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Simulation of emotional contagion using modified SIR model: A cellular automaton approach

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ABSTRACT

Emotion plays an important role in the decision-making of individuals in some emergency situations. The contagion of emotion may induce either normal or abnormal consolidated crowd behavior. This paper aims to simulate the dynamics of emotional contagion among crowds by modifying the epidemiological SIR model to a cellular automaton approach. This new cellular automaton model, entitled the "CA–SIRS model", captures the dynamic process 'susceptible–infected–recovered–susceptible', which is based on SIRS contagion in epidemiological theory. Moreover, in this new model, the process is integrated with individual movement. The simulation results of this model show that multiple waves and dynamical stability around a mean value will appear during emotion spreading. It was found that the proportion of initial infected individuals had little influence on the final stable proportion of infected population in a given system, and that infection frequency increased with an increase in the average crowd density. Our results further suggest that individual movement accelerates the spread speed of emotion and increases the stable proportion of infected population. Furthermore, decreasing the duration of an infection and the probability of reinfection can markedly reduce the number of infected individuals. It is hoped that this study will be helpful in crowd management and evacuation organization.

1. Introduction

In recent years, emergencies such as floods, fires and earthquakes, have attracted more and more public attention, because of their high uncertainty, tremendous damage and negative social influence. They usually cause large-scale evacuation, during which at least two important aspects are involved. One key consideration is the characteristics of individual movement, which can determine the efficiency of evacuation. The other is emotional contagion in a crowd, which can affect the response of crowd members, such as their initiation of evacuation. Various examples have shown that emotion spirals [1], especially in a crowd, can develop, causing devastating consequences. One representative example was the stampede on a bridge in India on October 13th, 2013 after a rumor was deliberately spread that the bridge was almost broken: this caused the propagation of panic through the crowd. There is an urgent need to reveal the core mechanisms underlying the propagation of emotion in order to develop predictive evacuation models enabling rapid analysis and decision making by the authorities.

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Both modeling and experimental approaches have been adopted to investigate the characteristics of pedestrian movement. Models such as the social force model [2], lattice gas model [3], multi-grid model [4] and visual hindrance model [5], have already identified many typical characteristics of pedestrian movement or human evacuation behaviors. Other such characteristics, for example the density–speed–flow relation, step length and frequency, merging behaviors and exit-selection behaviors, have been determined experimentally [6–10]. Individual mental states, such as emotions, indeed play a very important role in individual decision-making, and thus affect individual movement [11,12]. It has been suggested that in a large crowd, the dissemination of information can be constrained both on a temporal and spatial scale [13,14]. As a result, when the panic emotion emerges in someone in a crowd, his/her neighboring individuals tend to be infected via what is termed emotional contagion. Henein [15,16] et al. confirmed that information discovery and processing, communication and changing goals due to individuals' different belief in crowd dynamics led to complex inter-particle interactions, but they focused on the effect of information processing and communication on crowd movement and the physical domain (e.g. jamming transitions) with the force-enabled floor field model. Barsade [17] used a 2×2 experimental design, with a trained confederate enacting mood conditions, to examine group emotional contagion. Treur [18] discussed a neurologically-inspired dynamical system approach to the dynamics and interaction of emotions. Bosse et al. [1] used an existing agent-based model involving contagion of belief, emotion and intention states of agents to simulate a real incident, and provided evidence for the hypothesis that the incorporation of emotional contagion rendered models of pedestrian behaviors in panic situations more accurate. Minh et al. [19] proposed an agent-based evacuation model considering emotion propagation. Tsai [20] devised the multi-agent evacuation simulation tool ESCAPES, which incorporated emotional interactions. Durupinar [21] studied the overall behavior of virtual crowds with a range of personality traits in various psychological and emotional states and moods using a probabilistic threshold model that was derived from the extensive epidemiology literature [22], and demonstrated that emotions may be contracted among humans. Tsai et al. [23] examined computational models of emotional contagion by implementing Durupinar's [21] probabilistic threshold model and Bosse's [11] thermodynamics-based model, demonstrating that thermodynamics-style models produced superior results, due to the ill-chosen contagion mechanism at the core of epidemiological models.

A small-scale event may result in large-scale mass incidents, such us the Chinese rush for iodized salt in 2011, which was the result of social panic ensuing from an implausible rumor. To some degree, emotional contagion is similar to disease spread, wherein there is a greater risk of infection when the number of neighboring patients with infectious diseases increases [24]. We now refer to the SIR (susceptible–infected–recovered) model proposed by Kermack and Mckendrick [25] in 1927, which is the initial starting point for the design of modern mathematical models [26], and has been modified by several researchers [27–30] to study social phenomena, such as information [31] or rumor spread [32] and contagion of behavior [24]. Epstein et al. [33] modeled two interacting contagion processes, namely the spread of disease and of the fear of that disease, in which the coupled dynamics was quite rich with multiple waves of infection. The author also emphasized that the model could not only handle cases of disease, but also natural disasters, for example earthquakes or volcanoes.

Although the studies above have revealed many aspects of pedestrian movement and emotional contagion among crowds, few of them considered the effect of individual movement on emotional contagion in a crowd. Research in the field of emergency evacuation has concentrated on human behavior and movement, but usually ignored the mental state of individuals. The majority of existing mathematical models which simulate emotional contagion neglect the local characteristics of the spreading process in combination with individual movement.

In this paper, we modify the macroscopic SIR model to a microscopic model so as to integrate emotional contagion with individual movement. The aim is to understand how panic propagates through a dynamic crowd and what can be done to alleviate the panic of individuals effectively in a large-scale crowd. Surprisingly, this has still not been well investigated.

