

An Analysis of Heterogeneous Swarm Evacuation Model

Siti Juliana Abu-Bakar, W.A.F.W. Othman and S.S.N. Alhady

Abstract In an emergency situation, members of a crowd often exhibit unpredictable behavior which can lead to major catastrophes if not well managed. The focus of this work is to analyze the crowd dynamics of heterogeneous agents, at differing densities, within an enclosed arena. Each individual reacts differently to a panic, based on diverse factors like physical contact, emotion, attraction, sights and many others. It is the combination of these individual behaviors that ultimately affects crowd behavior. When a panic occurs, the motivation of each agent is to leave the arena as soon as possible by obeying the flocking rule, the follower rule, and obstacle avoidance rule. The analysis of this work focuses on evacuation time and response rate to clear the arena under the influence of type of agent, and crowd density. Result shows that as the percentage of agents with greater knowledge of the arena increases, the evacuation time and response rate are improving. Secondly, as the the crowd density increases, the response rate to clear the arena is getting quicker, however the average evacuation time is getting slower.

Keywords Crowd dynamics · Swarm · Emergent

Part of this work is funded by Universiti Sains Malaysia (USM) under grant no 304/PELECT/60313019.

S.J. Abu-Bakar (✉) · W.A.F.W. Othman · S.S.N. Alhady
School of Electrical and Electronic, Engineering Campus,
Universiti Sains Malaysia, 14300 George Town, Penang, Malaysia
e-mail: sjab15_eee017@student.usm.my

W.A.F.W. Othman
e-mail: wafw_othman@usm.my

S.S.N. Alhady
e-mail: sahal@usm.my

1 Introduction

The study of crowd dynamics is important to architecture and civil planning because it is a major factor in the prevention of injury and loss of life due to panics induced by emergency situations within architectural structures. There are many research has been carried out to model the crowd behavior in various situation [1–3].

When a panic occurs in a crowd, individuals tend to not operate independently, as they adopt the behavior of the crowd entity [4, 5]. The transition between normal rational behavior and irrational panicked behavior is controlled by many parameters, but nervousness is one factor which will influence fluctuation strength, desired speeds and herd tendencies [6].

Various factors affect the way people behave in normal, calm settings, versus chaotic and panic ridden situations. There are many aspects that might influence individual decision making, dependent on a series of physiological, emotional and social group attributes, together with external stimulus (events, object, and people) [7].

Refer to [8], when panicked, people who are unfamiliar with a building will evacuate using the same path they entered the building. When too many agents arrive together at an exit, a jam forms, typically in the form of a structurally sound arch, and the press of the crowd behind can then lead to injuries and even fatalities. However, this problem can be reduced if information is shared between agents, whereby those with knowledge of emergency exits can guide others.

When danger threatens, the target of each agent is to leave the arena as quick as possible [9]. The probability of an incident in front of an exit is higher due to crushing, and exit times subsequently increased. By understanding, then controlling human behavior via appropriate building structures, the number of injuries due to crowd panics may be reduced.

In this work, a crowd model which combined mulch-agent based model and Reynolds' flocking rule [10] has been created. There are two type of agents, namely agent *A* and agent *B*, occupying an enclosed hall-like arena. Agent *A* represents a normal agent that has limited visibility range, while agent *B* is assumed to be a well-trained agent that knows the environment of the arena better than agent *A*. The model is then simulated to analyze the behavior of the crowd when panic strikes.

2 Modeling Framework

As mentioned in Sect. 1, agent *A* has a shorter visibility range of 4 patches ahead, while agent *B* has a visibility of 15 patches ahead (refer Fig. 1). The visibility range of agent *B* has been set to be larger than the visibility of agent *A*. Therefore agent *B* will have a bigger perception range as compared to agent *A*. Hence, agent *B* can navigate the environment better than agent *A*, whom perceives smaller range. To create the most realistic analysis, the visibility angle for both agents *A* and *B* have been set to 135 degrees which is equal to field of view of the human eye [11].

Fig. 1 Visibility range of agent *A* and *B*

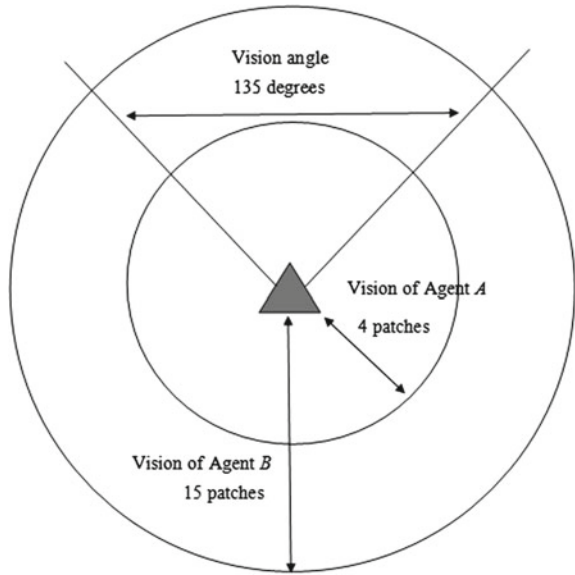


Figure 2 shows the simulation environment for this work. The size of the arena has been set to forty-one by forty-one patches, with four exits (set as red color), and the arena can only accommodate up to 800 agents at any one time. Agent *A* is represented by green color, while agent *B* is black. There are gray colored wall and an obstacle in the arena, which all agents must avoid.

