IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received February 6, 2020, accepted February 18, 2020, date of publication February 24, 2020, date of current version March 3, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2975808

Control Strategies for Crowd Emotional Contagion Coupling the Virtual and Physical Cyberspace in Emergencies

XIAO HONG, GUIJUAN ZHANG, AND DIANJIE LU
School of Information Science and Engineering, Shandong Normal University, Jinan 250358, China
Shandong Provincial Key Laboratory for Novel Distributed Computer Software Technology, Jinan 250358, China

Corresponding author: Guijuan Zhang (zhangguijuan@sdnu.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 61572299, Grant 61972237, and Grant 61876102, in part by the Shandong Provincial Natural Science Foundation of China under Grant ZR2019MF017, in part by the Shandong Key Research and Development Program under Grant 2019GSF111019, and in part by the Funding for Study Abroad Program by the Government of Shandong Province.

ABSTRACT Crowd emotional contagion occurs in both virtual and physical cyberspace at the same time. To realistically simulate the process of crowd emotional contagion, the influences of virtual cyberspace and physical cyberspace should be considered comprehensively. In addition, control strategies significantly affect the speed and scale of emotional contagion in a crowd. However, control strategies described by existing studies are inaccurate since few of them consider both physical and virtual cyberspace to jointly study the influence of control strategies on crowd emotional contagion. To achieve more accurate control, we first establish a novel personalized emotional contagion computational (NP-ECC) model to study control strategies of crowd emotional contagion coupling the physical and virtual cyberspace. Second, we construct a personalized BA scale-free network to calculate the phase transition threshold of the proposed NP-ECC model more accurately. Finally, we propose two algorithms, control strategies-BA (CS-BA) and threshold-BA (T-BA), to verify the stability of the NP-ECC model and the accuracy of the phase transition threshold, respectively. The experimental results show that our method can better control the speed and scale of crowd emotional contagion and thus can provide guidance for a large-scale crowd evacuation.

INDEX TERMS Control strategies, phase transition, personalized BA scale-free network, crowd emotional contagion.

I. INTRODUCTION

Recently, sudden natural disasters and public events such as earthquakes and fires have attracted increasing public attention and caused negative social impacts due to their extremely destructive nature [1], [2]. With the rapid development of society, an individual's emotions will be affected by information in physical and virtual cyberspace as well as individual personality. At present, control strategies and thresholds of crowd emotional contagion are mainly analyzed by two types of approaches. The first is the threshold and control strategies of emotional contagion in physical cyberspace, i.e., the study of threshold and control strategies of emotional contagion among geographically adjacent individuals. For example, Wang *et al.* [3] proposed a emotional contagion calculation model to solve the problem of emotional contagion control in physical cyberspace. Diefendorff and Gosserand [4] suggested that individuals could use emotion self-regulation strategies to control emotions and avoid large-scale occurrence of emotional contagion. Bertozzi *et al.* [5] considered an agent-based emotional contagion model coupled with one-dimensional motion and obtained the threshold of such a model. The second group of studies explore the threshold and control strategies of emotional contagion in virtual cyberspace, i.e., they study the threshold and control strategies of emotional contagion among individuals in social networks. For example, Rempala [6] tested susceptibility strategies to limit the ''capture'' of negative emotions from others by playing videos. Hadjikhani *et al.* [7] studied the emotional contagion threshold of panic by playing short

The associate editor coordinating the review of this manuscript and approving it for publication was Xiaogang Jin.

video clips. However, the existing studies independently explore the control strategies and threshold of emotional contagion in a single physical or virtual cyberspace without considering comprehensively the crowd emotional contagion that will be affected by both physical and virtual cyberspace. Therefore, they cannot accurately implement control strategies and obtain the phase transition threshold.

In fact, in the real world, an individual's emotions are affected by emotional contagion in physical and virtual cyberspace. While individuals are more susceptible to emotional contagion in the physical cyberspace, the range of emotional contagion in the virtual cyberspace is wider. Thus, emotional contagion in dual spaces may have more complex effects on the final emotional state of an individual. In addition, individual personality is also an important factor affecting emotional contagion. Thus, in the scenario of combining virtual cyberspace with a physical cyberspace, studying the control strategies of crowd emotional contagion and calculating the phase transition threshold more accurately is a challenging task.

To address this problem, we propose an NP-ECC model to study control strategies of emotional contagion coupling the physical and virtual cyberspace and to calculate the phase transition threshold more accurately. To the best of our knowledge, this is the first method developed to study control strategies while considering both the virtual cyberspace and the physical cyberspace. The contributions of this research are as follows.

1) We first propose the emotional contagion mechanism to consider the influences of the virtual and physical cyberspace as well as personality on crowd emotional contagion. Then, we propose the control strategies for emotional contagion coupling the physical and virtual cyberspace and construct a NP-ECC model to control the speed and scale of emotional contagion.
2) We construct a personalized BA scale-free network to consider the personality difference of individuals and calculate the phase transition threshold of the NP-ECC model in such a network.
3) We propose two algorithms CS-BA and T-BA to verify the stability of the NP-ECC model and the accuracy of the phase transition threshold, respectively.

The remainder of this paper is organized as follows. In Section II, we present a brief review of the previous studies of control strategies and thresholds of crowd emotional contagion. In Section III, we provide an overview of the framework of our method. In Section IV, we introduce in detail the control strategies of the NP-ECC model coupling the physical and virtual cyberspace. Afterwards, we study the phase transition threshold of the NP-ECC model in a personalized BA scale-free network in Section V. Section VI describes the simulation algorithm of the NP-ECC model in a personalized BA scale-free network. Experiments are presented in Section VII, and conclusions are stated in Section VIII.

II. RELATED WORK

Although numerous studies have explored crowd emotions from the perspective of calculations and simulations, few existing studies have discussed the problem of emotional contagion coupling the virtual and physical cyberspace [8]–[16]. The so-called emotional contagion refers to an individual's emotion being transmitted to individuals through interactions between individuals (such as face-to-face communication) [17]. Emotional contagion is very important when one's emotional state affects the behavior of other individuals. Specifically, an individual's negative emotion breaks out through emotional contagion and further affects collective behavior, thus having a relatively substantial social impact [18], [19]. Computational modeling of emotional contagion is an important challenge in understanding, predicting and controlling the process of emotional contagion. Fortunately, this field has been attracting more and more researchers [20]–[24].

A. CONTROL STRATEGIES

Because emotional contagion is similar to the spread of infectious diseases in a crowd, researchers have studied emotional contagion using dynamic epidemiological models, most of which are based on the susceptible-infected-recovered (SIR) model [25]–[28]. In addition, studies of emotional contagion mainly focus on modeling its process and rely on studies of emotional recognition methods to reveal the dynamic process of emotional contagion. Few studies have explored the strategies for controlling emotional contagion [29], [30]. Our ultimate goal of studying control strategies of crowd emotional contagion is to control the speed and scale of emotional contagion in emergencies and provide guidance for crowd evacuation. Some control strategies, including vaccination, quarantine and treatment, inspired by infectious disease control studies, can be used to suppress emotional contagion [31], [32]. Ledzewicz and Schättler [33] discussed an optimal single control strategy for general SIR models with vaccines and treatments; however, such control strategies are aimed at biological epidemics and are unsuitable for controlling emotional contagion. Zhang *et al.* [34] proposed an optimization strategy of positive emotion transmission during crowd evacuation, and established a model to maximize the use of positive emotional contagion.

In fact, most of the above studies of emotional contagion focus on modeling and simulating the emotional contagion process in a single space, and there is no coupling of the physical and virtual cyberspace in studying the control strategies of emotional contagion. Therefore, the speed and scale of emotional contagion can not be accurately predicted.

B. THRESHOLDS

To better study the phase transition threshold in a personalized emotional contagion model, we can refer to the epidemic threshold since the process of emotional contagion is similar to the infection process of an epidemic. At present, most studies on epidemic threshold are based on epidemiological studies of complex networks, most of which are based on the SIR model [35]–[37]. In [38] and [39], the authors regard the epidemic threshold as simply the average of those of complex networks. In previous studies, it was assumed that the infection rate of all links in complex networks was the same, as was the recovery rate of all nodes [40]. Chen [35] studied the heterogeneity of infection rate and recovery rate in complex networks, but simply divided infection rate and recovery rate into two tiers without considering the difference in individual personalities. Therefore, the researchers could not accurately obtain the epidemic threshold. We can consider the latter in a network to study the threshold of personalized emotional contagion spreading in complex networks.

C. EMOTION CONTAGION IN CROWD SIMULATION

Most studies about control strategies and thresholds of emotional contagion in crowd simulation have focused on a single contagion cyberspace. Huang *et al.* [41] proposed an Agent-Based Emotion Contagion (ABEC) model to simulate group violence in the physical cyberspace. Xiang *et al.* [42] studied on the emotion contagion in dynamic process of the virtual pedestrian. Li *et al.* [43] presented an antagonistic crowd simulation model (ACSEE) to simulate antagonistic crowd behaviors in the real-world scenarios. Park proposed a crowd simulation approach and algorithm to verify emotional contagion in crowd simulation [44], [45]. Xue *et al.* [46] proposed an improved emotional contagion model to simulate emotional contagion in crowd movement. Xu *et al.* [47] proposed a SMOG-FVDM (Smog Full Velocity Difference Model) model to simulate the emotional contagion in the real life. Lv *et al.* [48] proposed a new emotional contagion mechanism by combining the SIR model and the OCEAN personality model to simulate the crowd movement in the political rallies. They found that the emotion can affect individual behavior decision and the event from the virtual cyberspace can trigger group events in the physical cyberspace. However, the information in physical cyberspace and virtual cyberspace influence emotional contagion in crowd simulation jointly. Therefore, these approaches of crowd simulation can not realistically simulate the process of crowd emotional contagion, and can not accurately predict the speed and scale of emotional contagion.

III. OVERVIEW

Our goal is to study control strategies of crowd emotional contagion in scenarios in virtual and physical cyberspace and to calculate the phase transition threshold more accurately, so as to better control the speed and scale of emotional contagion in crowd evacuation. The framework proposed in this paper includes three main steps, as shown in Figure 1: the NP-ECC model construction, the phase transition threshold solution for the NP-ECC model, the NP-ECC model simulation algorithm. To achieve more accurate control, we first establish the NP-ECC model to study control strategies of crowd emotional contagion coupling the physical and virtual cyberspace. Second, we construct a personalized BA scale-free network to calculate the phase transition threshold of the proposed NP-ECC model more accurately. Finally, we propose two algorithms CS-BA and T-BA to verify the stability of the NP-ECC model and the accuracy of the phase transition threshold, respectively. We will introduce the details of this method in the following sections.

IV. CONTROL STRATEGIES FOR THE NP-ECC MODEL

To better control the speed and scale of crowd emotional contagion, we first propose a personalized emotional contagion mechanism, and then propose personalized emotional contagion control strategies coupling the physical and virtual cyberspace. These will be separately introduced in the following two subsections.

