ACSEE: Antagonistic Crowd Simulation Model with Emotional Contagion and Evolutionary Game Theory

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Abstract—Antagonistic crowd behaviors are often observed in cases of serious conflict. Antagonistic emotions, which is the typical psychological state of agents in different roles (i.e., cops, activists, and civilians) in crowd violent scenes, and the way they spread through contagion in a crowd are important causes of crowd antagonistic behaviors. Moreover, games, which refers to the interaction between opposing groups adopting different strategies to obtain higher benefits and less casualties, determine the level of crowd violence. We present an antagonistic crowd simulation model, ACSEE, which is integrated with antagonistic emotional contagion and evolutionary game theories. Our approach models the antagonistic emotions between agents in different roles using two components: mental emotion and external emotion. We combine enhanced susceptible-infectious-susceptible (SIS) and game approaches to evaluate the role of antagonistic emotional contagion in crowd violence. Our evolutionary game theoretic approach incorporates antagonistic emotional contagion through deterrent force, which is modelled by a mixture of emotional forces and physical forces defeating the opponents. Antagonistic emotional contagion and evolutionary game theories influence each other to determine antagonistic crowd behaviors. We evaluate our approach on real-world scenarios consisting of different kinds of agents. We also compare the simulated crowd behaviors with real-world crowd videos and use our approach to predict the trends of crowd movements in violence incidents. We investigate the impact of various factors (number of agents, emotion, strategy, etc.) on the outcome of crowd violence. We present results from user studies suggesting that our model can simulate antagonistic crowd behaviors similar to those seen in real-world scenarios.

Index Terms—Group violence, emotional contagion, evolutionary game theory

1 INTRODUCTION

Crowd simulation has received increased attention in virtual reality, games, urban modeling, and pedestrian dynamics. One of the most important tasks in crowd simulation is to generate realistic crowd behaviors. Physical methods [1], [2], [3], psychology principles [4], [5], [6], or approaches from other relatively matured disciplines [7], [8], [9], [10] are leveraged into the crowd simulation to improve the similarity between simulation results and real-world crowd movements. As pointed out in [4], emotion has a great influence on crowd behavior and it often invokes an agent to implement either a positive or negative behavioral response. Thus, the emotion modeling in crowd simulation is always the main focus in latest research work. However, the emotional aspect of antagonistic crowd behaviors among people in different roles is left unexplored [11]. Analyzing the emotions of antagonistic crowd behaviors is indeed extremely important, as it can help us understand evolution process of antagonistic crowd behaviors and predict trends of crowd movements.

In this paper, we mainly deal with the problem of simulating antagonistic crowd behaviors. Such behaviors are associated with acts of violation and destruction and are typically carried out as a sign of defiance against a central authority or an indication of conflict between opposing groups [12]. Our goal is to develop a new crowd simulation model that can predict trends of crowd movement in these situations while ignoring the trajectory of a particular individual, discuss the conditions of winning and losing sides, and help to develop measures to quell incidents of crowd violence. Not only will such a method be useful for training police officers, but it could also predict the trends of crowd movements and provide the decision for controlling crowd violence incidents.

It is difficult to simulate realistic antagonistic crowd behaviors because of complex influencing factors. In practice, such behaviors are closely related to antagonistic emotions [13], [4], i.e. the emotions between opposed groups, and evolutionary game theory [5], [12]. In the pursuit of more realistic antagonistic behaviors in virtual agents, antagonistic emotion simulation should be incorporated into crowd simulation models [6]. Most prior crowd simulation models ignore antagonistic emotions and individuals’ antagonistic behaviors. Fu et al. [15] focus on agents’ emotions for only one role without involving the antagonistic emotions between different types of agents. Some empirical methods of modeling antagonistic behaviors are presented in the form of riot games [16], game theoretic models [17], and social networks. These methods are based on statistical spatial-temporal analysis and role-playing dynamics in crowds and can generate emergent social phenomena. Other models use