Figure 3a shows the flowchart for the behavior of agent *A* in the arena. First, agent *A* will look if there is any obstacle in front of it. If there is any, then the agent will steer away from the obstacle, otherwise it will look for agent *B*. If agent *B* is found, then the agent *A* will steer towards and follow the agent *B*; if not, then the agent *A* will

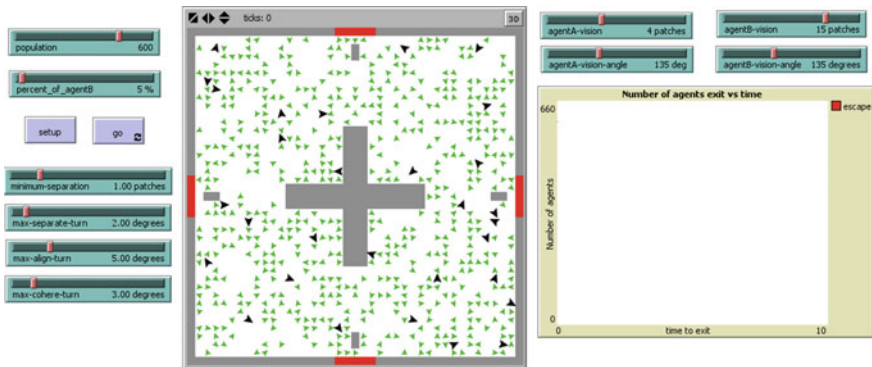


Fig. 2 Netlogo model implementation

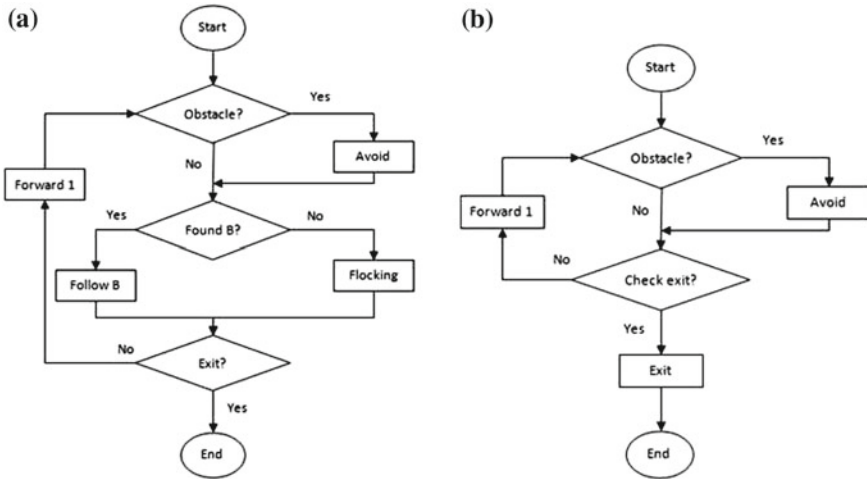


Fig. 3 Behavior model of agents in the arena. **a** Agent A. **b** Agent B

steer towards its neighbors by obeying the flocking behavior rule, based on Reynolds flocking rule-set. Finally, agent A will look for an exit within its perception range. If the exit is found, it will turn towards the exit; if not, then the agent will move forward 1 patch ahead.

Figure 3b shows the flowchart for the behavior of agent B. At the beginning of the simulation, agent B will identify is there any obstacle in front of it; if there is, agent B will avoid it. Agent B later on will look for an exit, if the exit is found, it will move towards it; if not then it will turn randomly and moves forward 1 patch ahead. This process repeats until all agent B are out of the arena.

3 Case Study and Results

In this work, two types of scenarios have been simulated. First, by varying proportions of agent B in the arena, ranging from 0 to 75 % in the population of 600 agents. The number of 600 agents has been selected such that the entire arena will be occupied by all agents. Secondly, by varying population sizes, ranging from 400 to 800 agents.

Twenty runs are made for each scenario with random initial placement of agents in the arena. The performance is then evaluated at the end of the simulation and all runs were executed for 1,000 ticks (simulation time steps) to give sample time for agents to evacuate the arena. The data for analysis were recorded at every 10 ticks during the simulation. The evacuation time and response rate (agents/tick) were then calculated. The response rate has been defined as the slope of the line from the origin to 50 % of the agents evacuated.