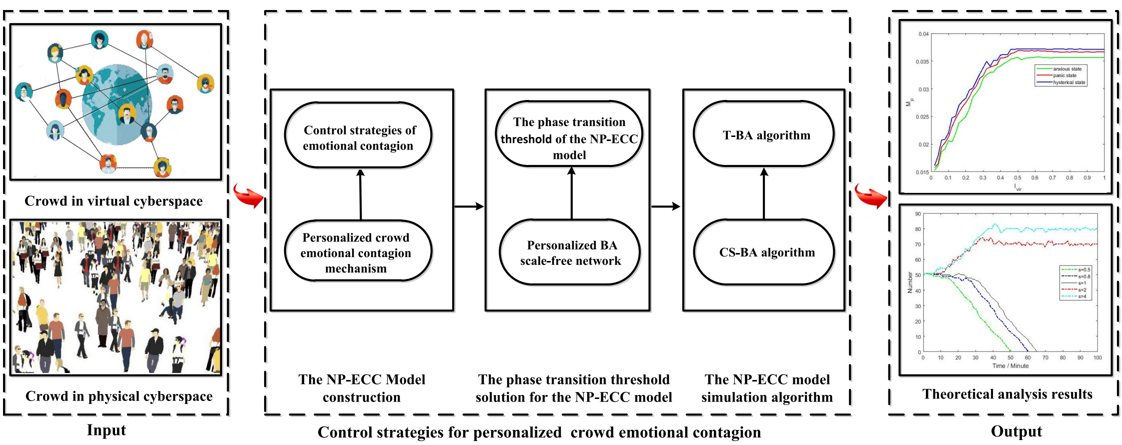


FIGURE 1. The framework of our method.

A. PERSONALIZED CROWD EMOTIONAL CONTAGION MECHANISM COUPLING THE VIRTUAL AND PHYSICAL CYBERSPACE

To realistically simulate the process of emotional contagion, we consider the influence of virtual and physical cyberspace and individual personality on emotional contagion. We assume that a region contains a mixed population of N individuals and can be in one of three states at any time: susceptible (S), infected (I), or recovered(R). Therefore, we refer to the classical SIR model [26], [27]. Since we consider the common influence of virtual and physical cyberspace on emotional contagion, we divide individuals into six categories according to their emotional states on the basis of SIR model as shown in Table 1. Similarly, we use the OCEAN personality model [49] to study personalized emotional contagion. The model has five factors: openness, extroversion, easygoing, neuroticism, and responsibility. The more neurotic an individual is, the more susceptible he or she is to emotional contagion [50]. In this paper, we consider the personality characteristics of ''Neuroticism'' in the OCEAN personality model. The emotional states of neurotic individuals are divided into the following four categories: calm state, anxious state, panic state, and hysterical state. We randomly assign emotional states to each individual and propose $S_{vir}(i)$, $P_{vir}(i)$, $S_{phy}(i)$ and $P_{phy}(i)$ based on personalized emotional states. According to the literature [52], the $S_{vir}(i)$, $P_{vir}(i)$, $S_{phy}(i)$ and $P_{phy}(i)$ of individuals can be divided into four levels corresponding to four different emotional states. Without loss of generality, we suppose that these variables are subject to a uniform distribution $U(\cdot)$, as shown in Table 2. In addition, according to the common sense that individuals have immersive experiences in the physical cyberspace, we believe that they are more susceptible to the influence of emotional contagion in the physical cyberspace, and their emotions are more easily recovered in the physical cyberspace. Therefore, we set the strength of emotional contagion and emotional recovery in the physical cyberspace to be larger than in the virtual cyberspace. Since the individuals in a calm state are unlikely to be affected by emotional contagion, we set $S_{vir}(i) = 0$, $P_{vir}(i) = 0$, $S_{phy}(i) = 0$ and $P_{phy}(i) = 0$ if the individual's personalized emotional state is calm.

TABLE 1. The individuals in the crowd are divided into six categories according to their emotional states.

parameter	Description
C_{VS}	virtual cyberspace's susceptible individuals
C_{PS}	physical cyberspace's susceptible individuals
C_{VI}	virtual cyberspace's infected individuals
C_{PI}	physical cyberspace's infected individuals
C_{VR}	virtual cyberspace's recovered individuals
C_{PR}	physical cyberspace's recovered individuals

When an infected individual i encounters a recovered individual, the former may probabilistically become a recovered individual. For example, a calm individual (an emotionally recovered individual) can help a panicking individual (an emotional infector) through face-to-face or online communication, thus making the panicking individual in an emergency become a calm individual with some probability. Similarly, when a susceptible individual i encounters an infected individual, the former may probabilistically become an infected individual. For example, a panicking individual (an emotional infector) can infect an emotionally susceptible individual through face-to-face and online communication, thus causing the latter individual in an emergency to become a panicking individual with some probability. To describe individual i more intuitively, we set up an eight-tuple $S(i) = (S_{vir}(i), P_{vir}(i), S_{phy}(i), P_{phy}(i), I_{vir}, I_{phy}, r_{vir}, r_{phy})$ to represent the individual's personalized emotional model. The parameters description of eight-tuple as shown in Table 3.

TABLE 2. Values of $S_{vir}(i)$, $P_{vir}(i)$, $S_{phy}(i)$ and $P_{phy}(i)$.

Value of $S_{vir}(i)$ and $P_{vir}(i)$	Personalized emotional state	Value of $S_{phy}(i)$ and $P_{phy}(i)$
0	Calm	0
$U(\cdot)(0, 0.2]$	Anxious	$U(\cdot)(0.2, 0.4]$
$U(\cdot)(0.4, 0.6]$	Panic	$U(\cdot)(0.6, 0.8]$
$U(\cdot)(0.8, 0.9]$	Hysterical	$U(\cdot)(0.9, 1]$

TABLE 3. The parameters used in the eight-tuple.

parameter	Description
$S_{vir}(i)$	the strength of emotional contagion in the virtual cyberspace
$P_{vir}(i)$	the strength of emotional recovery in the virtual cyberspace
$S_{phy}(i)$	the strength of emotional contagion in the physical cyberspace
$P_{phy}(i)$	the strength of emotional recovery in the physical cyberspace
I_{vir}	the infection rate of infectors in the virtual cyberspace
I_{phy}	the infection rate of infectors in the physical cyberspace
r_{vir}	the cure rate of recovered individuals in the virtual cyberspace
r_{phy}	the cure rate of recovered individuals in the physical cyberspace

The combination of physical cyberspace and virtual cyberspace as well as personality is neglected in the existing models of emotional contagion. This difference may lead to new causes of emotional contagion. In the [51], the individual's susceptibility positively related to the sensitivity of the individuals. In addition, individuals with different personalities have heterogeneous infection and cure rate which will affect the emotional contagion directly [52], [53]. Considering the individual personality differences, we regard that the infection rate of the individual is affected by the own strength of emotional contagion and the infection rate of the infected individuals. The cure rate of the individual is affected by the own strength of emotional recovery and the cure rate of the recovered individuals. That is to say, a susceptible individual who comes into contact with an infected individual will be affected by the infection rate of the latter and the former's own strength of emotional contagion. Similarly, an infected individual who comes into contact with a recovered individual will be affected by cure rate of the latter and the former's own strength of emotional recovery. Thus, we define the probability of a susceptible individual being infected by virtual cyberspace's infected individual is $I_{vir}S_{vir}(i)$, the probability of a susceptible individual being infected by physical cyberspace's infected individual is $I_{phy}S_{phy}(i)$, the probability of a infected individual being cured by virtual cyberspace's recovered individual is $r_{vir}P_{vir}(i)$, and the probability of a infected individual being cured by physical cyberspace's recovered individual is $r_{phy}P_{phy}(i)$. In this subsection, we consider the influence of physical cyberspace, virtual cyberspace and individual personality on the process of emotional contagion, and define the following new transition rules between states at any time t.

(1) If $i \in C_{PS}$, $j \in C_{VI}$ or $j \in C_{PI}$, i may be infected by j with probability $I_{vir}S_{vir}(i)$ or $I_{phy}S_{phy}(i)$ and become a member of C_{PI}.

(2) If $i \in C_{VS}$, $j \in C_{VI}$ or $j \in C_{PI}$, i may be infected by j with probability $I_{vir}S_{vir}(i)$ or $I_{phy}S_{phy}(i)$ and become a member of C_{VI}.

(3) If $i \in C_{PI}$, $j \in C_{VR}$ or $j \in C_{PR}$, i may be cured by j with probability $r_{vir}P_{vir}(i)$ or $r_{phy}P_{phy}(i)$ and become a member of C_{PR}.

(4) If $i \in C_{VI}$, $j \in C_{VR}$ or $j \in C_{PR}$, i may be cured by j with probability $r_{vir}P_{vir}(i)$ or $r_{phy}P_{phy}(i)$ and become a member of C_{VR}.

B. CONTROL STRATEGIES FOR EMOTIONAL CONTAGION

Based on the mechanism of crowd emotional contagion proposed above, in this subsection we further formulate the control strategies of crowd emotional contagion coupling the physical and virtual cyberspace, with such strategies designed to minimize the speed and scale of crowd emotional contagion in an emergency. To better control emotional contagion, we should set control strategies for individuals in infected and susceptible states, respectively. Therefore, we propose control strategies including preventive control strategies and treatment control strategies. Preventive control strategies are mainly aimed at individuals in the susceptible state, and treatment control strategies mainly target individuals in the infected state. Preventive and treatment control strategies will be introduced in the following two parts.

1) PREVENTIVE CONTROL STRATEGIES

Preventive control strategies entail prevention in the physical and virtual cyberspace. Physical cyberspace prevention, which tells susceptible individuals in the physical cyberspace that a dangerous event has been effectively controlled by the emergency management personnel, is expressed as $f_{phy1}(P^S_{phy}(t), V_{phy1}(t))$. Virtual cyberspace prevention, which tells susceptible individuals in the virtual cyberspace that a story about a dangerous event has been clarified by the official media on the network or that solution measures have been announced, is expressed as $f_{vir1}(P^S_{vir}(t), V_{vir1}(t))$. As a result, applying preventive control strategies against negative or panic emotions in advance will result in susceptible individuals never panicking about danger, and not spreading such panic emotions when perceiving them in the future.

2) TREATMENT CONTROL STRATEGIES

Treatment control strategies entail treatment in the physical and virtual cyberspace. Physical cyberspace treatment, which allows emergency administrators to spread a positive emotion to infected individuals in the physical cyberspace to eliminate panic or negative emotions of infected individuals in the physical cyberspace, is expressed as $f_{phy2}(P^I_{phy}(t), V_{phy2}(t))$. Virtual cyberspace treatment, which allows official media to spread a positive emotion to infected individuals in the virtual cyberspace to eliminate panic or negative emotions of infected individuals in the virtual cyberspace, is expressed as $f_{vir2}(P^I_{vir}(t), V_{vir2}(t))$. As a result, emergency managers and official media can relieve the panic and negative emotions of infected individuals through such treatment strategies as comfort and care. After treatment, infected individuals become recovered individuals and no longer spread such panic and negative emotions.