We use a cellular automaton (CA for short) approach, which provides a powerful modeling framework for the description of physical systems consisting of interacting components [34] and displays system dynamics, to study emotion propagation among crowds. The two-dimensional CA simulation is a method of temporal and spatial discretization based on a specific rule of a domain endowed with a state varying in discrete time steps [26], allowing us to investigate the effect of spatial inhomogeneity in population concentrations on the dynamics of emotion spread. In particular, the intensity of panic of individuals and the number of infected individuals during the emotion spread can be estimated. As noted in Ref. [2], the fluctuation strength of nervousness influences the velocity of pedestrians. In this regard, quantitative analysis of the measurement of the nervousness of individuals under an emergency is one of the main contributions of this paper. To exemplify the CA approach, numerous simulation runs are implemented in a domain with scenarios that include different characteristics of individuals.

The remainder of this paper comprises the following. In Section 2, the emotional contagion model is constructed by modifying the SIR model, and its basic simulation rules are introduced. Then, the simulation results for the emotional contagion process using artificially selected parameters are presented in Section 3. Finally in Section 4, the study is concluded.

2. Model

2.1. Original SIR model

In the original SIR model [25], the population is divided into three classes, namely susceptible (S), infected (I), and recovered (R) individuals. The classic SIR model is composed of differential equations [30] as follows, $S(t)$, $I(t)$, $R(t)$,

$\beta, \gamma \geq 0$:

$$S + I + R = \text{constant}, \tag{1a}$$

$$\frac{dS}{dt} = -\beta SI, \tag{1b}$$

$$\frac{dI}{dt} = \beta SI - \gamma I, \tag{1c}$$

$$\frac{dR}{dt} = \gamma I. \tag{1d}$$

The multiplicative product $S \times I$ represents the random mixing of susceptible and infected individuals. The transmission coefficient β is defined based on infectivity of a disease and contact rate between susceptible individuals and infected individuals. The rate of infected individuals recovering is defined as γ. Eq. (1a) implies that the total number of susceptible, infected and recovered individuals is a constant. This model clearly reflects the macroscopic mechanism. Through interaction with the infected crowd members, the population of susceptible individuals will decrease, while inevitably that of those infected ones will increase. Conversely, as some individuals are cured, the population of infected individuals drops correspondingly, populating the class of those recovered [27].

2.2. Modified SIR model, CA–SIRS

As the original SIR model is a macroscopic, static mathematical model based on ordinary differential equations, it may be not appropriate to describe human crowds with abnormal emotions, especially crowds with moving individuals. In order to intervene in and manage a large-scale crowd in which individuals can move freely in the case of large-scale panic, some managers or guides should be organized to calm the crowd members. Therefore, the original SIR model should be modified to be microscopic and dynamic to reflect emotional contagion in such a system.

In our model, each individual may be in one of three states: susceptible (S), infected (I) or recovered (R). These biological terms have a social context. As stated in Ref. [21], an individual who may be "uninformed" about rumors or a "non-adopter" in the matter of emotional responses is regarded as a susceptible individual. Similarly, an "informed" individual or an "adopter" who adopts other individuals' emotional states is deemed an infected individual. When susceptible individuals come into contact with those who are infected, they are likely to be infected in turn. For example, when perceiving a fire, some individuals may be afraid, while others may not, initially because of empathy [19] with members of the first group. Individuals have the capacity to grow calm over time, thus reducing the strength of their emotion [19] and recovering. In the original SIR model, a recovered individual is removed from the infected system, and cannot be infected again. In order to reflect diverse individual characteristics and accord with the reality of the emotional contagion process, we consider that recovered individuals may become susceptible again after a period, since it may be difficult for some persons in a crowd to maintain a recovered state. Accordingly, SIRS (susceptible–infected–recovered–susceptible) contagion [35] is more suitable for describing emotional contagion. Hence, when using the CA approach, a modified discrete model, named CA–SIRS, is proposed, which states that individuals under an emergency may experience different states of the circle of infection as a result of emotion spread and imitative behaviors.

In this modified model, a cellular space of $W \times H$ cells is defined. Each cell is an identical square area of 0.4 m × 0.4 m, and may be occupied by an individual. The emotion experienced by individuals may be spread through occupied cells. 'Null boundary conditions' [26] are used. That is, the system in our model is grounded or bounded by edges, and the state of the cells beyond the system edges is endowed with a constant value of zero, following the update rule below.

In order to calculate the strength of emotions, several parameters are proposed. We set different ranges of emotional influence on a CA cell in the cellular space, and one range is shown in Fig. 1. The core red cell can be influenced by $n \times n$ cells ($n = 11$ in Fig. 1) in the blue area, i.e. an individual can be affected by anyone in an area of radius $r = 0.4 \times (n-1)/2$ m ($r = 2.00$ m in Fig. 1) around him/her. It is noteworthy that the maximum radius should be less than 2.00 m, according to Ref. [36]. We introduce some personal parameter settings (stated in Ref. [37]) as individuals have distinct characteristics. The intensity of expression of individual i's emotion is set as E_i in the interval $(0, 1]$, and is related to individual personality. The parameter $A_{j,i} (A_{j,i} \in (0, 1])$ is used to represent the strength attribute by which an emotion is received by i from sender j, and $B_{i,j}$ ($B_{i,j} \in (0, 1]$) is used to represent the strength attribute by which an emotion is sent from i to receiver j. Then the increase in strength of individual i's emotion (D_{ji}) received from j is defined as Ref. [37]:

$$D_{ji} = \left[1 - \frac{1}{(1 + \exp(-L))}\right] \times E_i \times A_{j,i} \times B_{i,j}. \tag{2}$$

Here $D_{ji} \in (0, 1]$. Parameter L represents the distance between individual i and j. If the coordinates of i and j are (x_1, y_1) and (x_2, y_2) respectively, $L = \max\{|x_1 - x_2|, |y_1 - y_2|\}$. Thus, the range of emotional influence is $0 < L \leq 2$ m in our model. At each time step, we update the inner strength of individual i's panic emotion $M(i, t)$ as follows:

$$M(i, t) = M(i, t-1) + \sum_{j=1}^{K} D_{ji} \tag{3}$$

Table 1
The description of parameters within the CA–SIRS model.