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evolutionary game theory to simulate the behaviors and interactions between different kinds of agents [12], [18]. Evolutionary game theory has successfully helped explain many complex and challenging aspects of biological and social phenomena in recent decades [18]. Inspired by the idea that more offspring will be produced by more fit biological organisms in a given environment, evolutionary game theory provides us with the methodology to study strategic interactions among agents in incidents of crowd violence [19]. There is considerable work on evaluating individuals’ emotions [20], [21]. Panic, for example, destroys an individual’s normal mental function, transforms the individual into an irrational state, and can lead to unpredictable abnormal behaviors. Furthermore, Durupinar et al. [5] point out that agents’ emotions dominate their decision-making process in games and other behaviors. However, the relationship between antagonistic emotion and antagonistic crowd behavior has not been fully explored [15]. It is challenging to accurately model antagonist emotions among agents in different roles because the antagonism is complex and changes constantly and dynamically [23]. Moreover, prior methods do not consider the effect of antagonistic emotion on evolutionary game theory despite the fact that emotion influences an agent’s behavior significantly. For example, Lv et al. [23] calculate emotions based on political viewpoints of individuals at political rallies. Their method doesn’t involve evolutionary game theory or explore the relationship between evolutionary game theory and antagonistic emotion.

Recent advances in crowd simulation models attempt to simulate plausible human behavior by introducing psychological phenomena to virtual agents [6]. Inspired by the psychological theory in [24], which shows the characterization and simulation of emotional contagion, these psychological phenomena effectively improve the reliability of simulations. Fu et al. [15] integrate emotional contagion with individual movement to obtain realistic emotions and behaviors in a crowd during an emergency. Based on this method, we propose an enhanced SIS model considering the benefits of games and test our antagonistic emotional contagion method among agents in different roles. Moreover, we integrate antagonistic emotional contagion with evolutionary game theory through deterrent force, which describes the differences between agents more accurately. Finally, we determine antagonistic crowd behaviors combining antagonistic emotional contagion and evolutionary theories.

Our main contributions include:

- We propose a method to simulate emotion contagion between antagonistic agents in different roles, which is determined by combing the enhanced SIS and game approaches.
- We propose a kind of deterrent force, which is modelled by a mixture of emotional forces and physical forces defeating the opponents, and it helps individuals make reasonable decisions in the games.
- We integrate antagonistic emotions into an evolutionary game theoretic method through deterrent force to model antagonistic crowd behaviors more realistically.

Our model can generate simulation results that are closest to the real-world scenarios in the overall trends of crowd movements. We have implemented our model and tested it on several outdoor scenarios with varying ratios of different types of roles. Our simulation results are compared with the real-world videos and we evaluate the benefits of our model by performing user studies. The results indicate that the behaviors of agents generated by our model are closer to real-world scenes in the overall trend of crowd movements than those seen in other methods.

The rest of this paper is organized as follows. We review related work in Section 2. We give an overview of our method in Section 3. We introduce our model in Section 4 and show it can be used to generate antagonistic crowd behaviors. We describe the implementation and highlight its performance on complex scenarios in Section 5. We also present results from our preliminary user studies in Section 6.

2 Related Work

In this section, we provide a brief overview of prior works in emotional contagion, evolutionary game theory, and agent-based crowd simulation.

2.1 Emotional contagion

Emotion is a psychological parameter and has a significant influence on individuals in a crowd [5], [25], [26], [27]. Emotional contagion is closely related to human movement [28], [29], [30]. In this subsection, we introduce some representative works about emotional contagion [4].