Functions $f_{phy1}(P^S_{phy}(t), V_{phy1}(t))$, $f_{vir1}(P^S_{vir}(t), V_{vir1}(t))$, $f_{phy2}(P^I_{phy}(t), V_{phy2}(t))$ and $f_{vir2}(P^I_{vir}(t), V_{vir2}(t))$ represent the actions of control strategies. Without losing generality, we define these functions as follows:

$$f_{phy1}(P^S_{phy}(t), V_{phy1}(t)) = \phi_{phy1}P^S_{phy}(t)V_{phy1}(t), \quad (1)$$

$$f_{phy2}(P^I_{phy}(t), V_{phy2}(t)) = \phi_{phy2}P^I_{phy}(t)V_{phy2}(t), \quad (2)$$

$$f_{vir1}(P^S_{vir}(t), V_{vir1}(t)) = \phi_{vir1}P^S_{vir}(t)V_{vir1}(t), \quad (3)$$

$$f_{vir2}(P^I_{vir}(t), V_{vir2}(t)) = \phi_{vir2}P^I_{vir}(t)V_{vir2}(t). \quad (4)$$

The parameters used in the above functions are summarized in Table 4. Here, $V_{phy1}(t)$, $V_{vir1}(t)$, $V_{phy2}(t)$ and $V_{vir2}(t)$ are face-to-face control signals (e.g., facial expressions, language or official documents) that emergency managers and official media can adjust at any time. The ϕ_{phy1}, ϕ_{phy2}, ϕ_{vir1} and ϕ_{vir2} represent the probabilities of successfully implementing control strategies for individuals in the respective different states, where $\phi_{phy1}, \phi_{phy2}, \phi_{vir1}, \phi_{vir2} \in [0, 1]$. Combining the above control strategies with the crowd emotional contagion mechanism proposed in the above subsection, a control framework of crowd emotional contagion is established, as shown in Figure 2. The definition of each arc in Figure 2 is shown in Table 5. Therefore, we can obtain the average field equation of the NP-ECC model control strategies as follows:

$$\begin{aligned}\frac{dP^I_{vir}(t)}{dt} &= f(P^S_{vir}(t), P^I_{vir}(t)) + f(P^S_{vir}(t), P^I_{phy}(t)) \\ &\quad - f(P^I_{vir}(t), P^R_{vir}(t)) - f(P^I_{vir}(t), P^R_{phy}(t)) \\ &\quad - f_{vir2}(P^I_{vir}(t), V_{vir2}(t)) - kP^I_{vir}(t), \quad (5)\end{aligned}$$

$$\begin{aligned}\frac{dP^S_{vir}(t)}{dt} &= -f(P^S_{vir}(t), P^I_{vir}(t)) - f(P^S_{vir}(t), P^I_{phy}(t)) \\ &\quad - f_{vir1}(P^S_{vir}(t), V_{vir1}(t)) - kP^S_{vir}(t), \quad (6)\end{aligned}$$

TABLE 4. The constant parameters used in the functions.

parameter	Description
$P^S_{vir}(t)$	the proportions of C_{VS} in the crowd at time t
$P^S_{phy}(t)$	the proportions of C_{PS} in the crowd at time t
$P^I_{vir}(t)$	the proportions of C_{VI} in the crowd at time t
$P^I_{phy}(t)$	the proportions of C_{PI} in the crowd at time t
$P^R_{vir}(t)$	the proportions of C_{VR} in the crowd at time t
$P^R_{phy}(t)$	the proportions of C_{PR} in the crowd at time t

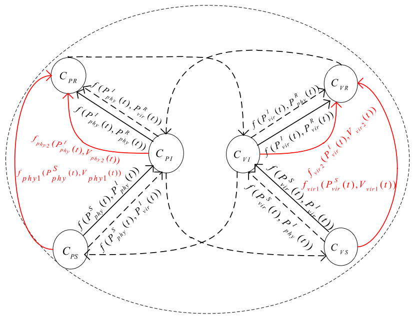


FIGURE 2. Framework of the NP-ECC model. Each circle represents an individual set in different states in the physical and virtual cyberspace. Each arc represents a transition rule between each pair of states, and the weight on each arc represents a change of individual proportions from one state to another over time. Note that the red arc represents control strategies.

$$\begin{aligned}\frac{dP^R_{vir}(t)}{dt} &= f(P^I_{vir}(t), P^R_{phy}(t)) + f(P^I_{vir}(t), P^R_{vir}(t)) \\ &\quad - kP^R_{vir}(t) + f_{vir1}(P^S_{vir}(t), V_{vir1}(t)) \\ &\quad + f_{vir2}(P^I_{vir}(t), V_{vir2}(t)), \end{aligned} \tag{7}$$

$$\begin{aligned}\frac{dP^I_{phy}(t)}{dt} &= f(P^S_{phy}(t), P^I_{vir}(t)) + f(P^S_{phy}(t), P^I_{phy}(t)) \\ &\quad - f(P^I_{phy}(t), P^R_{vir}(t)) - f(P^I_{phy}(t), P^R_{phy}(t)) \\ &\quad - f_{phy2}(P^I_{phy}(t), V_{phy2}(t)) - kP^I_{phy}(t), \end{aligned} \tag{8}$$

$$\begin{aligned}\frac{dP^S_{phy}(t)}{dt} &= -f(P^S_{phy}(t), P^I_{vir}(t)) - f(P^S_{phy}(t), P^I_{phy}(t)) \\ &\quad - f_{phy1}(P^S_{phy}(t), V_{phy1}(t)) - kP^S_{phy}(t), \end{aligned} \tag{9}$$

$$\begin{aligned}\frac{dP^R_{phy}(t)}{dt} &= f(P^I_{phy}(t), P^R_{phy}(t)) + f(P^I_{phy}(t), P^R_{vir}(t)) \\ &\quad - kP^R_{phy}(t) + f_{phy1}(P^S_{phy}(t), V_{phy1}(t)) \\ &\quad + f_{phy2}(P^I_{phy}(t), V_{phy2}(t)). \end{aligned} \tag{10}$$

It is clear that Equations (5)-(10) establish a dynamic system based on ordinary differential equations, which is called the NP-ECC model. It is a personalized emotional contagion model that combines physical and virtual cyberspace in prevention and treatment strategies. Since individuals may overlap slightly in the physical and virtual cyberspace, to represent the NP-ECC model more accurately we consider the overlap of individuals in a group and use k to denote it. S_{vir} and P_{vir} represent the average emotional contagion and recovery strength of susceptible and infected individuals, respectively, in the same emotional state in the virtual cyberspace. S_{phy} and P_{phy} represent the average emotional contagion and recovery strength of susceptible and infected individuals, respectively, in the same emotional state in the physical cyberspace. The NP-ECC model has the following initial values:

$$\begin{aligned} P^S_{vir}(t) \geq 0, \quad P^S_{phy}(t) \geq 0, P^I_{vir}(t) \geq 0, \\ P^I_{phy}(t) \geq 0, \quad P^R_{vir}(t) \geq 0, P^R_{phy}(t) \geq 0. \end{aligned} \tag{11}$$

$$\begin{aligned} 0 \leq V_{vir1}(t) = V_{vir2}(t) \leq 1 \times 10^{-6}, \\ 0 \leq V_{phy1}(t) = V_{phy2}(t) \leq 1 \times 10^{-5}. \end{aligned} \tag{12}$$

The solutions of the NP-ECC model must satisfy the following constraint at any time:

$$P^S_{vir}(t) + P^S_{phy}(t) + P^I_{vir}(t) + P^I_{phy}(t) + P^R_{vir}(t) + P^R_{phy}(t) = 1. \tag{13}$$

Considering the practical meanings of $P^S_{vir}(t)$, $P^S_{phy}(t)$, $P^I_{vir}(t)$, $P^I_{phy}(t)$, $P^R_{vir}(t)$ and $P^R_{phy}(t)$ in emotion contagion, we define the domain of the solutions of the NP-ECC model by $\Omega = \{(P^S_{vir}(t), P^S_{phy}(t), P^I_{vir}(t), P^I_{phy}(t), P^R_{vir}(t), P^R_{phy}(t)) | P^S_{vir}(t), P^S_{phy}(t), P^I_{vir}(t), P^I_{phy}(t), P^R_{vir}(t), P^R_{phy}(t) \geq 0, P^S_{vir}(t) + P^S_{phy}(t) + P^I_{vir}(t) + P^I_{phy}(t) + P^R_{vir}(t) + P^R_{phy}(t) = 1\}$. We call $P^S_{vir}(t)$, $P^S_{phy}(t)$, $P^I_{vir}(t)$, $P^I_{phy}(t)$, $P^R_{vir}(t)$ and $P^R_{phy}(t)$ the state variables of the NP-ECC model, and apply the tuple $(P^S_{vir}(t), P^S_{phy}(t), P^I_{vir}(t), P^I_{phy}(t), P^R_{vir}(t), P^R_{phy}(t))$ to represent the state of the NP-ECC model at time t.

V. THE PHASE TRANSITION THRESHOLD OF THE NP-ECC

To better control the speed and scale of crowd emotional contagion, we need to calculate the phase transition threshold of the NP-ECC model more accurately. We first construct a personalized BA scale-free network, and then calculate the phase transition threshold of the NP-ECC model in such a network more accurately. We will describe these operations in detail in the following two subsections.

TABLE 5. Definition of arcs shown in FIGURE 2.

Function	Description
$(C_{PS}, C_{PR}, f_{phy1}(P^S_{phy}(t), V_{phy1}(t)))$	Preventive control strategy for susceptible individuals in the physical cyberspace
$(C_{VS}, C_{VR}, f_{vir1}(P^S_{vir}(t), V_{vir1}(t)))$	Preventive control strategy for susceptible individuals in the virtual cyberspace
$(C_{PI}, C_{PR}, f_{phy2}(P^I_{phy}(t), V_{phy2}(t)))$	Treatment control strategy for infected individuals in the physical cyberspace
$(C_{VI}, C_{VR}, f_{vir2}(P^I_{vir}(t), V_{vir2}(t)))$	Treatment control strategy for infected individuals in the virtual cyberspace
$(C_{VS}, C_{VI}, f(P^S_{vir}(t), P^I_{vir}(t)))=I_{vir}S_{vir}P^S_{vir}(t)P^I_{vir}(t)$	The probability that C_{VS} were infected by C_{VI}
$(C_{VS}, C_{VI}, f(P^S_{vir}(t), P^I_{phy}(t)))=I_{phy}S_{phy}P^S_{vir}(t)P^I_{phy}(t)$	The probability that C_{VS} were infected by C_{PI}
$(C_{PS}, C_{PI}, f(P^S_{phy}(t), P^I_{vir}(t)))=I_{vir}S_{vir}P^S_{phy}(t)P^I_{vir}(t)$	The probability that C_{PS} were infected by C_{VI}
$(C_{PS}, C_{PI}, f(P^S_{phy}(t), P^I_{phy}(t)))=I_{phy}S_{phy}P^S_{phy}(t)P^I_{phy}(t)$	The probability that C_{PS} were infected by C_{PI}
$(C_{VI}, C_{VR}, f(P^I_{vir}(t), P^R_{vir}(t)))=r_{vir}P_{vir}P^I_{vir}(t)P^R_{vir}(t)$	The probability that C_{VI} were cured by C_{VR}
$(C_{VI}, C_{VR}, f(P^I_{vir}(t), P^R_{phy}(t)))=r_{phy}P_{phy}P^I_{vir}(t)P^R_{phy}(t)$	The probability that C_{VI} were cured by C_{PR}
$(C_{PI}, C_{PR}, f(P^I_{phy}(t), P^R_{vir}(t)))=r_{vir}P_{vir}P^I_{phy}(t)P^R_{vir}(t)$	The probability that C_{PI} were cured by C_{VR}
$(C_{PI}, C_{PR}, f(P^I_{phy}(t), P^R_{phy}(t)))=r_{phy}P_{phy}P^I_{phy}(t)P^R_{phy}(t)$	The probability that C_{PI} were cured by C_{PR}