i, j	Individual
E_i	The intensity of expression of individual i's emotion
$A_{j,i}$	The strength attribute by which an emotion is received by i from sender j
$B_{i,j}$	The strength attribute by which an emotion is sent from i to receiver j
D_{ji}	The increase in strength of individual i's emotion received from j
L	The distance between individual i and j
$M(i, t)$	An individual's inner strength of panic emotion at time step t
K	The overall number of the relevant neighbors
ρ_0	A small proportion of initial infected individuals
λ	The threshold of an individual's inner strength of panic emotion
p	The probability of the infected individuals recovering
t_1	Time steps for the infected individuals recovering
T_1	The average duration of the infected state
δ_1, δ_2	The variance of the normal distribution
q	The probability of the recovered individuals becoming susceptible again
t_2	Time steps for the recovered individuals becoming susceptible again
T_2	The average duration of the recovered state

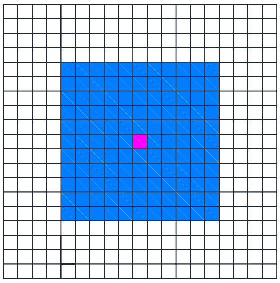


Fig. 1. A range of emotional influence. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

where t represents the time steps and $M(i, t) \in (0, 1]$. We are not concerned with the specific interval of the time step. K is the overall number of the relevant neighbors affecting individual i. Eq. (3) demonstrates that memory of past events plays a role, and therefore this model is more realistic than the classic SIR model, as observed in Ref. [35]. Table 1 summarizes most of the important parameters within the model.

Thus, the rule for updating the state of cells is as follows:

(1) Initially, individuals are in the susceptible state, except for a small proportion (ρ_0) of infected individuals whose panic is triggered by stimuli under a given emergency. Then, as a result of emotion spread, under the influence of infected individuals, if the inner strength of panic (M) of a susceptible individual reaches a threshold (λ), he/she will enter the infected state, contracting panic with probability E_i and infecting others nearby [37].

There are some similarities between this process and the probabilistic threshold model described in Ref. [22].

(2) Because of self-adjustment and emotion decay, after several time steps t_1, infected individuals will recover, with probability p. Here t_1 for different individuals satisfies normal distribution $N(T_1, \delta_1)$ which reflects differences in individual characteristics. T_1 is the average duration of the infected state.

(3) Once recovered, an individual becomes susceptible again with probability q after t_2 time steps. t_2 satisfies normal distribution $N(T_2, \delta_2)$, where T_2 is the average duration of the recovered state. It is worth noting that a relationship between parameters p, q and the cure rate and infection rate respectively exists, according to the SIR model [25]. t_1 and t_2 reflect the duration of infected and recovered states respectively, which are related to external conditions.

To consider individual movement, a simple random walking mechanism is integrated into the CA–SIRS model. It is supposed that there is an equal probability that a person in a given cell will move to his/her Von Neumann neighborhood randomly, or stay at his/her current cell, as illustrated in Fig. 2. The blue circle represents an individual, and the diagonal stripe represents his/her Von Neumann neighbors. If there is no neighbor, there is an equal probability of 1/5 that the individual will move in any of four directions, i.e., up, down, left and right, or stay at his/her current cell at the next time step (Fig. 2(a)). If the cell above is occupied, for example, there is an equal probability of 1/4 that an individual will move in any of the other three directions, or stay at the next time step (Fig. 2 (b)), and so on. The individual cannot move when there is no unoccupied neighboring cell (Fig. 2(e)). Thus, each individual may travel over the whole grid during emotion spread.

Here, we can employ the modified model to study the evolution of the susceptible, infected and recovered populations, the effect of changing values of some parameters on the system, and the influence of individual movement on emotional contagion. The simulation results and discussion will be presented in the next section.

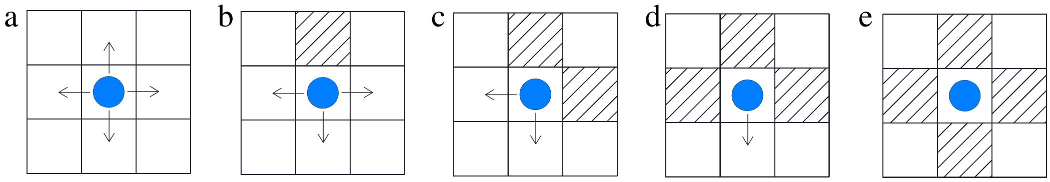


Fig. 2. Configurations that an individual may encounter.