The epidemiological susceptible-infectious-recovered (SIR) model [31] divides the individuals in a crowd into three categories: infected, susceptible, and recovered. The analysis of the spread of epidemic among these three groups has also been extended to other fields. In [32], the extended model is used to simulate the spread of rumors. Some researchers use the epidemiological SIR model in conjunction with other models to describe emotion propagation under specific situations. In [5], the epidemiological SIR model is improved by combining it with the OCEAN (openness, conscientiousness, extraversion, agreeableness, neuroticism) personality model [33]. In [34], a qualitatively simulated approach to model emotional contagion is proposed for large-scale emergency evacuation. The method shows that the effectiveness of rescue guidance is influenced by the leading emotions in a crowd. Moreover, in [15], the cellular automata model based on the SIR model (CA-SIR) is used to describe emotional contagion in a crowd during an emergency, capturing the dynamic process “susceptible-infected-recovered-susceptible.” However, in some case, people only need to consider two emotional states: infected and susceptible. Hill et al. [35] evaluate the spread of long-term emotional states across a social network based on the classical SIS (Susceptible Infected Susceptible) model. Cai et al. [36] combine the OCEAN and SIS models to simulate emotional contagion on crowd evacuation. Song et al. [37] discuss the factors influencing individual evacuation decision making in the view of social contagion based on Susceptible-Infective (SI) model. Emotional contagion can also be used in traffic simulation [38], [39], [40] and crowd queuing simulation [41].
Fig. 1: Overview of our ACSEE model. (a) Crowd violence occurs. Civilians, activists, and cops are specified in our model and they can perceive environmental information. The basic attributes of these agents are introduced in Section 4.2. (b) Our antagonistic emotional contagion method consists of two components: mental emotion and external emotion. After the outbreak of the crowd violence, the antagonistic emotions of each agent are updated at each time step (Section 4.3). (c) We calculate the antagonistic emotion and deterrent force of each agent. The situation of the cops and activists is determined based on the deterrent force, which is defined according to antagonistic emotion. The game between antagonistic cops and activists is carried out in different situations. Agents use different strategies to carry out game interactions and their benefits are analyzed (Section 4.4). Their strategies are evolved over time using the evolutionary learning method. (d) We present behavior control method based on deterrent force, strategy, and benefit (Section 4.5). Agents choose rational movement directions and actions and their positions are updated. We use step (b) to calculate the positions of all the agents at the next time step. (e) If the crowd violence subsides, the incident ends.

A thermodynamic-based emotional contagion model is introduced by Bosse et al. [42] in the ASCRIBE system. The authors use a multi-agent based approach to define emotional contagion within groups. Their study focuses on the emotions of a collective entity rather than the emotions of single individuals. Neto et al. [6] adapt the model proposed by Bosse et al. [43] into BioCrowds and cope with different groups of agents. Tsai et al. [44] present an emotional contagion model that spreads the highest level of emotion to surrounding agents in their ESCAPES framework. In [45], dynamic emotion propagation is described from the perspective of social psychology, combining thermodynamic-based models and epidemiological-based models.

According to the behaviors of different agents in antagonistic scenarios, we define three kinds of agents. Each kind of agents is assigned a role separately: civilians, activists, and cops. Because of the antagonism between agents with different roles, the above-mentioned emotional contagion models can’t be directly applied to crowd violent scenes. In this paper, we propose antagonistic emotions. Antagonistic emotions are the opposite emotions of agents in different roles. Different roles of agents come from opposing groups in crowd violent scenes. In our model the emotions of cops and activists are the antagonistic emotions. Antagonistic emotional contagion is the emotional contagion process of antagonistic agents in different roles under certain situations. Our antagonistic emotional contagion method can quantitatively characterize dynamic changes in the antagonistic emotions between different roles.

2.2 Evolutionary game theory

In this subsection, we summarize some representative works about evolutionary game theory.

Evolutionary game theory has solved many biological problems. For example, in [46], genome-driven evolutionary game theory helps to explain the rise of metabolic interdependencies in microbial communities.

Some researchers have applied evolutionary game theory to the recommendation system. Saab et al. [47] use classical and spatial evolutionary game theory as a possible solution to the Sybil attack in recommender systems. Li et al. [48] propose a new stability analysis of repeated games and evolutionary games based on a subset of Nash equilibrium.

Evolutionary game theory can help us understand the behaviors of individuals better. Huang et al. [49] present a model in which every mutation leads to a new game between the mutants and the residents based on an evolutionary game theoretic approach. Evolutionary game theory is one of the most effective approaches to understand and analyze widespread cooperative behaviors among individuals [50]. In [51], the combination of evolutionary game theory and graph theory provides an extended framework to investigate cooperative behavior in social systems. Quek et al. [12] focus on the development of a spatial evolutionary multiagent social network to study the macroscopic-
behavioral dynamics of civil violence due to microscopic game-theoretic interactions between goal-oriented agents.