A. PERSONALIZED BA SCALE-FREE NETWORK

During the process of crowd emotional contagion, the crowd can be regarded as a complex network with humans being nodes and human-to-human relationships being the edges that connect nodes. The BA scale-free network [54], [55] is commonly used to study emotional contagion in social networks since its growth and the preferential attachment characteristic approximate the process of emotional contagion in real-world networks. Previous studies have focused on determining thresholds of crowd emotional contagion under homogeneous infection and cure rates or heterogeneous infection rates, without considering the influence individual personality differences on infection and cure rates. That is to say, the probability of any node to transmit emotion to its neighbor nodes is equal in the BA scale-free network, but the infection rate between nodes will be affected by individual personality differences during the process of emotional contagion.

To address this problem, we consider the influences of individual personality differences on crowd emotional contagion in this paper. Therefore, we construct a personalized BA scale-free network to analyze and simulate the threshold of the NP-ECC model. The emotional contagion behavior of the physical and virtual cyberspace, which is individuals with a certain probability for emotional contagion walking on a personalized BA scale-free network. The personalized BA scale-free network constructed in this paper is a multiplex network formed by two layers. The bottom layer is formed by the network of physical cyberspace, while the top one is formed by the network of virtual cyberspace. The coupling of virtual cyberspace and physical cyberspace is that the nodes of two layers are connected by randomly generated edges. The individuals in physical and virtual cyberspace are mapped to the nodes of two layers in BA scale-free network, respectively. That is, the individuals in physical and virtual cyberspace spread emotion on BA scale-free network through the link edges between nodes. We use $G(V, E)$ to represent the personalized BA scale-free network, where $\mid V \mid$ is the set of individuals, and $\mid E \mid$ is the set of edges that link individuals.

In the personalized BA scale-free network constructed in this paper, infection rate and cure rate are heterogeneous of the each link in network. This is because infection rates of the links between susceptible nodes and infected nodes are affected by infection rates of the latter and the relevant node's own strength of emotional contagion, and the cure rates of the links between infected nodes and recovered nodes are affected by cure rates of the latter and the relevant node's own strength of emotional recovery. We denote by $LI(i, j)$ the infection rates of links between susceptible nodes and infected nodes, and by $Lr(i, j)$ the cure rates of the links between infected nodes and recovered nodes as follows:

$$LI(i,j) = \begin{cases} LI^{vir}(i,j) = I_{vir}S_{vir}(i) & \text{if } i \in C_{VS} \bigcup C_{PS}, \\ & j \in C_{VI}. \\ LI^{phy}(i,j) = I_{phy}S_{phy}(i) & \text{if } i \in C_{VS} \bigcup C_{PS}, \\ & j \in C_{PI}. \end{cases} \tag{14}$$

$$Lr(i,j) = \begin{cases} Lr^{vir}(i,j) = r_{vir}P_{vir}(i) & \text{if } i \in C_{VI} \bigcup C_{PI}, \\ & j \in C_{VR}. \\ Lr^{phy}(i,j) = r_{phy}P_{phy}(i) & \text{if } i \in C_{VI} \bigcup C_{PI}, \\ & j \in C_{PR}. \end{cases} \tag{15}$$

where i is a node in the personalized BA scale-free network, and j is one of its neighbor nodes.

B. PHASE TRANSITION THRESHOLD OF THE NP-ECC MODEL FOR A PERSONALIZED BA SCALE-FREE NETWORK

The threshold of crowd emotional contagion is actually equivalent to the critical point in the non-equilibrium phase transition, and is the basic index used to determine the survival or disappearance conditions of emotional contagion. In this subsection, we study the phase transition threshold of the NP-ECC model in a personalized BA scale-free network to better control the speed and scale of emotional contagion and obtain the number of individuals who change from the susceptible state to the infected state with the change of the phase transition threshold.

Since the process of emotional contagion is similar to the infection process of infectious diseases, we refer to the threshold of infectious disease spread in a network to study the threshold of emotional contagion spread in a network. Previous studies [40] have shown that if both infection and recovery rates are homogeneous, the threshold of an epidemic satisfies the following conditions: if $\beta/\delta > \tau$, the epidemic survives, and if $\beta/\delta < \tau$, the epidemic dies out. Here, β represents the infection rate, δ represents the cure rate, and τ represents the epidemic threshold. The literature [35] has shown that if infection rates are heterogeneous, the epidemic threshold in BA scale-free networks satisfies the following conditions: if $\frac{\sum_{(i,j)\in E} \beta_{ij}/|E|}{\sum_{i\in V} \delta_i/|V|} > \tau$, the epidemic survives, and if $\frac{\sum_{(i,j)\in E} \beta_{ij}/|E|}{\sum_{i\in V} \delta_i/|V|} < \tau$, the epidemic dies out. Here, β_{ij} represents that if node i is currently in the susceptible state, it can be infected by its neighbor node j with probability β_{ij}. Variable δ_i represents that if node i is currently in the infected state, it can be cured by itself with probability δ_i. $\mid V \mid$ represents the number of nodes, $\mid E \mid$ represents the number of edges, and τ represents the epidemic threshold.

To research the threshold of crowd emotional contagion when infection rate and cure rate are heterogeneous, we used studies [40] and [35] to further explore the phase transition threshold in the personalized BA scale-free network. Our proposed NP-ECC model takes into account the heterogeneity of infection rate and cure rate. Therefore, we assume that when phase transition not occurs, the phase transition threshold of the NP-ECC model satisfies the following conditions:

$$\frac{\sum_{(i,j)\in E} LI(i,j)/\mid E \mid}{\sum_{(i,j)\in E} Lr(i,j)/\mid E \mid} < \tau. \tag{16}$$

We assume that when phase transition occurs, the phase transition threshold of the NP-ECC model satisfies the following conditions:

$$\frac{\sum_{(i,j)\in E} LI(i,j)/\mid E\mid}{\sum_{(i,j)\in E} Lr(i,j)/\mid E\mid} > \tau. \tag{17}$$

Under this condition, Equation (17) indicates that emotional contagion can survive and infect a non-zero number of nodes. Otherwise, emotional contagion disappears. We consider heterogeneous infection rate and cure rate due to differences in individual personalities. In Equations (16) and (17), $\sum_{(i,j)\in E} LI(i,j)/\mid E\mid$ represents the mean infection rate in the network under the case of a heterogeneous infection rate, $\sum_{(i,j)\in E} Lr(i,j)/\mid E\mid$ represents the mean cure rate in the network under the case of a heterogeneous cure rate, and τ represents the threshold of emotional contagion. $\tau = \frac{1}{\langle k_A\rangle}$, where $\langle k_A\rangle$ represents the average degree of the personalized BA scale-free network [40].

We define a metric S to evaluate the phase transition threshold of our NP-ECC model in the personalized BA scale-free network, where

$$S = \frac{\sum_{(i,j)\in E} LI(i,j)/\mid E\mid}{\sum_{(i,j)\in E} Lr(i,j)/\mid E\mid}\langle K_A\rangle. \tag{18}$$

Equation (18) provides conditions for the disappearance ($S < 1$) or survival ($S > 1$) of emotional contagion in our NP-ECC model. We regard the spread of emotion as a random walk on a complex network. The emotion spreads at the rate of $(\sum_{(i,j)\in E} LI(i,j)/\mid E\mid)\langle K_A\rangle$. On the other hand, emotion is cured at the rate of $\sum_{(i,j)\in E} Lr(i,j)/\mid E\mid$. Therefore, the effective rate of propagation is approximately $\frac{\sum_{(i,j)\in E} LI(i,j)/|E|}{\sum_{(i,j)\in E} Lr(i,j)/|E|}\langle K_A\rangle$, which is exactly equal to S. To have any possibility of emotional contagion, S must be greater than 1, which is the critical condition for the phase transition occurring under the NP-ECC model.

Considering the preventive control strategies we proposed in subsection IV. B, the emotion spreads at the rate of $(\sum_{(i,j)\in E} LI(i,j)/\mid E\mid)\langle K_A\rangle$. On the other hand, emotion is cured at the rate of $((\sum_{(i,j)\in E} Lr(i,j)/\mid E\mid)+\phi_{phy1}V_{phy1}(t)+\phi_{vir1}V_{vir1}(t))$. Therefore, we define S under preventive control strategies as

$$S = (\sum_{(i,j)\in E} LI(i,j)/\mid E\mid)/((\sum_{(i,j)\in E} Lr(i,j)/\mid E\mid) + \phi_{phy1}V_{phy1}(t) + \phi_{vir1}V_{vir1}(t))\langle K_A\rangle. \tag{19}$$

Considering the treatment control strategies we proposed in subsection IV. B, the emotion spreads at the rate of $(\sum_{(i,j)\in E} LI(i,j)/\mid E\mid)\langle K_A\rangle$. On the other hand, emotion is cured at the rate of $((\sum_{(i,j)\in E} Lr(i,j)/\mid E\mid)+\phi_{phy2}V_{phy2}(t)+\phi_{vir2}V_{vir2}(t))$. Therefore, we define S under treatment control strategies as

$$S = (\sum_{(i,j)\in E} LI(i,j)/\mid E\mid)/((\sum_{(i,j)\in E} Lr(i,j)/\mid E\mid) + \phi_{phy2}V_{phy2}(t) + \phi_{vir2}V_{vir2}(t))\langle K_A\rangle. \tag{20}$$

Considering the preventive and treatment control strategies we proposed in subsection IV. B, the emotion spreads at the rate of $(\sum_{(i,j)\in E} LI(i,j)/\mid E\mid)\langle K_A\rangle$. On the other hand, emotion is cured at the rate of $((\sum_{(i,j)\in E} Lr(i,j)/\mid E\mid) + \phi_{phy1}V_{phy1}(t) + \phi_{vir1}V_{vir1}(t) + \phi_{phy2}V_{phy2}(t) + \phi_{vir2}V_{vir2}(t))$. Therefore, we define S under preventive and treatment control strategies as

$$S = (\sum_{(i,j)\in E} LI(i,j)/\mid E\mid)/((\sum_{(i,j)\in E} Lr(i,j)/\mid E\mid) + \phi_{phy1}V_{phy1}(t) + \phi_{vir1}V_{vir1}(t) + \phi_{phy2}V_{phy2}(t) + \phi_{vir2}V_{vir2}(t))\langle K_A\rangle. \tag{21}$$

We will verify the results of our theoretical analysis in the experimental section.