3.1 Varying Proportion of Agent B in population of 600 Agents

The model was simulated from a population of 600 agents with a 5 % proportion of agent B in the arena. In Fig. 4a, at the beginning of the simulation (tick = 0), all agents were spread randomly in the arena. Figure 4b shows a snapshot of the simulation run at tick sixty, and all agents B have left the arena, and only a few agents A remain. At this moment, the remaining agents A will only follow the crowd and this process will continue until all the agents have left the arena as shown in Fig. 4c.

Refer to the result in Table 1, an average evacuation time decreases as the proportion of agent B in the population increases. This is because, agent B has better vision and knowledge of the arena so they are able to identify the exit quicker, and then act to help others to evacuate the arena. Higher percentage of agent B in the arena leads to quicker overall evacuation time.

The response rate for the 75 % proportion of agent B was the highest, followed by 50, 25, 0 %, and then the 5 % proportion of agent B. Hypothetically, the more agents B in the arena, the higher the rate of evacuation (response rate) should be. However, the response rate with no agent B was higher than the response rate for a 5 % proportion of agent B, violating the hypothesis.

The explanation for this can be found in Fig. 5. For the case of a 0 % proportion of agent B, the response rate was higher because the movement of each agent was only affected by flocking behavior, and as such the agents moved faster because they

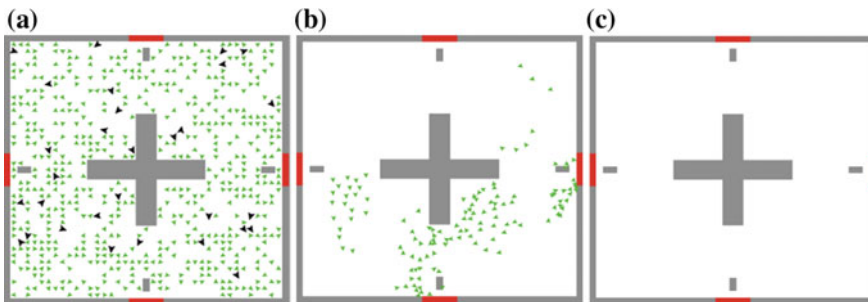


Fig. 4 Snapshot of the simulation. a Tick = 0. b Tick = 60. c Tick = 200

Table 1 Average evacuation time and response rate for varying percentage of agent B in population of 600 agents

Results	Percentage of agent B				
	0 %	5 %	25 %	50 %	75 %
Average evacuation time (ticks)	236	229	219	190	187
Response rate (agents/tick)	9.22	7.38	9.53	15.45	18.78

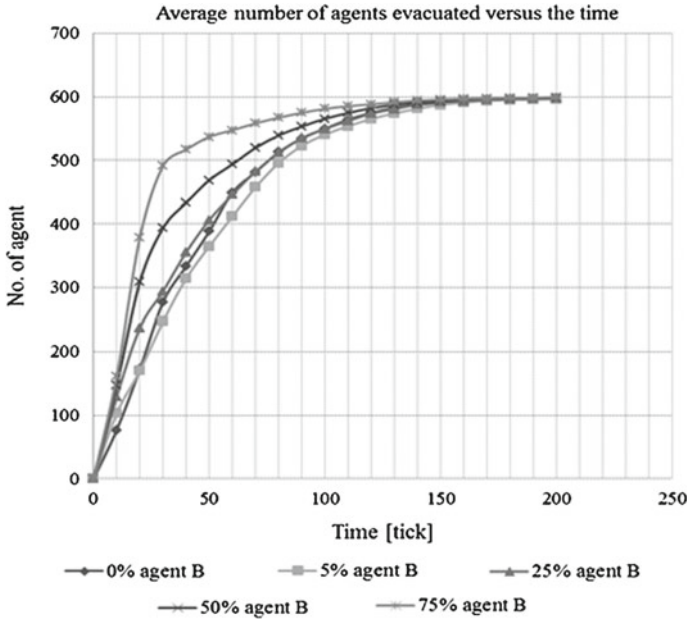


Fig. 5 Evacuation time for varying proportions of agent B in a population of 600 agents

can reach a stable state early. In contrast, with a 5 % proportion of agent B in the arena, the movement of agents in the arena is affected by both the influence of agent B and also the flocking behavior.

After tick 31, when all agents B have left the arena, the overall movement of the crowd was slowed as the remaining agent A were paused to re-adjust their alignment and movement and reach a new equilibrium with their neighbors. Although the response rate for 5 % of agent B was smaller than 0 % of agent B, the evacuation time was shorter, with all agents evacuated by tick 300. While for the case of 0 % agent B, only 99.83 % of the agents were evacuated by tick 300.