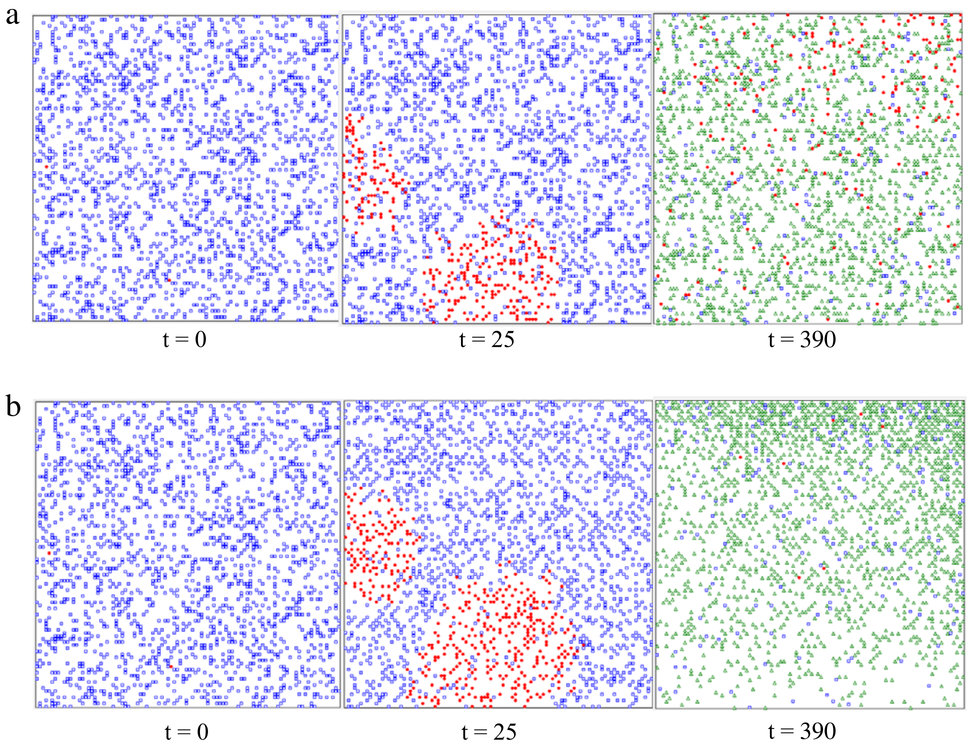


Fig. 3. Emotion spread: (a) without individual movement; (b) with individual movement. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3. Simulation and results

Our CA–SIRS emotional contagion model is tested in a cellular space of 100 × 100 cells, i.e. the system size is 40 m × 40 m ($W = H = 40$ m), including N individuals initially distributed randomly. The state of each individual is indicated by different colors, namely blue for susceptible individuals, red for infected individuals and green for recovered individuals (Fig. 3). We vary cellular and individual states using sequential updating [38]. All simulations last for 10 000 time steps, and each time step corresponds to 0.4 s. The parameters of the model are set artificially as: $n = 11$, $N = 2000$, $\lambda = 0.6$, $\rho_0 = 0.001$ (2 persons), $T_1 = 300$, $p = 0.7$, $q = 0.3$, $T_2 = 300$ and $\delta_1 = \delta_2 = 1$. E_i, $A_{j,i}$, $B_{i,j}$ of each cell are assigned values in the interval (0, 1] obtained from the computer random number generator. Initially, 2 infected individuals are distributed randomly in the cellular space. Then emotion begins to spread through the crowd, even if there is no individual movement, as shown in Fig. 3. The number of infected individuals (red points) will increase over time, but decrease when some of them recover (green triangles): these will become susceptible (blue quadrangles) again in an emergency situation. From the screenshots of simulations at the same time step with and without individual movement, we can see that such movement accelerates the spread speed of emotion, because of increased communication between individuals.

Figs. 4(a) and (b) depict the evolution of the susceptible (S), infected (I), and recovered (R) populations of the CA–SIRS model where individuals are static and dynamic, respectively. The y-axis represents the proportion of individuals in a given state (susceptible (ρ_S), infected (ρ_I) or recovered (ρ_R)), and $\rho_S + \rho_I + \rho_R = 1$. Interestingly, the proportion of individuals in each state fluctuates with the amplitude becoming increasingly small (including multiple waves of infection [33]): it is dynamically stable at a mean value with a variation of ±0.05. This is a typical feature in our model. The mean values of susceptible, infected and recovered individuals after nearly 3500 time steps are 0.1023, 0.3349 and 0.5628 respectively, as shown in Fig. 4(a), while they are 0.1044, 0.3362 and 0.5594 respectively after nearly 3000 time steps in Fig. 4(b). The difference in ρ_I between tests with and without individual movement is evident from Fig. 4(c). Though the trends of the two

Table 2
The initial probability of human-to-human contact without individual movement, given different ranges and average crowd densities.

n	ρ									
	0.02	0.04	0.05	0.06	0.08	0.10	0.20	0.40	0.60	0.80
3	0.1492	0.2786	0.3366	0.3904	0.5278	0.6126	0.8658	0.9899	0.9997	1.0000
5	0.3842	0.6246	0.7080	0.7735	0.8648	0.9202	0.9953	1.0000	1.0000	1.0000
7	0.6208	0.8591	0.9147	0.9487	0.9817	0.9936	1.0000	1.0000	1.0000	1.0000
9	0.8014	0.9618	0.9835	0.9929	0.9987	0.9998	1.0000	1.0000	1.0000	1.0000
11	0.9115	0.9925	0.9979	0.9994	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

curves are almost the same, with the mean value in Fig. 4(b) just a little larger than that in Fig. 4(a), an important difference exists in their spread speed, as illustrated in the sub-graph of Fig. 4(c) from time step 600–1400. The speed of emotional contagion for a given individual movement is greater than that where no such movement occurs. This can be explained by the fact that information is more easily obtained by individuals when there is movement. Furthermore, we can see that most of the individuals depicted in Figs. 4(a) and (b) (approximately 90%) are in the infected or recovered state by the end of the tests. These results demonstrate that emotional contagion in a crowd will be dynamically stable, and provide useful information, such as the likely proportion of infected individuals, for large-scale management.

As illustrated in Fig. 4, when we set the range of emotional influence to $n = 11$ in a system including 2000 individuals, the difference in the final stable proportion of infected individuals between models with and without individual movement is not pronounced. However, the difference is noticeable if $n = 5$, for example (see Fig. 5). In this case, the proportion of infected individuals in the dynamic system is considerably larger than that without movement. Therefore, it is necessary to analyze other cases where the range (n) and average crowd density ($N/10\,000$) are different (see Fig. 6). Here, the number of initial infectors for all scenarios is set as 2. In general, the final stable proportion of infected individuals (ρ_I) increases with an increase in the average crowd density, whether individual movement is a factor or not. Such movement can result in more infected individuals, however. This phenomenon is consistent with what is described in Fig. 4. Nevertheless, there is a sharp change in the value of ρ_I without individual movement for different ranges (n), and this induces the marked difference between results for the dynamic and static systems. More specifically, the value of ρ_I in the dynamic system is markedly larger than that without individual movement when the average crowd density is less than 0.6, 0.4, 0.2, 0.08 or 0.06 and $n = 3, 5, 7, 9$ or 11 respectively. Reasons for those considerable differences in the static system data may be hypothesized to relate to the initial probability of human-to-human contact. For a given range of emotional influence in the static system in our model, an essential condition for propagation of emotion is that other individuals are present within range: this is not a limitation in the dynamic system, as individuals can move, and affect others. Accordingly, we seek to calculate the probability of the initial presence of randomly distributed neighboring persons around a given individual (P) in the static system with the following formula (4):