VI. ALGORITHM

In this section, we propose the CS-BA algorithm and the T-BA algorithm to describe the simulation process of the NP-ECC model in the personalized BA scale-free network. The CS-BA algorithm verifies the stability of the NP-ECC model by calculating the changes of infected nodes in a personalized BA scale-free network. By calculating the phase transition threshold of the NP-ECC model under different control strategies, the T-BA algorithm further obtains the number of individuals changing from the susceptible state to the infected state with the phase transition threshold so that we can verify the conditions of survival and disappearance of emotional contagion proposed in subsection V. B.

In the simulation process, each individual is regarded as a node. We define $P_n(C_{VI})$ and $P_n(C_{PI})$ to represent that the proportions of C_{VI} and C_{PI}, respectively, in the crowd at the nth iteration. $P_n(C_{VI})$ and $P_n(C_{PI})$ can be represented, respectively, as follows:

$$P_n(C_{VI}) = \parallel C_{VI}\parallel /N, \tag{22}$$

$$P_n(C_{PI}) = \parallel C_{PI}\parallel /N. \tag{23}$$

Here, $\parallel\cdot\parallel$ is the size of the set and N represents the number of nodes. We define M_v and M_p to represent, respectively, the mean values of $P_n(C_{VI})$ and $P_n(C_{PI})$ in each experiment as follows:

$$M_v = \sum_{n=0}^{T} P_n(C_{VI})/T, \tag{24}$$

$$M_p = \sum_{n=0}^{T} P_n(C_{PI})/T. \tag{25}$$

Here, T represents the iteration times of each experiment and we repeat the experiment W times.

CS-BA Algorithm: The CS-BA algorithm obtains the change in the number of infected nodes in the physical and virtual cyberspace in a personalized BA scale-free network of the NP-ECC model. The stability of the NP-ECC model is assessed based on whether the output of the CS-BA algorithm tends to converge.

T-BA Algorithm: The T-BA algorithm provides the phase transition threshold of the NP-ECC model under different

Algorithm 1 CS-BA Algorithm

Input: N, T, W, r_{vir}, r_{phy}, k, I_{vir}, I_{phy}, ϕ_{phy1}, ϕ_{vir1}, ϕ_{phy2}, ϕ_{vir2}, $V_{phy1}(t)$, $V_{phy2}(t)$, $V_{vir1}(t)$, $V_{vir2}(t)$, $\langle K_A \rangle$
Output: M_v, M_p
begin
  Generate a personalized BA scale-free network $G(V, E)$ with N nodes for simulation;
  for $Cycle = 0$; $Cycle < W$; $Cycle{+}{+}$ **do**
    Generate $P^I_{vir}(t)$, $P^I_{phy}(t)$, $P^S_{vir}(t)$, $P^S_{phy}(t)$, $P^R_{phy}(t)$ and $P^R_{vir}(t)$ randomly;
    for $Tcycle = 0$; $Tcycle < T$; $Tcycle{+}{+}$ **do**
      for $i = 0$; $i < N$; $i{+}{+}$ **do**
        Generate $S_{vir}(i)$, $S_{phy}(i)$ or $P_{phy}(i)$, $P_{phy}(i)$ randomly according to personalized emotional state;
      Calculate $LI(i, j)$ or $Lr(i, j)$ according to Equation (14) or Equation (15);
      Calculate $P^I_{vir}(t)$, $P^I_{phy}(t)$ according to Equation (5), Equation (8);
      Calculate $P_n(C_{VI})$ and $P_n(C_{PI})$ according to Equation (22) and Equation (23);
    Calculate M_v and M_p according to Equation (24) and Equation (25);

Algorithm 2 T-BA Algorithm

Input: N, W, r_{vir}, r_{phy}, k, I_{vir}, I_{phy}, ϕ_{phy1}, ϕ_{vir1}, ϕ_{phy2}, ϕ_{vir2}, $V_{phy1}(t)$, $V_{phy2}(t)$, $V_{vir1}(t)$, $V_{vir2}(t)$, $\langle K_A \rangle$
Output: S, $P^I_{vir}(t)$, $P^I_{phy}(t)$
begin
  Generate a personalized BA scale-free network $G(V, E)$ with N nodes for simulation;
  for $Cycle = 0$; $Cycle < W$; $Cycle{+}{+}$ **do**
    Generate $P^I_{vir}(t)$, $P^I_{phy}(t)$, $P^S_{vir}(t)$, $P^S_{phy}(t)$, $P^R_{phy}(t)$ and $P^R_{vir}(t)$ randomly;
    for $i = 0$; $i < N$; $i{+}{+}$ **do**
      Generate $S_{vir}(i)$, $S_{phy}(i)$ or $P_{phy}(i)$, $P_{phy}(i)$ randomly according to personalized emotional state;
    Calculate $LI(i, j)$ or $Lr(i, j)$ according to Equation (14) or Equation (15);
    Calculate $P^I_{vir}(t)$, $P^I_{phy}(t)$ according to Equation (5), Equation (8);
    switch *control strategies* **do**
      case
        no control strategies:
      Calculate S according to Equation (18); **case**
        preventive control strategies:
      Calculate S according to Equation (19); **case**
        treatment control strategies:
      Calculate S according to Equation (20); **case**
        preventive and treatment control strategies:
      Calculate S according to Equation (21);

control strategies and the number of individuals from susceptible state to infected state change with phase transition threshold.

VII. EXPERIMENTS

The experimental results consist of two parts: the first part performs the numerical simulation for the NP-ECC model, and the second part performs the simulation of the NP-ECC model in the personalized BA scale-free network. All reported results were obtained on a machine with a 3.3 GHz Intel Core 2 Duo CPU with 2 GB of RAM.

A. NUMERICAL SIMULATION FOR THE NP-ECC

In this subsection, we perform numerical simulation of the NP-ECC model to further explore the influence of control strategies on crowd emotional contagion. In real life, the virtual cyberspace exhibits greater variability of the process of crowd emotional contagion, but individuals are more susceptible to the influence in the physical cyberspace. Thus, we set $I_{phy} = 3 \times 10^{-5}$, $I_{vir} = 3 \times 10^{-6}$, $r_{vir} = 0.007$, $r_{phy} = 0.07$, $C_{VS} = 4080000$, $C_{PS} = 90000$, $C_{VI} = 1875$, $C_{PI} = 60$, $C_{PR} = 0$, $C_{VR} = 0$, $N = 4171935$, and $k = 10^{-8}$ as the default values in our experiments unless otherwise specified. $S_{vir}(i)$, $S_{phy}(i)$, $P_{vir}(i)$ and $P_{phy}(i)$ are randomly generated in different intervals according to the personalized emotional state. The above parameter setting refers to the data from the Framingham Heart Research Center (FHS). This data is mainly used to prove that the positive and negative emotional contagion process is similar to the dynamic infection of infectious diseases in crowd, and thus it confirms the rationality of the application of the epidemic model in the field of emotional contagion [56].

In this subsection, we first analyze the changes in the sizes of the six groups in the NP-ECC model over time. Secondly, we compare the NP-ECC model with models of control strategies in the physical and virtual cyberspace. Thirdly, we compare and analyze the influence of the NP-ECC model under various control strategies. Finally, we verify our model with the real datasets.

1) ANALYSIS OF THE SIZES OF THE SIX GROUPS

We perform experiments under different personalized emotional states to analyze the changes in the sizes of the six groups in the NP-ECC model over time, as shown in Figure 3. In Figure 3(a) and Figure 3(b), individuals are influenced by preventive control strategies and emotional interactions between individuals, and the numbers of individuals in C_{VS} and C_{PS} decline to zero at different speeds over time. The numbers of individuals in C_{VS} and C_{PS} decline to zero more readily in the hysterical state. As Figure 3(c) and Figure 3(d) show, individuals are influenced by treatment control strategies and emotional interactions between individuals, and the

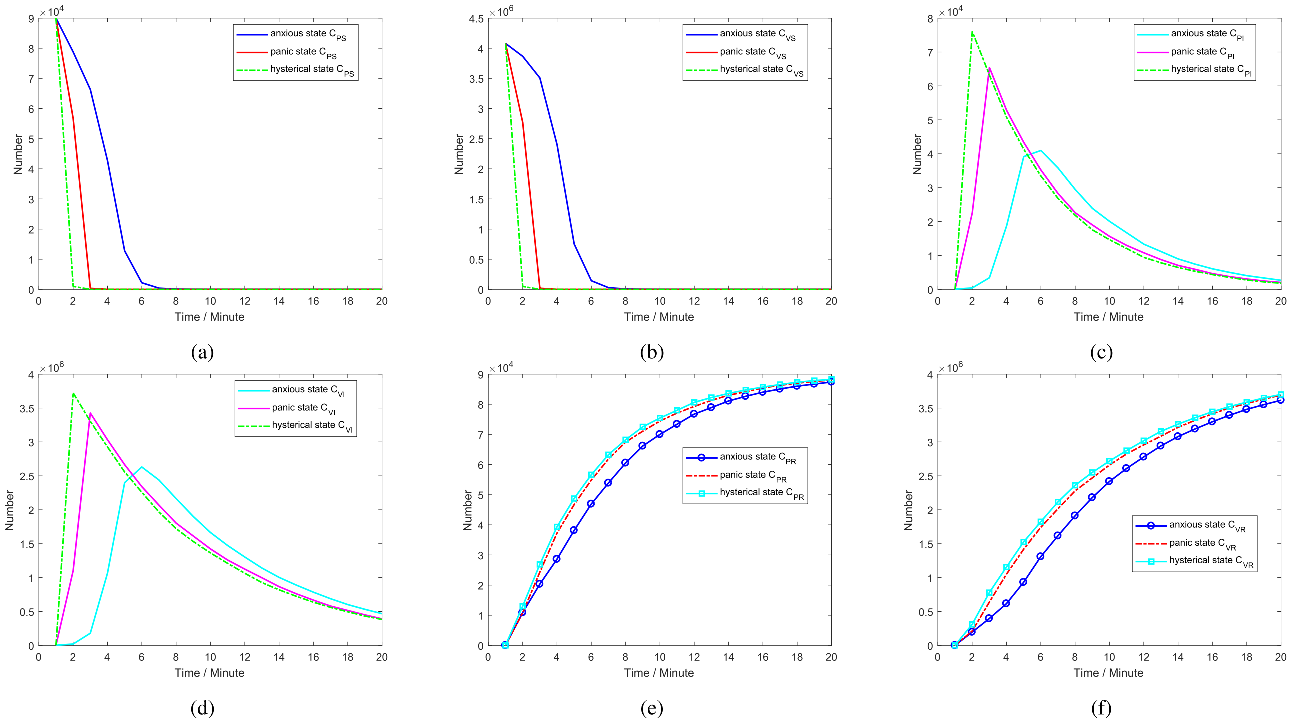


FIGURE 3. Changes in the sizes of the six groups over time under different personalized emotional states. (a) Changes in the size of C_{PS} over time. (b) Changes in the size of C_{VS} over time. (c) Changes in the size of C_{PI} over time. (d) Changes in the size of C_{VI} over time. (e) Changes in the size of C_{PR} over time. (f) Changes in the size of C_{VR} over time.

numbers of individuals in C_{VI} and C_{PI} reach their maxima at different times. The numbers of individuals in C_{VI} and C_{PI} reach their maxima more rapidly in the hysterical state. As Figure 3(e) and Figure 3(f) show, individuals are influenced by preventive and treatment control strategies as well as emotional interactions between individuals, and the numbers of individuals in C_{VR} and C_{PR} increase significantly over time. The number of individuals experiencing hysteria increases faster than the numbers of individuals in the anxious state or the state of panic. Figure 3 shows clearly that the more neurotic the individuals are, the more susceptible they are to emotional contagion. The experimental results prove that the personalized emotional states of individuals affect the process of crowd emotional contagion.