3.2 Varying Population Size

For the second scenario, four types of simulation were conducted to determine the effect of different proportions of agent B on varying population sizes (400, 600 and 800). From the result in Table 2, the relationship between the response rate and the population size seems linear. As the population size increases, the response rate increases proportionally. This can be explained by the fact that, in more dense crowds, there is a higher probability of agents meeting and sharing information about the environment.

Table 2 Response rate for varying population size and percentage of agent *B*

Percentage of agent <i>B</i>	Response rate (agent/ticks)		
	400 populations	600 populations	800 populations
(Scenario 1) 5 %	5.47	7.38	9.22
(Scenario 2) 25 %	6.52	9.53	12.79
(Scenario 3) 50 %	10.23	15.47	20.88
(Scenario 3) 50 %	10.23	15.47	20.88
(Scenario 4) 75 %	12.41	18.78	25.10

Table 3 Average evacuation time for varying population size and proportions of agent *B*

Percentage of agent <i>B</i>	Average evacuation time (ticks)		
	400 populations	600 populations	800 populations
(Scenario 1) 5 %	198	229	250
(Scenario 2) 25 %	191	219	227
(Scenario 3) 50 %	187	190	211
(Scenario 4) 75 %	184	188	207

Comparing the response rate of the 5 % proportion of agent *B* with the 75 % proportion of agent *B* in a population of 800 agents from Table 2, the response rate of the 75 % proportion is much higher. This can be explained that, by increasing the proportion of agents with a greater knowledge of the arena, it should facilitate smoother and faster egress, especially with mechanism of information sharing in use for instance.

Table 3 shows the result of average evacuation time for varying population size and proportions of agent *B*. As shows in Table 3, the average evacuation time is increases as the population size increases. This was because the evacuation time was defined as the time between when the first agent exited the arena, to the last. Realistically, more agents in a closed arena should result in longer evacuation times. Therefore it is reasonable that evacuation time increases with population size. Although the average evacuation time is slower for larger population, increasing the proportion of agent *B* in the arena will help to speed up evacuation time.

4 Conclusions and Future Works

In this study, we have modeled two-individual crowd behaviors and study their effect in a macroscopic swarm level. Results show that by increasing the number of agents with broader knowledge about the environment, the average evacuation time can be shortened. This can be brought into practical scenarios by training people on how to react to and handle emergency situations, which in turn will help to further improve evacuation time and even avoid serious injury and death.

Future directions of this work will include investigation on how the altruism and egoism of agents in the arena affects the performance and convergence rate. Also, further work will be carried out in scenarios with more walls in the arena in order to understand emergent behaviors that obstructions may produce.

References

1. Vizzari G, Manenti L, Crociani L (2013) Adaptive pedestrian behaviour for the preservation of group cohesion. *Complex Adapt Syst Model* 1(17):1–29
2. Akinwande OJ, BI H, Gelenbe E (2015) Managing crowds in hazards with dynamic grouping. In: *IEEE Access*, vol 3. pp 1060–1071
3. Olivier A-H, Bruneau J, Cirio G, Pettre J (2014) A virtual reality platform to study crowd behaviors. In: *The Conference on Pedestrian and Evacuation Dynamics*, vol 2. Delft, The Netherlands, pp 114–122
4. Wijermans N, Jorna RJ, Jager W, van Vliet T (2007) Modelling Crowd dynamics, Influence factors related to the probability of a riot. In: *Proceedings of the fourth European social simulation association conference (ESSA)*. pp 531–541
5. Bode NWF, Codling EA (2013) Human exit route choice in virtual crowd evacuations. *Anim Behav* 86(2):347–358
6. Helbing D, Farkas I, Molnar P, Vicsek T (2002) Simulation of pedestrian crowds in normal and evacuation situations, See (Schreckenberg and Sharma, 2002). In: *Pedestrian and evacuation dynamics*. Springer, Heidelberg, pp 21–58
7. Luo L, Zhou S, Cai W, Low MYH, Tian F, Wang Y, Xiao X, Chen D (2008) Agent-based human behavior modeling for crowd simulation. *Comp Anim Virtual Worlds* 19:271281
8. Pelechano N, Badler NI (2006) Modeling crowd and trained leader behaviour during building evacuation, vol 26(6). pp. 80–86
9. Klmpfel H, Schreckenberg M, Meyer-Knig T (2005) Models for Crowd Movement and Egress Simulation. In: *Traffic and Granular Flow 03*. S. Hoogendoorn et al. Springer, Berlin Heidelberg
10. Reynolds CW (1987) *Flocks, Herds, and Schools: A Distributed Behavioral Model*
11. Gibson JJ (1979) *The ecological approach to visual perception*. Houghton Mifflin, Boston