$$P = 1 - (1 - \rho)^{n^2-1} \tag{4}$$

where ρ equals the initial average crowd density and $n^2 - 1$ ($n = 3, 5, 7, 9, 11$) represents the total number of neighboring individuals within the range of emotional influence. The many results of this calculation are presented in Table 2. It is readily apparent that points in Fig. 6, whose ρ_I value is markedly lower, fulfill $P < 0.999$ (marked in red in Table 2). As P, i.e., the initial probability of human-to-human contact, decreases, it will of course be more difficult for emotion spread, even resulting in $\rho_I = 0$ in some cases. Our data confirm that decreasing the crowd density and reducing movement are helpful in crowd management.

For succinctness, we employ $n = 11$ in the following analysis.

For large-scale crowd management, it is important to understand how many individuals will be infected by rumor or abnormal behavior and, equally important, to understand how many initial infectors can cause serious consequences. Therefore, the initial proportion of infected individuals in our system may be an important concern. As noted above, the proportion of infected individuals (ρ_I) dynamically stable at a mean value. Here, we investigate the influence of the initial proportion of infected individuals (ρ_0) on this value. Fig. 7 shows the mean values of the proportion of infected individuals (ρ_I) given different ρ_0. It may be seen that the value of ρ_I remains almost stable at 0.34, which implies that the initial proportion of infected individuals has little effect on the evolution of the system employed in our model (2000 individuals). Fig. 7 also confirms that individual movement results in slightly more infected individuals than in the static system. To further investigate whether the proportion of infected individuals is affected by the average crowd density in the system, we conducted simulations with different total number of individuals (see Fig. 8). Here, the number of initial infected individuals is set as 2. It is apparent that the infection frequency (the average infection time of each individual at each time step) increases with increasing average crowd density, but the growth rate drops markedly when the average crowd density reaches approximately 0.5 where individual movement is permitted and 0.6 in the static system, because the influence of the number of infected individuals in the cognitive area weakens with further increasing density. We conclude that a larger number of individuals can strengthen emotional propagation through crowds, and this renders large-scale crowds harder to control. However, decreasing the crowd density can be a useful method of managing a panicking crowd, especially in situations where the crowd density exceeds 0.5 and individual movement is possible. Our results also demonstrate that

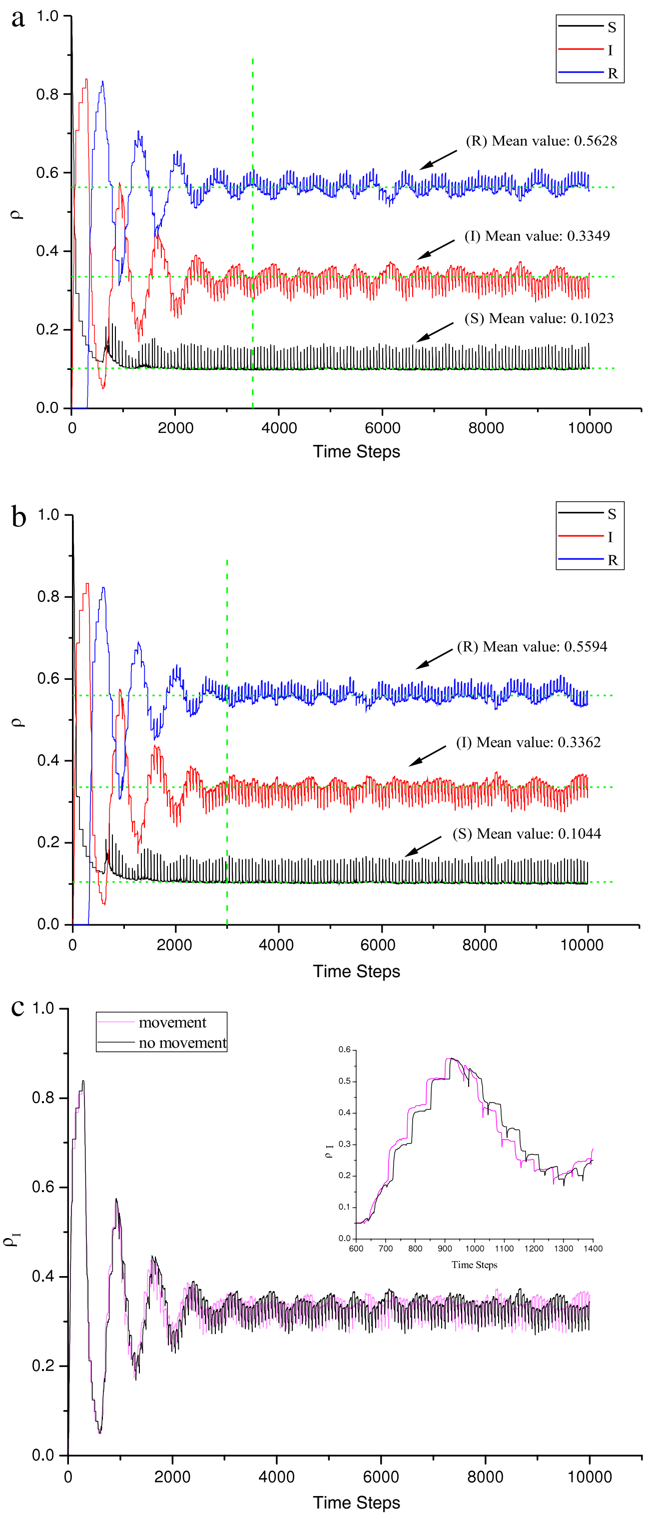


Fig. 4. Evolution of the susceptible (S), infected (I), and recovered (R) populations of the CA–SIRS model: (a) without individual movement; (b) with individual movement; (c) comparison of the infected (I) population in simulation with and without individual movement. ($n = 11$, $N = 2000$, $\rho_0 = 0.001$, $p = 0.7$, $q = 0.3$).

movement can cause more infected individuals, and immobilizing the members of a crowd may be a reasonable way to manage panicking crowds.