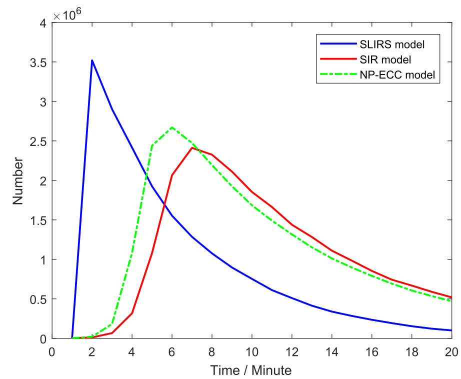


FIGURE 4. Relationship between the number of infected individuals and the time of emotional contagion under different control strategies.

2) COMPARATIVE ANALYSIS OF MODELS OF CONTROL STRATEGIES

To explore the influences of control strategies in contagion cyberspace on the process of crowd emotional contagion, the relationship between the number of infected individuals and the time of contagion under different control strategies was compared and analyzed by considering the "anxious" state as an example in this experiment. In Figure 4, the SLIRS (Susceptible-Latent-Infectious-Recovered-Susceptible) model [3] represents the control strategies where only a single physical cyberspace exists, the SIR model [40] represents the control strategies where only a single virtual cyberspace exists, and the NP-ECC model represents the control strategies where both contagion cyberspace exist simultaneously. We use the SLIRS model, the SIR model and the NP-ECC model to simulate the influence of control strategies on emotional contagion. It is shown that the SIR model results in the longest time of emotional contagion, as it does not consider the influence of information and control strategies in the physical cyberspace on emotional contagion, whereas the SLIRS model obtains the shortest time of emotional contagion, as it only considers the influence of information and control strategies in the physical cyberspace on emotional contagion. This result shows that these models can improve or reduce the time of emotional contagion in

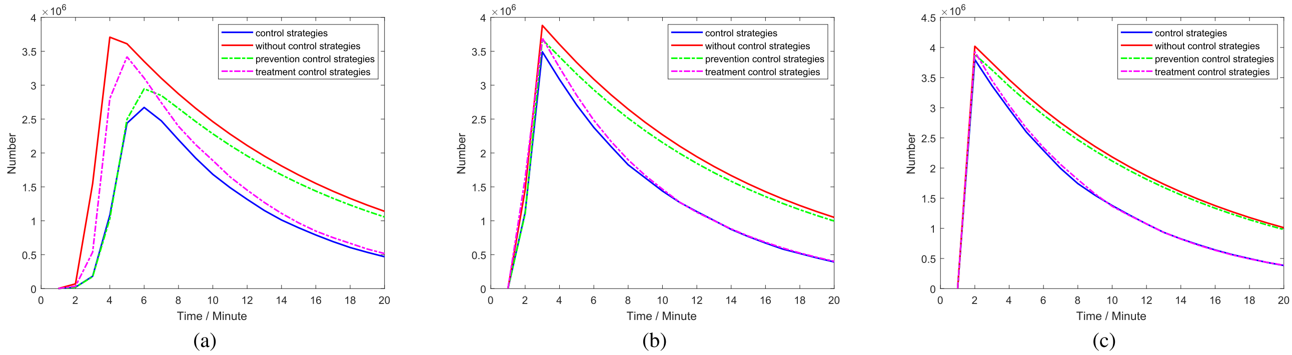


FIGURE 5. **Relationship between the number of infected individuals and the time of emotional contagion under different personalized emotional states. (a) The NP-ECC model under the anxious state. (b) The NP-ECC model under the panic state. (c) The NP-ECC model under the hysterical state.**

real life because they only consider information and control strategies in single contagion cyberspace. However, in real life, individual emotions are not only affected by information and control strategies in a single cyberspace. In the NP-ECC model, we jointly consider the influence of information and control strategies in the virtual cyberspace and the physical cyberspace on emotional contagion to present the simulation results of emotional contagion more realistically.

3) COMPARATIVE ANALYSIS OF CONTROL STRATEGIES

To explore the influences of the control strategies on the process of crowd emotional contagion, this experiment compares the relationship between the number of infected individuals and the time of contagion under different personalized emotional states. Figure 5 analyzes the influence of control strategies on the process of emotional contagion in anxious, panic, and hysterical states. As Figure 5(a) show, if no control strategies are implemented, the process of emotional contagion can easily reach a peak and the number of infected individuals is the highest. If only preventive control strategies or treatment control strategies are being used, emotional contagion is controlled to a certain extent, but if both control strategies are used at the same time, the number of infectors is the lowest, and the time it takes to reach the peak of emotional contagion is the longest. As Figure 5(b) and Figure 5(c) show, if there are no control strategies being used or only preventive and treatment strategies are being used, the number of infectors is higher and the duration of emotional contagion is shorter. The experimental results show that control strategies have a certain impact on the process of emotional contagion, and can control the speed and scale of such contagion, enabling a better control of such contagion.

4) EXPERIMENTS ON REAL-WORLD DATA

We further verify our model with the real dataset obtained from Twitter [57], [58]. The dataset called "NEWS" includes 49.7 million tweets. The dataset is available at https://github.com/s-mishra/featuredriven-hawkes. In the "NEWS" dataset, the spread rate and forgetting rate of news are equivalent to the infection rate and cure rate of the NP-ECC model. In addition, according to the common sense that individuals have immersive experiences in the physical cyberspace, we believe that they are more susceptible to the influence of emotional contagion in the physical cyberspace, and their emotions are more easily recovered in the physical cyberspace. Therefore, we set $I_{phy} = 0.75$, $I_{vir} = 0.075$, $r_{phy} = 0.64$, and $r_{vir} = 0.064$. $S_{vir}(i)$, $S_{phy}(i)$, $P_{vir}(i)$ and $P_{phy}(i)$ are randomly generated in different intervals according to the personalized emotional state. The proportions of the individuals in anxious, panic and hysteria state are equal. $V_{vir1}(t)$, $V_{vir2}(t)$, $V_{phy1}(t)$, $V_{phy2}(t)$ and ϕ_{vir1}, ϕ_{vir2}, ϕ_{phy1}, ϕ_{phy2} are randomly generated in the defined interval. In this subsection, we perform the two experiment to further verify that our model works well on real-world data. We assume that the number of infected individuals in physical and virtual cyberspace accounts for 10%, 20% and 30%. We assume that there are small proportions of the infected individuals in physical cyberspace. This result is obtained because the virtual cyberspace has a wider range in the process of crowd emotional contagion. In Figure 6 (a), we show the experimental results after 300 time steps. The larger the initial proportion of infected individuals is, the wider the range of emotional contagion. The proportion of infected individuals accounts for 30% reach their maxima more rapidly. The experimental results show the initial proportion of infected individuals have a certain impact on the process of emotional contagion.

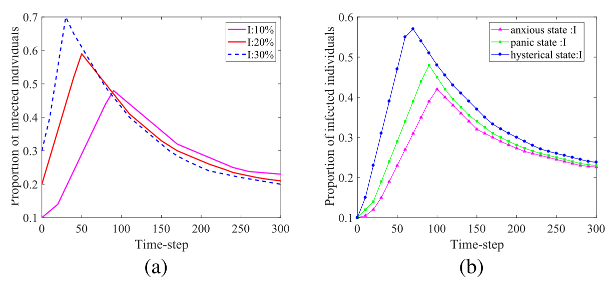


FIGURE 6. **The real Twitter dataset is applied to the NP-ECC model simulation. (a) Changes in the size of *I* over time steps. (b) Changes in the size of *I* over time steps under different personalized emotional states.**

To explore the influence of the personalized emotional state on the process of crowd emotional contagion, this experiment takes the number of infected individuals accounts for 10% as an example to perform a comparative analysis. In Figure 6 (b), we show the experimental results after 300 time steps. The proportion of infected individuals reach their maxima more rapidly in the hysterical state, and the range of emotional contagion is wider. The experimental results prove that the personalized emotional states of individuals affect the process of crowd emotional contagion. The above two simulation results show that our model is well in the application of crowd emotional contagion.

B. PHASE TRANSITION IN A PERSONALIZED BA SCALE-FREE NETWORK

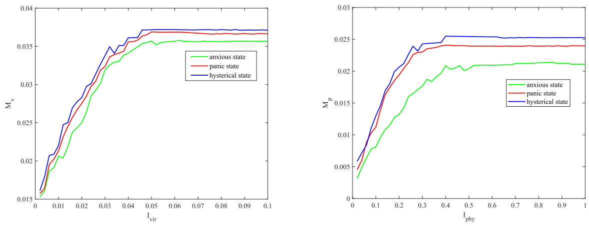
In this subsection, we perform the CS-BA algorithm and the T-BA algorithm to carry out simulation experiments of the NP-ECC model in the personalized BA scale-free network. In this subsection, we use a personalized BA scale-free network with 300 nodes in the NP-ECC simulation to further analyze the phase transition threshold of the NP-ECC model. We first explore the change in the number of infected nodes over time under different personalized emotional states in the NP-ECC model, so as to analyze the stability of this model. Secondly, we explore the influence of S on the speed and scale of emotional contagion when the phase transition occurs. Finally, we verify the theoretical analysis results of the phase transition threshold of the NP-ECC model is whether more accurate.

In this subsection, we set $W = 50$, $T = 500$, $r_{vir} = 0.007$, $r_{phy} = 0.07$ and $k = 10^{-8}$, and $\langle K_A \rangle = 5$ and increase I_{phy} from 0 to 1. We assume that there are small proportions of individuals in C_{PI} and C_{PS}, and I_{vir} is always 0.1 times I_{phy}. This result is obtained because the virtual cyberspace exhibits a greater variability of the process of crowd emotional contagion, but individuals are more susceptible to influence in the physical cyberspace. $V_{vir1}(t)$, $V_{vir2}(t)$, $V_{phy1}(t)$, $V_{phy2}(t)$ and ϕ_{vir1}, ϕ_{vir2}, ϕ_{phy1}, ϕ_{phy2} are randomly generated in the defined interval. The above experimental settings are the default values for our experiments, unless otherwise specified.