Some previous works [12], [52] study antagonistic crowd behaviors in crowd violence incidents based on evolutionary game theory but do not fully consider the differences of antagonistic emotions and deterrent forces of agents with different roles. In this paper, we further improve the evolutionary game theoretic method. At first, game in our model is established between opposing groups (cops and activists). When these agents confront different scenarios and situations, they adopt different strategies such as defection or cooperation to get higher benefits and less casualties. Evolutionary game theory is a modeling approach of strategic interactions among agents in crowd violent incidents based on natural selection mechanism. Natural selection mechanism means that more offspring will be produced by more fit biological organisms in a given environment. We use evolutionary game theory to analyze the strategies and benefits of agents. Our model incorporates antagonistic emotions into evolutionary game theory to describe the differences between agents, which estimates situations of antagonistic scenes more accurately.

2.3 Agent-based crowd simulation

Agent-based model is a kind of versatile method can simulate complex scenarios. In an agent-based model, all the agents are endowed with greater autonomy and have their own inherent attributes and properties. Agents can receive information from the surrounding environment, which will influence their actions and decisions [53]. They have separate velocities and moving directions. Hence, an agent-based model can produce complex crowd behaviors. In contrast to agent-based models, flow-based and particle-based models cannot accurately describe the differences between agents [54]. A flow-based model is mainly used to simulate high-density crowds and has no individuals or groups. A particle-based model cannot model high-level decision-making behaviors. Therefore, we integrate the proposed model with an agent-based method. In this subsection, we summarize this kind of methods.

An agent-based approach is the most common way to simulate crowd movements [55]. Kountouriotis et al. [54] use the agent-based model to simulate thousands of agents in real time, which integrates a high level of individual parametrization, such as group behaviors between friends and between a leader and a follower. Luo et al. [56] introduce a novel framework for proactive steering in agent-based crowd simulation. The Social Forces Model is combined with an agent-based method to simulate crowds [57]. In this model, repulsive and tangential forces of each agent are introduced to avoid collisions with surrounding agents and obstacles. However, all the agents share the same attributes and move with the same speed, which doesn’t conform to real-world scenarios.

Some agent-based methods are used to simulate crowd movements in emergency scenarios. In these scenarios, the emotional state of an agent is a very important influencing factor in simulating realistic behaviors. Shendarkar et al. [58] present a novel crowd simulation model for emergency response using BDI (belief, desire, intention) agents. Luo et al. [59] describe the human-like decision-making process based on various physiological, emotional, and social group attributes for agents under normal and emergency situations. Aydt et al. [60] propose an emotion model integrated with an agent-based method in serious games based on modern appraisal theory. In contrast to the above methods, which don’t involve antagonistic scenes or emotions between agents in different roles, our method focuses on antagonistic emotions and the relationship between antagonistic emotions and evolutionary game theory.

| Notation     | Description                                      |
|--------------|-------------------------------------------------|
| FR           | The radius of perceived range                   |
| $e_{e,m}^i(t)$| External emotion of agent $i$ at time $t$        |
| $e_{i}$      | Mental emotion of agent $i$                     |
| $\Delta e_{e,m}^i(t)$ | The increase in the strength of agent $i$'s external emotion at time $t$ |
| $T_{c2a}$    | If the emotion value of an activist exceeds the threshold $T_{c2a}$, role transition from activist to civilian occurs. |
| $T_{c2a}$    | If the emotion value of a civilian less than the threshold $T_{c2a}$, role transition from civilian to activist occurs. |
| $f_i(t)$     | The deterrent force of agent $i$ at time $t$   |
| $F_i(t)$     | The total deterrent force of agents of the same type for agent $i$ at time $t$ |
| $\Delta F_i$| The difference of the total deterrent forces between cops and activists that agent $i$ can perceive at time $t$ |
| $P\text{\_die}$ | The death probability                          |
| $T\text{\_warn}$ | The early warning threshold                      |
| $\text{\_warn$\_time}$ | The time of early warning                        |

3 OVERVIEW OF OUR APPROACH

In this section, we introduce some basic and important concepts about crowd behavior simulation and crowd emotional contagion. We also give an overview of our method.

