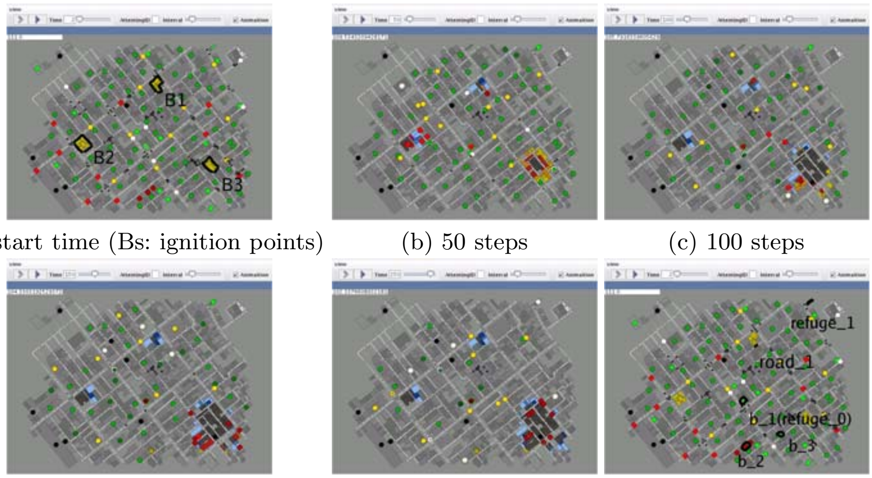
eigenvalues are of the same order and the ratio of the 1st and 2nd eigenvalues is close to 1.0. In case the agents visit one place, the 1st eigenvalue becomes dominant, the eigenvalues diminish in size, and the ratios decrease to 0.0. Columns 2/1 and 3/1 in Table 2 show the ratios of the dominant eigenvalue to the 2nd and the 3rd values, respectively. It is interesting that the ratios become less at the Half-vision condition than at the Base condition. It is inferred that sensing ability restricts the agents to search and rescue at new places.

Analysis from time sequence changes: Figure 5 shows the snapshots of simulations on the Kobe, Japan. The map consists of 820 roads, 766 nodes and 754 buildings. Thirteen firefighter agents, 7 ambulances, 11 police persons, and 85 civilians are involved in this simulation. The followings can be interpreted from the snapshots.

(a) Initially, three fires break out at B1, B2 and B3.
(b) At 50 steps, fires at B1 and B2 are extinguished, while the fire at B3 continues to spreads.
(c) Agents gather to extinguish the fire at B3.
(d, e) After 150 steps, the spread of the fire is prevented by fire fighting actions.

Table 3 shows the time sequence changes of the burning rate $(1 - B/Bmax)$ and the properties of $\mathbb{F}$ for the fire brigade agents. The properties are the ones in Table 2 and the positions of the biggest components of the dominant, the second and the third eigenvectors.

– The rank of the matrix increases with the simulation steps. This indicates that the range of the fire brigade agents becomes wider with time.
– The first eigenvalue becomes dominant over time. It indicates that, initially, the agents move separately and later they behave in a similar manner as the simulation proceeds.



(a) start time (Bs: ignition points) (b) 50 steps (c) 100 steps

(d) 150 steps (e) 300 steps (f) key locations

Fig. 5. Time sequences of disaster simulations (Black and blue squares indicate the houses that are burnt down and the houses where the fire is extinguished, respectively. The other squares indicate the burning houses. Red, yellow, white, and black circles indicate fire brigades, civilians, ambulances and dead agents, respectively.)

Table 3. Time sequence of burning rate, size of matrix and eigenvectors

step	burning rate	matrix			key locations corresponds to component of dominant e.vectors		
		size/rank	ratio of E.V.s 2/1	3/1	1st	2nd	3rd
50	2.6%	155/135	0.38	0.38	b_1	b_2	road_1
100	4.0%	246/217	0.11	0.10	b_1	road_1	b_2
150	4.9%	300/271	0.06	0.06	b_1	road_1	b_2
200	5.0%	355/325	0.05	0.04	b_1	road_1	b_2
250	5.0%	422/388	0.04	0.04	b_1	road_1	b_3
300	5.1%	484/442	0.03	0.03	b_1	b_3	road_1

(f) The figure shows the locations that correspond to the key components of dominant vectors in Table 3.