1) CHANGE IN THE NUMBER OF INFECTED NODES

In this part of the paper, we use the CS-BA algorithm to study the change in the number of infected nodes in a personalized BA scale-free networks to verify the stability of the NP-ECC model. After 50 experiments and 500 iterations of each experiment, the values of M_p and M_v of C_{PI} and C_{VI}, respectively, can be obtained, as shown in Figure 7.

Figure 7 shows that C_{PI} and C_{VI} under different personalized emotional states have different M_p and M_v. The more neurotic the individuals in C_{VI} and C_{PI} are, the more susceptible they are to emotional contagion, and C_{VI} and C_{PI} have greater M_v and M_p, respectively. Figure 7(a) shows that although I_{vir} is increasing from 0 to 0.1, the M_v of C_{VI} first increases and then tends to stabilize. At the same time, we can obtain the M_p of C_{PI}. Although I_{phy} is increasing from 0 to 1, the experimental results show that the M_p of C_{PI} first increases and then tends to stabilize, as shown in Figure 7(b). The experimental results prove that the NP-ECC model has good stability.



(a) (b)

FIGURE 7. Changes in the M_v and M_p of the C_{VI} and C_{PI} over time under different personalized emotional states. (a) M_v of the C_{VI}. (b) M_p of the C_{PI}.

2) COMPARATIVE ANALYSIS OF S

In this subsection, we use the T-BA algorithm to study the phase transition value of the NP-ECC model when the phase transition occurs under different control strategies and further verify the conditions of survival and disappearance of emotional contagion proposed in subsection V. B. In the initial stage of emotional contagion, we set the initial number of infected nodes to 50. After 50 rounds of experiments, the number of infected nodes changes with time as shown in Figure 8. In Figure 8(a)-(d), the case of $S = 1$ is shown using black solid lines. There is a significant difference between the number of infected nodes if $S>1$ and if $S<1$. If $S<1$, emotional contagion dies out rapidly, while if $S>1$, emotional contagion survive. The experimental results show that the phase transition occurrence threshold of the NP-ECC model is more accurate, which is our proposed condition for persistence or disappearance of emotional contagion.

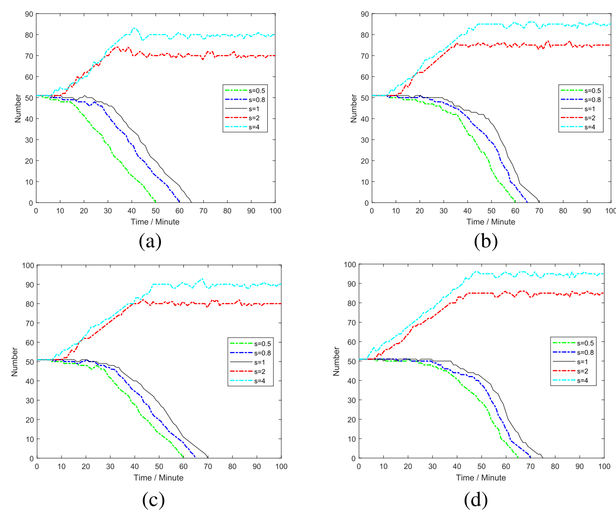


FIGURE 8. Relationship between the number of infected individuals and the time of emotional contagion under different S. (a) Both preventive and treatment control strategies are used. (b) Only preventive control strategies are used. (c) Only treatment control strategies are used. (d) Neither prevention nor treatment control strategies are used.

Comparing Figure 8 (a) - (d), we observe that if both treatment and preventive control strategies are used simultaneously, emotional contagion disappears most quickly, and the number of infected nodes is the lowest. If neither treatment nor preventive control strategies are used, emotional contagion takes the longest amount of time to disappear, and the number of infected nodes is the highest. The experimental results show that control strategies can control the speed and scale of crowd emotional contagion.

3) COMPARATIVE ANALYSIS OF MODEL

To further verify that the phase transition threshold of the NP-ECC model is more accurate, we carry out comparative experiments in a constructed personalized BA scale-free network since it approximate the process of emotional contagion in real-world networks. We explore the relationship between the number of infected nodes and the S. The Equation (21) determines S by performing the T-BA algorithm. In this subsection, we use the personalized BA scale-free network with 1000 nodes for simulation.

In Figure 9, the NLDS (Non-Linear Dynamical System) model [40] represents the phase transition threshold when both infection and recovery rates are homogeneous, the SIS model [35] represents the phase transition threshold when infection rates are heterogeneous, and the NP-ECC model represents the phase transition threshold when both infection and recovery rates are heterogeneous. For each model, we show the experimental results after 500 time steps, 1000 time steps and 2000 time steps. The phase transition thresholds of NLDS model, SIS model and NP-ECC model are 0.51, 0.78 and 1, respectively. Through the analysis of theoretical results in subsection V. B, we know that the closer the threshold value is to 1, the more accurate it is. In Figure 9, we see a sharp increase in the size of the infected nodes at our model threshold of $S = 1$, while the NLDS model and the SIS model do not have a sharp increase at the phase transition threshold. The experimental results show the NP-ECC model is much more accurate than the SIS model and the NLDS model since it considers the control strategies and construct the heterogeneous network coupling the physical and virtual cyberspace.

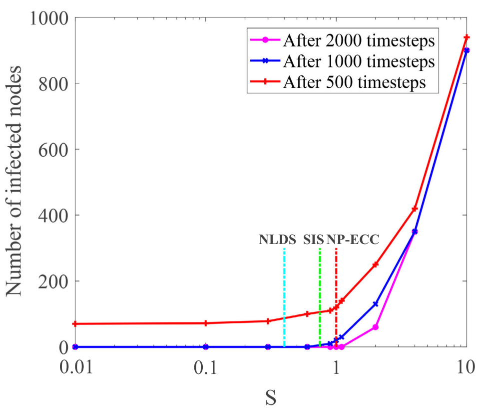


FIGURE 9. **Comparison with the NLDS model and SIS model.**

VIII. CONCLUSION AND FUTURE WORK

To better control the speed and scale of emotional contagion in crowd evacuation, the influence of control strategies on such contagion must be considered in both virtual and physical cyberspace. First, we establish the NP-ECC model to study control strategies of crowd emotional contagion coupling the physical and virtual cyberspace. Second, we construct a personalized BA scale-free network to calculate the phase transition threshold of the proposed NP-ECC model more accurately. Finally, we propose two algorithms CS-BA and T-BA to verify the stability of the NP-ECC model and the accuracy of the phase transition threshold, respectively.

Our framework provides flexible and controllable modeling tools for studying the control strategies of crowd emotional contagion and the phase transition thresholds in the scenario of jointly considering the physical and virtual cyberspace. The proposed method can better control the speed and scale of crowd emotional contagion, and thus can provide guidance for prevention and control of large-scale crowd emotional contagion.

In the future, we plan to study how to use devices of Internet of Things to collect the real data in crowd movement, and combine deep learning methods to improve the accuracy of our model. In addition, we will further explore the differences in details about the emotional contagion between the physical and virtual cyberspace to make our model more applicable.

REFERENCES

[1] L. Fu, W. Song, W. Lv, and S. Lo, "Simulation of emotional contagion using modified SIR model: A cellular automaton approach," *Phys. A, Stat. Mech. Appl.*, vol. 405, pp. 380–391, Jul. 2014.
[2] W. Ross, A. Gorod, and M. Ulieru, "A socio-physical approach to systemic risk reduction in emergency response and preparedness," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 45, no. 8, pp. 1125–1137, Aug. 2015.
[3] X. Wang, L. Zhang, Y. Lin, Y. Zhao, and X. Hu, "Computational models and optimal control strategies for emotion contagion in the human population in emergencies," *Knowl.-Based Syst.*, vol. 109, pp. 35–47, Oct. 2016.
[4] J. M. Diefendorff and R. H. Gosserand, "Understanding the emotional labor process: A control theory perspective," *J. Org. Behav.*, vol. 24, no. 8, pp. 945–959, 2003.
[5] A. L. Bertozzi, J. Rosado, M. B. Short, and L. Wang, "Contagion shocks in one dimension," *J. Stat. Phys.*, vol. 158, no. 3, pp. 647–664, May 2014.
[6] D. M. Rempala, "Cognitive strategies for controlling emotional contagion," *J. Appl. Social Psychol.*, vol. 43, no. 7, pp. 1528–1537, May 2013.
[7] N. Hadjikhani, N. R. Zürcher, O. Rogier, L. Hippolyte, E. Lemonnier, T. Ruest, N. Ward, A. Lassalle, N. Gillberg, E. Billstedt, A. Helles, C. Gillberg, P. Solomon, K. M. Prkachin, and C. Gillberg, "Emotional contagion for pain is intact in autism spectrum disorders," *Translational Psychiatry*, vol. 4, no. 1, p. e343, Jan. 2014.
[8] S. Zheng and H. Liu, "Improved multi-agent deep deterministic policy gradient for path planning-based crowd simulation," *IEEE Access*, vol. 7, pp. 147755–147770, 2019, doi: 10.1109/ACCESS.2019.2946659.
[9] G. Zhang, D. Lu, L. Lv, H. Yu, and H. Liu, "Knowledge-based crowd motion for the unfamiliar environment," *IEEE Access*, vol. 6, pp. 72581–72593, 2018.
[10] Q. Wang, H. Liu, K. Gao, and L. Zhang, "Improved multi-agent reinforcement learning for path planning-based crowd simulation," *IEEE Access*, vol. 7, pp. 73841–73855, 2019.
[11] S. Wang, H. Liu, K. Gao, and J. Zhang, "A multi-species artificial bee colony algorithm and its application for crowd simulation," *IEEE Access*, vol. 7, pp. 2549–2558, 2019.

[12] Y. Li, H. Liu, X. Zheng, Y. Han, and L. Li, "A top–bottom clustering algorithm based on crowd trajectories for small group classification," *IEEE Access*, vol. 7, pp. 29679–29698, 2019.

[13] L. Lyu and J. Zhang, "Toward modeling emotional crowds," *IEEE Access*, vol. 6, pp. 55893–55906, 2018.

[14] Z. Yao, G. Zhang, D. Lu, and H. Liu, "Data-driven crowd evacuation: A reinforcement learning method," *Neurocomputing*, vol. 366, pp. 314–327, Nov. 2019.

[15] H. Liu, B. Xu, D. Lu, and G. Zhang, "A path planning approach for crowd evacuation in buildings based on improved artificial bee colony algorithm," *Appl. Soft Comput.*, vol. 68, pp. 360–376, Jul. 2018.

[16] H. Liu, B. Liu, H. Zhang, L. Li, X. Qin, and G. Zhang, "Crowd evacuation simulation approach based on navigation knowledge and two-layer control mechanism," *Inf. Sci.*, vols. 436–437, pp. 247–267, Apr. 2018.