3.1 Crowd behavior simulation

Crowd behavior simulation can be defined as a process of emulating or simulating the movement of large amount of entities, characters or agents [61]. At a broad level, crowd movement is governed by psychological status of individuals and their surrounding environment [22]. When humans form a crowd, interaction becomes an essential part of the overall crowd movement [9]. For agent-based methods of crowd simulation used in this paper, each agent is assumed as an independent decision-making entity, which has knowledge of the environment and a desired goal position.
at each step of the simulation. The interactions between
an agent with others or with the environment are often
performed at a local level [62]. A typical crowd simulation
model can be defined as in Equation 1. $P^t$ represents the
positions of all the agents in the scene at time $t$ and $P^{t+1}$
is the positions of all the agents at time $t + 1$, which can be
induced by crowd simulation model $f$.

$$P^{t+1} = f(P^t)$$  

(1)

3.2 Crowd emotional contagion

Crowd simulation research has recently taken a new di-
rection for modeling emotion of individuals to generate
believable, heterogeneous crowd behaviors. Emotion of an
agent can greatly affect its ability to perceive, learn, behave,
and communicate within the surrounding environment [5].
The emotion owned by one agent provides information
about other agents’ behavioral intentions and modulates his
or her behavioral decision-making process. Based on
their appraisal of the environment, emotions of the agents
in a crowd are updated dynamically at different time. In
antagonistic scenes, such emotional changes become more
obvious and play a vital role in crowd interaction behaviors.
As shown in Equation 2, the emotion values of all the agents
$E^{t+1}$ at time $t + 1$ can be computed according to their
relative positions $P^t$ and emotions of the agents $E^t$ at time
$t$.

$$E^{t+1} = g(E^t, P^t)$$  

(2)

3.3 Overview of our ACSEE model

This paper mainly discusses the influence of antagonistic emotions on agents’ behaviors, whose purpose is to com-
pute and update the status of all the agents at different
time steps according to their emotions and roles. The crowd
emotion is fully integrated into crowd behavior simulation,
also with considering the confrontation between agents
with different roles, such as civilians, activists, and cops.
Given the positions $P^t$, the emotions $E^t$, and the roles $R^t$
of all the agents at time $t$, our crowd simulation model
ACSEE($P^t$, $E^t$) estimates the positions $P^{t+1}$, the emotions
$E^{t+1}$, and the roles $R^{t+1}$ of all the agents at next time step
as Equation 3.

$$\{P^{t+1}, E^{t+1}, R^{t+1}\} = \text{ACSEE}(f(P^{t-1}), g(E^{t-1}, P^{t-1}), R^t)$$

$$\text{ACSEE}(P^t, E^t, R^t)$$  

(3)

4 ACSEE MODEL

We present a novel Antagonistic Crowd behavior Simulation
model (ACSEE) based on Emotional contagion and
Evolutionary game theories. Our model consists of three
important modules: antagonistic emotional contagion, an-
tagonistic evolutionary gaming, and behavior control. The
antagonistic emotional contagion method is designed by
combining the enhanced SIS and game approaches. Using
the antagonistic emotions of agents, we define their deter-
rent forces in Section 4.4. The enhanced evolutionary game
theoretic approach is determined based on the deterrent
forces of agents. Our ACSEE model computes the behavior
of each agent by modeling the influence from antagonistic
emotional contagion and evolutionary game theories. The
flowchart of our ACSEE model is presented in Figure 1.

4.1 Symbols and Notations

For convenience, the important parameters used in the
ACSEE model and their descriptions are listed in Table 1.

4.2 Agent modeling in antagonistic scenes

In this section, we mainly describe the role of different kinds
of agents and the assumptions we formulated.