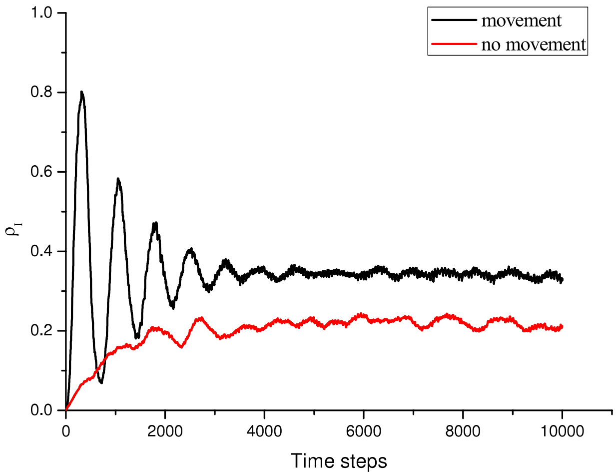


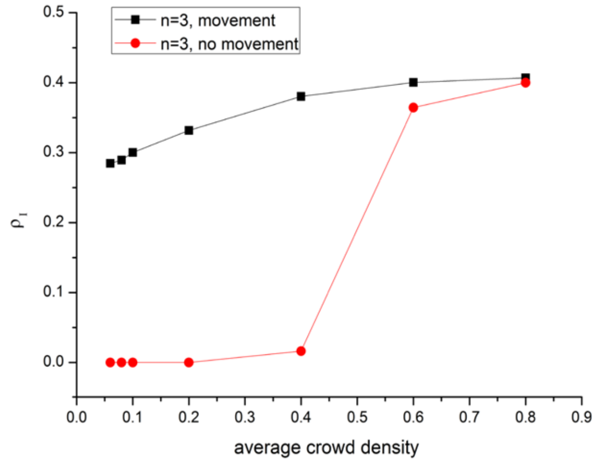
Fig. 5. The influence of individual movement on the infected population. ($n = 5$, $N = 2000$, $\rho_0 = 0.001$, $p = 0.7$, $q = 0.3$).

As discussed above, the mean value of the final stable infected individuals was rarely affected by the number of initial infected individuals in the system size we employed. However, in different situations with individual movement, the probability of individuals recovering or becoming susceptible is indeterminate. Thus, the number of infected individuals may alter with different values of p and q. Fig. 9 clearly shows that the average number of infected individuals will decrease, with an increasing probability of recovery (p), if q is invariable, but will increase, with an increasing probability of becoming susceptible (q), if p is invariable. It is worthy of note that approximately 90% of crowd members were finally infected when p was 0.1, i.e. there were no measures available which could alleviate panic in a given emergency. In addition, the stable proportion of infected individuals will fall greatly if the probability of becoming susceptible (q) drops to 0.1, as illustrated in Fig. 9. Hence, appropriate evacuation strategies or rescue guidance may be required to ease individuals' panic and prevent recovered individuals from becoming susceptible again.

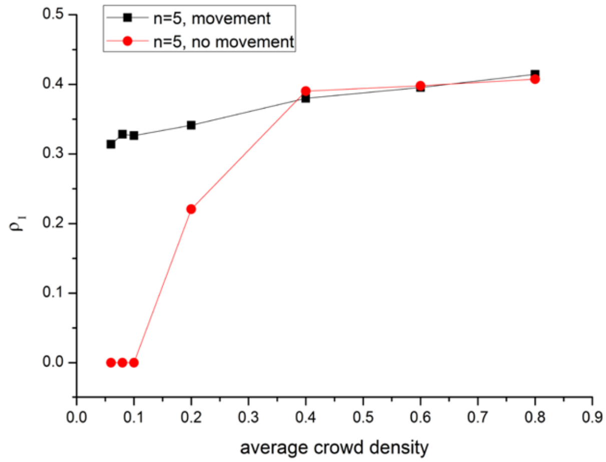
In fact, the mean value is also highly associated with T_1 and T_2, which represent the average duration of an individual state, and depend on local conditions under emergencies. Therefore, we recommend that departments involved in an emergency engage in useful measures or rescue guidance to calm infected individuals, that is to say, reducing the value of T_1 while keeping the other parameters, especially the number of crowd members (2000 individuals), unchanged. It is readily apparent from Fig. 10 that the infected population decreases after such measures are taken ($T_1 = 100$), regardless of whether individual movement is permitted. The greater the reduction of t_1, the smaller the infected population will be (Fig. 11). The results show that finally infected individuals will decrease by 25% if $T_1 = 50$, as compared with $T_1 = 300$. This demonstrates the importance of relevant measures to allay panic. It is worthy of note that the effect of individual movement on the infected individuals stated in Fig. 4 is also contained in the evolution, though the effect is not marked.