- Refuge 0 (b_1) is the key building in all the steps,
- from 100 and 250 step, a place (road 1) near the fire (B1) is an important place that corresponds to the second dominant eigen vector,
- after from 250 step, a place(b 3) near the other fire (B3) appears to be the key place.

The interpretations correspond well to the interpretations from the snapshots.

5 Discussion and Summary

MAS provides tools to simulate and analyze complex social phenomena. To put ABSS into practical use, the following features are required.

– human behaviors are involved.
– the simulation results are validated.

The validations of ABSS have been done by comparing the simulation data and real-world data. The real-world data of disasters are obtained from the reports that are published from governments or insurance companies. The real-world data are macro level ones and it is difficult to take account of microscopic agent behaviors.

In this paper, we review how the rescue agents have been evaluated in the RCRS agent competitions by the macro-level properties, and propose a method of analyzing agents' behavior based on probability model. The method presents the agent behaviors with a stochastic matrix and analyzes the behaviors by the matrix's properties such as size, rank, eigenvalues and eigenvectors. The method is applied to disaster and rescue simulations, and the experimental results show interpretations that are acceptable from the rescue task knowledge.

The probability model has been widely used to model the variations in the parameters of simulation and agent characters. A large number of simulations with changing them statistically are used to verify simulation results. For example, Johnson et al. have simulated the evacuation of public buildings and proposed risk assessment techniques [4]. Our approach uses a stochastic approach to represent the states of the agents and analyze their behaviors. It shows the range of agents' activities and key locations of their rescue actions and gives clues to interpret the results of ABSS.

The analysis method is based on mathematical quantity such as rank, eigenvalue, etc. They are independent of domain specific evaluations and suggest the potential of the method that will be applied to other fields. For example, when the motions of individual in a crowd will be video tracked, the method can assess the validity of ABSS by comparing its outputs and the behaviors in the real-world data. And the ABSS approach will be used to support decision-making in the future, the proposed method will provide a function to explain the results.

References

1. Farkas, I., Helbing, D., Vicsek, T.: Simulating dynamical features of escape panic. Nature 407, 487–490 (2000)
2. Feynman, R.P.: The Character of Physical Law. MIT Press, Cambridge (1967)
3. Jennings, N.R.: Agent-based computing: Promise and perils. In: Proc. IJCAI 1999, pp. 1429–1436 (1999)
4. Johnson, C.W.: The application of computational models for the simulation of large scale evacuations following infrastructure failures and terrorist incidents. In: Proc. NATO Research Workshop on Computational Models of Risk to Infrastructure, pp. 9–13 (May 2006)

5. Kitano, H., Tadokoro, S., Noda, I., Matsubara, H., Takahashi, T., Shinjou, A., Shimada, S.: Robocup rescue: Search and rescue in large-scale disasters as a domain for autonomous agents research. In: IEEE International Conference on System, Man, and Cybernetics (1999)
6. Moss, S., Edmonds, B.: Towards good social science. Journal of Artificial Societies and Social Simulation 8(4) (2005)
7. RoboCup2004 (2004), http://robot.cmpe.boun.edu.tr/rescue2004/
8. Schurr, N., Marecki, J., Kasinadhuni, N., Tambe, M., Lewis, J.P., Scerri, P.: The defacto system for human omnipresence to coordinate agent teams: The future of disaster response. In: AAMAS 2005, pp. 1229–1230 (2005)
9. Takahashi, T., Ito, N.: Preliminary study to use rescue simulation as check soft of urban's disasters. In: Workshop: Safety and Security in MAS (SASEMAS) at AAMAS 2005, pp. 102–106 (2005)
10. Weiss, G.: Multiagent Systems. MIT Press, Cambridge (2000)