4.2.1 Civilians, activists, and cops

Crowd violence incidents are often caused by some serious
social contradictions, where a certain amount of activists
challenge or break the normal and peaceful social order
or stability in different ways of violence such as large-
scale gathering, group activities, and physical conflicts. We
classify the agents in the crowd under such situations as
civilians, activists, or cops based on their roles according to
[12], [63].

Civilians are neutral agents in the environment and pose
no danger to the central authority. In general, civilians are
vulnerable groups and do not participate in confrontation.
The cops do their best to protect civilians while the activists
persecute them. However, civilians may change their roles if
conditions are favorable to express their anger and frustra-
tion publicly. For example, because of the instigation of the
surrounding activists, the civilians may turn into activists
to participate in the riot. Activists aim to create havoc and
fuel the ongoing unrest while avoiding being defeated by
cops. Cops maintain public order by suppressing activists
and play a key role in preventing terrorist attack. In real-
world scenarios, cops and activists can represent any two an-
tagonistic groups [13]. Civilians can also represent onlookers
and neutral parties.

4.2.2 Assumptions

Antagonistic crowds arise for many complex influencing
factors. The simulation of antagonistic crowd behaviors
considering all the influencing factors is an insoluble prob-
lem. From the observations of the real antagonistic crowd
behaviors, we formulate the following assumptions to make
this problem solvable.

- Emotions of cops are positive while those of activists
  are negative. Civilians are neutral agents. The pro-
  cess of emotional contagion can change their emo-
  tions. Cops with high positive emotions will make
  the agents around them more positive. Activists with
  high negative emotions will make the agents around
  them more negative. Civilians don’t actively affect
  the emotions of surrounding agents [5].
- An agent can maintain a perceived range that is
  centered around it. We regard the perceived range
  of an agent as a circular area with a fixed radius $PR$
  [5], [64].
4.3 Antagonistic emotional contagion module

Since emotion has an important influence on people’s behavior decision-making, accurate emotion modeling is essential and fundamental for a crowd simulation model [9]. In this section, we present our antagonistic emotional contagion module. Emotions in our model incorporate the antagonism between agents in different roles. $e_i$ denotes the emotion of agent $i$. $e_i \in (-1, 1)$ and $e_i \neq 0$. There are two different types of emotion: positive emotion and negative emotion. When the emotion value is greater than 0, the emotion is positive. The higher the emotion value of an agent, the more positive his/her emotion. When the emotion value is less than 0, the emotion of the agent becomes negative. The lower the emotion value of an agent, the more negative his/her emotion. When an emotion value is closer to 0, the agent is regarded as being in a peaceful state and he or she tends to be conservative. The descriptions of different emotion values of different roles are listed in Table 2.

| Descriptions of emotion | Lower to 1 | Lower to 0 | Lower to −1 |
|-------------------------|-----------|-----------|-----------|
| Roles                   | Cops      | Activists | Civilians |
|                         | huge morale; brave to subdue the activists | peaceful | arrogrant and attack cops |
|                         | low morale; afraid of activists | not fear of activists | peaceful |

TABLE 2: The descriptions of different emotion values of different roles

In such an antagonistic game scenario, individuals will be influenced by external and internal stimuli. External stimuli mainly come from the external environment and are often accepted by individuals passively. Internal stimuli come from the subjective perception and judgment of individuals by themselves. Both the internal and external stimuli in the antagonistic scenarios are able to produce emotions, so the emotion of an agent $e_i$ consists of two parts. The first part is the external emotion $e^{ex}_i$, which is influenced by surrounding agents. The second part is the mental emotion $e^{me}_i$ [66], which is determined by an agent’s own subjective consciousness. Therefore, the final emotion value is defined as follows [67], [68]:

$$e_i = e^{ex}_i + e^{me}_i$$  (4)

4.3.1 External emotion

Our method for calculating external emotion is inspired by the emotional contagion model in [15]. An agent can be affected by others in his or her perceived range. The increase in the strength of external emotion of agent $i$ ($\Delta e^{ex}_{i,j}(t)$) received from agent $j$ at time $t$ is defined as:

$$\Delta e^{ex}_{i,j}(t) = [1 - \frac{1}{(1 + \exp(-L))}] \times e_i(t) \times A_{j,i} \times B_{i,j}$$  (5)

where $L$ represents the distance between agent $i$ and $j$, $e_i$ denotes the emotion of agent $i$, $A_{j,i}$ is the intensity of emotion received by $i$ from sender $j$, and $B_{i,j}$ is the intensity of emotion which is sent from $i$ to receiver $j$.