4. Conclusions

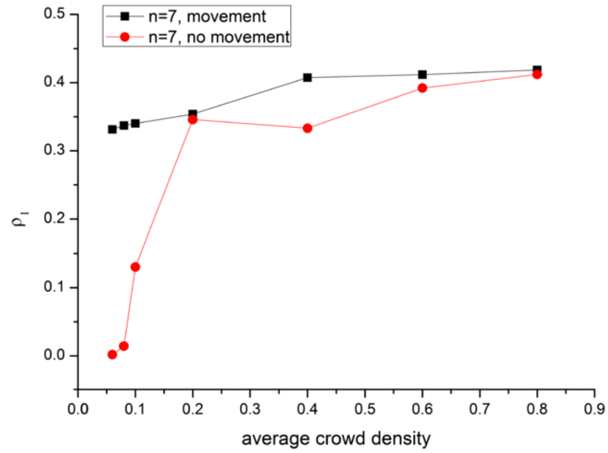
In this paper, we have modified the epidemiological SIR model, and proposed a CA–SIRS emotional contagion model. The modified model can not only actualize the dynamic propagation of emotion in analogy with the original model at the macro level, but also achieve the microscopic characteristics of emotional contagion. There are some interesting observations in this work that the model presents multiple waves of infection, and the proportion of infected individuals is dynamically stable at a mean value after a period of propagation. The mean value may alter with different probabilities of individuals recovering or becoming susceptible, depending on external conditions. Those are useful information to estimate the number of infected individuals in large-scale evacuation. It is suggested that intervention approaches, such as correct guidance to prevent recovered individuals from becoming susceptible again, may be of significant benefit for large-scale crowd management. Compared with the simulation without individual movement given different ranges of emotional influence and average crowd densities, the spread speed of emotion and the proportion of finally stable infected individuals of the test with individual movement are greater. This implies that immobilizing the members of a crowd may be an effective measure to manage large-scale crowds under emergencies. Through simulation, we conclude that the initial infected population has little influence on the proportion of the infected population in the dynamically stable process. Nevertheless, the infection frequency increases with an increase in average crowd density. This demonstrates that it is more difficult to conduct large-scale crowds in a larger system size. It confirms that decreasing crowd density to be less than 0.5 will markedly drop the infected population with movement. In addition, rescue guidance, which is involved in our model by reducing the average duration of the infected state, is important to manage crowd members. Our results clearly identify that finally infected individuals will decrease by 25% if the average duration of the infected state equals 50, as compared with original 300.



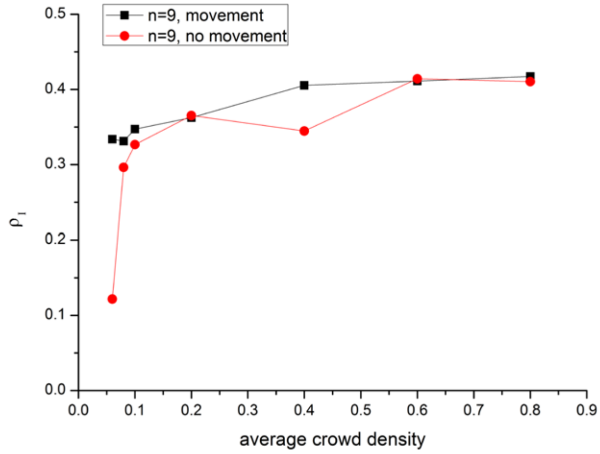
(a) $n = 3$.



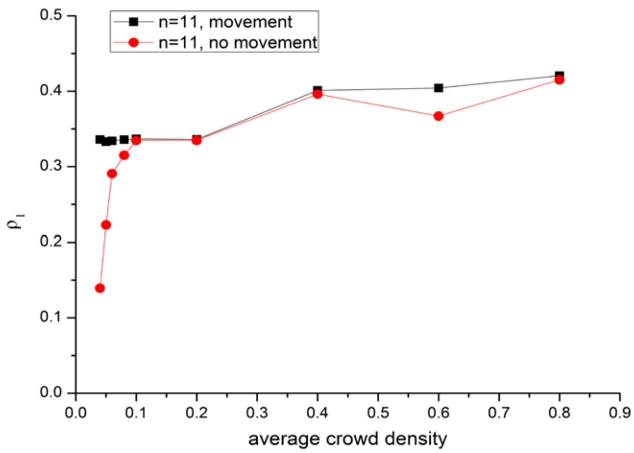
(b) $n = 5$.



(c) $n = 7$.



(d) $n = 9$.



(e) $n = 11$.

Fig. 6. The final stable proportion of infected individuals (ρ_I) in the dynamic and static systems for various average crowd densities, considering different ranges of emotional influence (n): (a) $n = 3$; (b) $n = 5$; (c) $n = 7$; (d) $n = 9$; (e) $n = 11$. ($p = 0.7$, $q = 0.3$).

In the proposed model, what is interesting is that we are able to identify the cases, namely special values of the model parameters, where one can make long-time predictions as to the number of infected individuals. It is worthy of note that

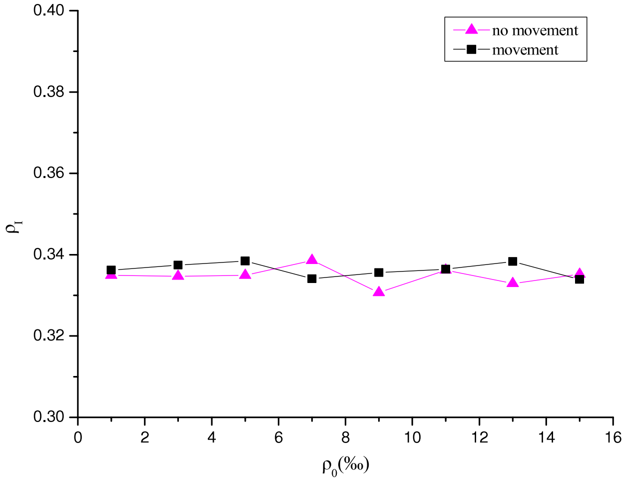


Fig. 7. The influence of the initial proportion of infectors (ρ_0) on the final stable proportion of infected individuals (ρ_I). ($n = 11$, $N = 2000$, $p = 0.7$, $q = 0.3$).