[17] H. Fujita, J. Hakura, and M. Kurematu, "Intelligent human interface based on mental cloning-based software," *Knowl.-Based Syst.*, vol. 22, no. 3, pp. 216–234, Apr. 2009.

[18] T. Bosse, M. Hoogendoorn, M. C. A. Klein, J. Treur, C. N. van der Wal, and A. van Wissen, "Modelling collective decision making in groups and crowds: Integrating social contagion and interacting emotions, beliefs and intentions," *Auto. Agents Multi-Agent Syst.*, vol. 27, no. 1, pp. 52–84, Jun. 2012.

[19] B. Galitsky, "Exhaustive simulation of consecutive mental states of human agents," *Knowl.-Based Syst.*, vol. 43, pp. 1–20, May 2013.

[20] C. Busso, S. Mariooryad, A. Metallinou, and S. Narayanan, "Iterative feature normalization scheme for automatic emotion detection from speech," *IEEE Trans. Affect. Comput.*, vol. 4, no. 4, pp. 386–397, Oct. 2013.

[21] R. Reisenzein, E. Hudlicka, M. Dastani, J. Gratch, K. Hindriks, E. Lorini, and J.-J.-C. Meyer, "Computational modeling of emotion: Toward improving the inter- and intradisciplinary exchange," *IEEE Trans. Affect. Comput.*, vol. 4, no. 3, pp. 246–266, Jul. 2013.

[22] B. Li, D. Sun, Z. Lin, and C. Ou, "Agent-based simulation research on group emotion evolution of public emergency," in *Proc. IEEE/ACM Int. Conf. Adv. Social Netw. Anal. Mining (ASONAM)*, Aug. 2014, pp. 497–502.

[23] A. Hakim, S. Marsland, and H. W. Guesgen, "Computational analysis of emotion dynamics," in *Proc. Humaine Assoc. Conf. Affect. Comput. Intell. Interact.*, Sep. 2013, pp. 185–190.

[24] S. Mukherjee, D. Goswami, and S. Chatterjee, "A lagrangian approach to modeling and analysis of a crowd dynamics," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 45, no. 6, pp. 865–876, Jun. 2015.

[25] S. Riley, "Large-scale spatial-transmission models of infectious disease," *Science*, vol. 316, no. 5829, pp. 1298–1301, Jun. 2007.

[26] N. C. Grassly and C. Fraser, "Mathematical models of infectious disease transmission," *Nature Rev. Microbiol.*, vol. 6, no. 6, pp. 477–487, May 2008.

[27] K. Zhu and L. Ying, "Information source detection in the SIR model: A sample path based approach," *IEEE/ACM Trans. Netw.*, vol. 24, no. 1, pp. 408–421, Nov. 2012.

[28] C. Ji and D. Jiang, "Threshold behaviour of a stochastic SIR model," *Appl. Math. Model.*, vol. 38, nos. 21–22, pp. 5067–5079, Nov. 2014.

[29] A. Kazemzadeh, S. Lee, and S. Narayanan, "Fuzzy logic models for the meaning of emotion words," *IEEE Comput. Intell. Mag.*, vol. 8, no. 2, pp. 34–49, May 2013.

[30] A. Halder, A. Konar, R. Mandal, A. Chakraborty, P. Bhowmik, N. R. Pal, and A. K. Nagar, "General and interval Type-2 fuzzy face-space approach to emotion recognition," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 43, no. 3, pp. 587–605, May 2013.

[31] K. Kandhway and J. Kuri, "How to run a campaign: Optimal control of SIS and SIR information epidemics," *Appl. Math. Comput.*, vol. 231, pp. 79–92, Mar. 2014.

[32] L. Chen and J. Sun, "Global stability and optimal control of an SIRS epidemic model on heterogeneous networks," *Phys. A, Stat. Mech. Appl.*, vol. 410, pp. 196–204, Sep. 2014.

[33] U. Ledzewicz and H. Scháttler, "On optimal singular controls for a general SIR-model with vaccination and treatment," *Discrete Continuous Dyn. Syst.*, vol. 30, pp. 981–990, Oct. 2011.

[34] G. Zhang, D. Lu, and H. Liu, "Strategies to utilize the positive emotional contagion optimally in crowd evacuation," *IEEE Trans. Affect. Comput.*, to be published.

[35] Z. Chen, "Epidemic thresholds in networks: Impact of heterogeneous infection rates and recovery rates," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2018, pp. 1–6.

[36] C.-Y. Huang, Y.-S. Tsai, C.-T. Sun, J.-L. Hsieh, and C.-Y. Cheng, "Influences of resource limitations and transmission costs on epidemic simulations and critical thresholds in scale-free networks," *Simulation*, vol. 85, no. 3, pp. 205–219, Apr. 2009.

[37] K. Ma, W. Li, Q. Guo, X. Zheng, Z. Zheng, C. Gao, and S. Tang, "Information spreading in complex networks with participation of independent spreaders," *Phys. A, Stat. Mech. Appl.*, vol. 492, pp. 21–27, Feb. 2018.

[38] R. Pastor-Satorras and A. Vespignani, "Epidemic dynamics in finite size scale-free networks," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 65, no. 3, pp. 1–4, Mar. 2002.

[39] P. V. Mieghem, J. Omic, and R. Kooij, "Virus spread in networks," *IEEE/ACM Trans. Netw.*, vol. 17, no. 1, pp. 1–14,

[40] D. Chakrabarti, Y. Wang, C. Wang, J. Leskovec, and C. Faloutsos, "Epidemic thresholds in real networks," *ACM Trans. Inf.and Syst. Secur.*, vol. 10, no. 4, pp. 1–26, Jan. 2008.

[41] L. Huang, G. Cai, H. Yuan, and J. Chen, "From public gatherings to the burst of collective violence: An agent-based emotion contagion model," in *Proc. IEEE Int. Conf. Intell. Secur. Inform. (ISI)*, Nov. 2018, pp. 193–198.

[42] X. Nan, Z. Zehong, and P. Zhigeng, "Dynamic crowd aggregation simulation using SIR model based emotion contagion," in *Proc. Int. Conf. Virtual Reality Vis. (ICVRV)*, Oct. 2017, pp. 352–353.

[43] C. Li, P. Lv, D. Manocha, H. Wang, Y. Li, B. Zhou, and M. Xu, "ACSEE: Antagonistic crowd simulation model with emotional contagion and evolutionary game theory," *IEEE Trans. Affect. Comput.*, to be published.

[44] W. Park, D. B. Chaffin, and B. J. Martin, "Toward memory-based human motion simulation: Development and validation of a motion modification algorithm," *IEEE Trans. Syst., Man, Cybern. A, Syst. Humans*, vol. 34, no. 3, pp. 376–386, May 2004.

[45] W. Park, D. B. Chaffin, B. J. Martin, and J. Yoon, "Memory-based human motion simulation for computer-aided ergonomic design," *IEEE Trans. Syst., Man, Cybern. A, Syst. Humans*, vol. 38, no. 3, pp. 513–527, May 2008.

[46] J. Xue, H. Yin, P. Lv, M. Xu, and Y. Li, "Crowd queuing simulation with an improved emotional contagion model," *Sci. China Inf. Sci.*, vol. 62, no. 4, pp. 1–3, Feb. 2019.

[47] M. Xu, H. Wang, S. Chu, Y. Gan, X. Jiang, Y. Li, and B. Zhou, "Traffic simulation and visual verification in smog," *ACM Trans. Intell. Syst. Technol.*, vol. 10, no. 1, pp. 1–17, Nov. 2018.

[48] P. Lv, Z. Zhang, C. Li, Y. Guo, B. Zhou, and M. Xu, "Crowd behavior evolution with emotional contagion in political rallies," *IEEE Trans. Comput. Social Syst.*, vol. 6, no. 2, pp. 377–386, Apr. 2019.

[49] R. M. Favaretto, L. Dihl, S. R. Musse, F. Vilanova, and A. B. Costa, "Using big five personality model to detect cultural aspects in crowds," in *Proc. 30th SIBGRAPI Conf. Graph., Patterns Images (SIBGRAPI)*, Oct. 2017, pp. 223–229.

[50] J. T. Cacioppo, E. Hatfield, and R. L. Rapson, *Emotional Contagion: Studies in Emotion and Social Interaction*. Cambridge, U.K.: Cambridge Univ. Press, 1993.

[51] R. W. Doherty, "The emotional contagion scale: A measure of individual differences," *J. Nonverbal Behav.*, vol. 21, no. 2, pp. 131–154, 1997.

[52] M. Cao, G. Zhang, M. Wang, D. Lu, and H. Liu, "A method of emotion contagion for crowd evacuation," *Phys. A, Stat. Mech. Appl.*, vol. 483, pp. 250–258, Oct. 2017.

[53] M. Xu, X. Xie, P. Lv, J. Niu, H. Wang, C. Li, R. Zhu, Z. Deng, and B. Zhou, "Crowd behavior simulation with emotional contagion in unexpected multihazard situations," *IEEE Trans. Syst., Man, Cybern. Syst.*, to be published, doi: 10.1109/TSMC.2019.2899047.

[54] A.-L. Barabási, R. Albert, and H. Jeong, "Mean-field theory for scale-free random networks," *Phys. A, Stat. Mech. Appl.*, vol. 272, nos. 1–2, pp. 173–187, Oct. 1999.

[55] A.-L. Barabási and R. Albert, "Emergence of scaling in random networks," *Science*, vol. 286, no. 5439, pp. 509–512, Oct. 1999.

[56] A. L. Hill, D. G. Rand, M. A. Nowak, and N. A. Christakis, "Emotions as infectious diseases in a large social network: The SISa model," *Proc. Roy. Soc. B, Biol. Sci.*, vol. 277, no. 1701, pp. 3827–3835, Jul. 2010.

[57] A. Bodaghi and S. Goliaei, "A novel model for rumor spreading on social networks with considering the influence of dissenting opinions," *Adv. Complex Syst.*, vol. 21, no. 06n07, Jan. 2019, Art. no. 1850011, doi: 10.1142/S021952591850011X.

[58] V. Qazvinian, E. Rosengren, and D. R. Radev, "Rumor has it: Identifying misinformation in microblogs," in *Proc. Conf. Empirical Methods Natural Lang. Process. Assoc. Comput. Linguistics*, 2011, pp. 1589–1599.

XIAO HONG is currently pursuing the M.S. degree with the School of Information Science and Engineering, Shandong Normal University, Jinan, China. Her research interests include computer simulation and emotional contagion.

GUIJUAN ZHANG received the Ph.D. degree from the Institute of Computing Technology (ICT), Chinese Academy of Sciences, in 2011. She is currently a Professor with the School of Information Science and Engineering, Shandong Normal University, China. Her current research interests include emotional contagion, affective computing, and computer simulation.

DIANJIE LU received the Ph.D. degree from the Institute of Computing Technology (ICT), Chinese Academy of Sciences, in 2012. He is currently a Professor with the School of Information Science and Engineering, Shandong Normal University, China. His current research interests include affective computing, resource allocation, and routing in cognitive radio networks.