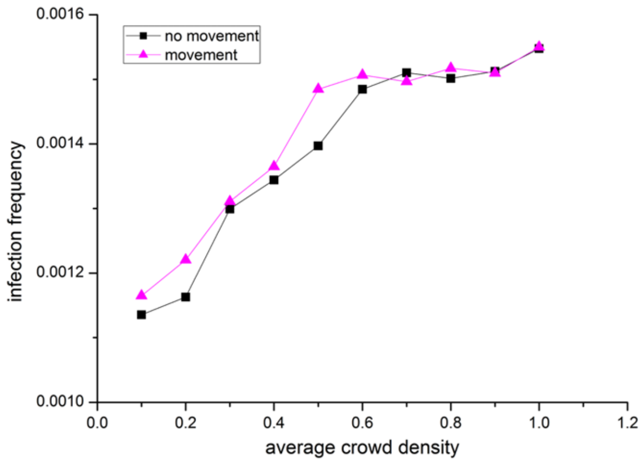


Fig. 8. The relationship between infection frequency and average crowd density. ($n = 11$, $p = 0.7$, $q = 0.3$).

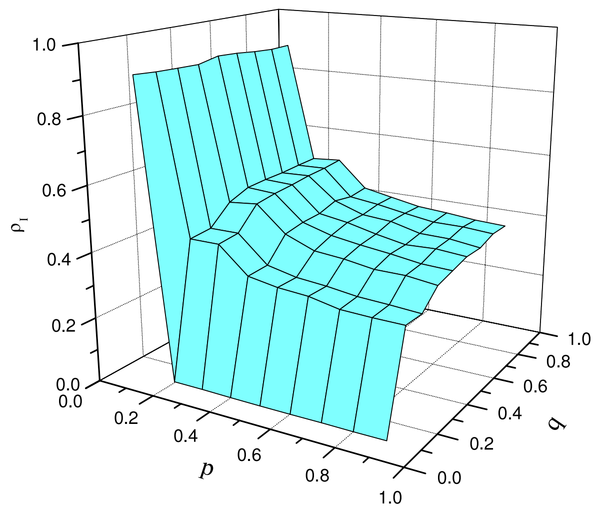


Fig. 9. The influence of different values of p and q on the final proportion of infected individuals (ρ_I). ($n = 11$, $N = 2000$, $\rho_0 = 0.001$).

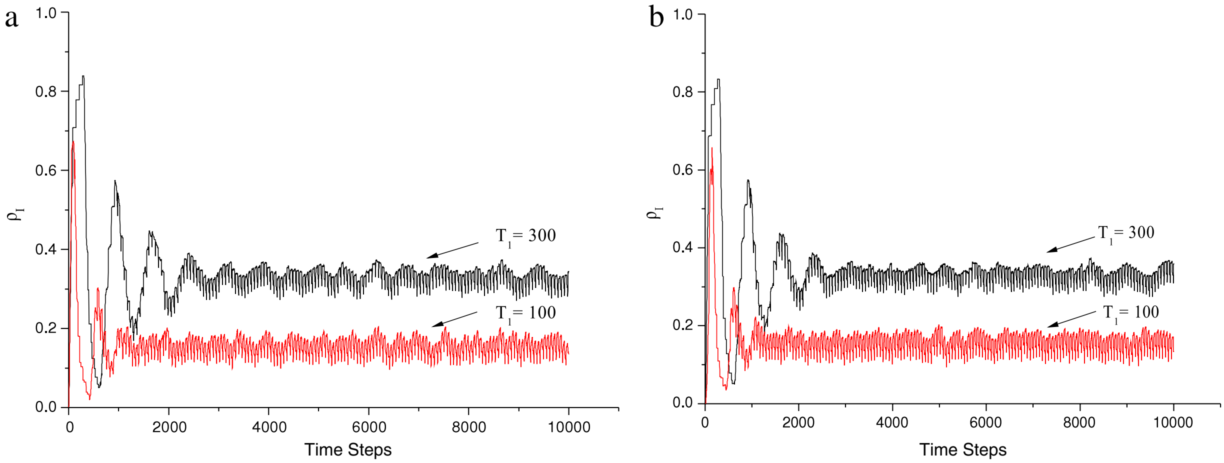


Fig. 10. Evolution of the infected (I) population of the CA–SIRS model when $T_1 = 100$ and $T_1 = 300$: (a) without individual movement; (b) with individual movement. ($n = 11$, $N = 2000$, $\rho_0 = 0.001$, $p = 0.7$, $q = 0.3$).

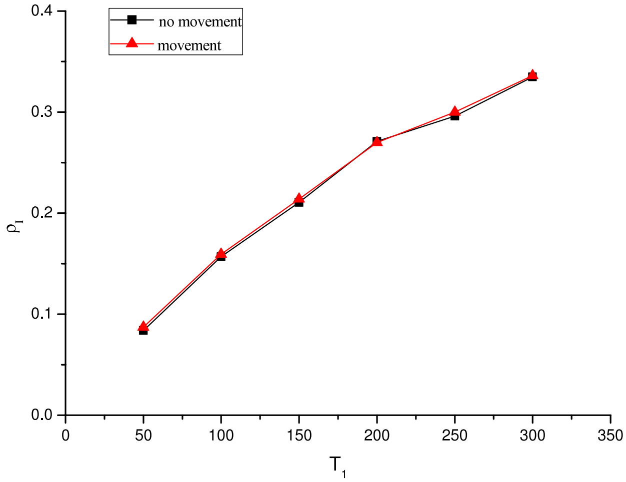


Fig. 11. The relationship between the mean value of the proportion of infected individuals (ρ_I) in the dynamically stable process and the average duration of the infected state (T_1). ($n = 11$, $\rho_0 = 0.001$, $p = 0.7$, $q = 0.3$).

our model can be used to quantify the varying strength of individual nervousness, whose influence on the desired velocity during an evacuation process can be analyzed. Moreover, the behavior of emotional contagion in our model can be employed to assess the level of panic and the role of control measures to reduce the hazard of the outbreak of comprehensive panic. This research may make some contributions for related departments to deal with evacuation under emergencies. Several extensions of our model, such as setting the related parameters by experimental data, can be conducted in some future publication.

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