Civilians can only passively receive the emotional contagion from surrounding agents and cannot actively influence others. The increment of external emotion of agent $o$ at time $t$ is denoted as $\Delta e^{ex}_o(t)$. $\Delta e^{ex}_o(t)$ includes emotional influences received from all the cops and activists in the perceived range of agent $o$. $\Delta e^{ex}_o(t)$ is defined as follows:

$$\Delta e^{ex}_o(t) = \sum_{i=1}^{k} \Delta e^{ex}_{o,i}(t) + \sum_{j=1}^{n} \Delta e^{ex}_{o,a_j}(t)$$  (6)

where $\Delta e^{ex}_{o,i}(t)$ and $\Delta e^{ex}_{o,a_j}(t)$ denote the increase in the strength of the external emotion transmitted from cop $c_i$ and activist $a_j$ to agent $o$.

4.3.2 Mental emotion

Each agent establishes game play with agents in the opposing group who are in his or her perceived range. Because civilians are neutral members and remain peaceful, we assume that no game interaction will occur between civilian agents. The benefits of each game are determined according to the method outlined in Section 4.3. Mental emotion is defined as the difference between the benefits of two games and the mental emotion of civilians is a constant [69].

The difference between the benefits of the games at time $t$ and $t-1$ for agent $i$ is denoted as $\Delta \text{benef}_i(t) = \text{benef}_i(t) - \text{benef}_i(t-1)$. The threshold that leads to emotional fluctuations is $\delta$. The relationship between the increment of mental emotion and the difference between the benefits at time $t$ is defined by:

$$\Delta e^{me}_i(t) = \begin{cases} \text{rand}(-0.01, 0.01), & |\Delta \text{benef}_i(t)| < \delta \\ \delta - \exp(\delta / \Delta \text{benef}_i(t)) / \delta, & \Delta \text{benef}_i(t) \geq \delta \\ 0, & \text{otherwise} \end{cases}$$  (7)

In Equation 7, $|\Delta \text{benef}_i(t)| < \delta$ means that the difference between benefits fails to reach the emotional fluctuation threshold $\delta$. Therefore, there is little change in the emotion of agent $i$. In this case, the mental emotion value is a random number on the interval (-0.01, 0.01). $\Delta \text{benef}_i(t) \geq \delta$ means that the benefit at time $t$ is higher than that at time $t-1$. The benefit increase makes the cops more positive and activists more negative. $\Delta \text{benef}_i(t) \leq -\delta$ means that the difference between the benefits of time $t$ and $t-1$ is higher than the emotional fluctuation threshold $\delta$. The benefit at time $t$ is lower than that at time $t-1$. The benefit decrease makes cops more negative and activists more positive.
### 4.3.3 Emotion updating

Our emotion updating method for agents is presented in Figure 2. The mental and external emotions of each agent are updated according to the evolution of the games and changes in agents’ locations. The external emotion of an agent is determined by the emotional contagion (external stimulus) of surrounding cops and activists. The differences between the benefits of games (internal stimulus), which is defined in Section 4.3.2, lead to the changes in the mental emotions of cops and activists.

![Emotion updating method](image)

The increment of the total emotion (\(\Delta e_o(t)\)) of agent \(o\) at time \(t\) is defined as follows:

\[
\Delta e_o(t) = \Delta e_o^{ex}(t) + \Delta e_o^{me}(t)
\]

(8)

For each time step, the total emotion value is updated. At time \(t\), the total emotion value of agent \(o\) is defined as follows:

\[
e_o(t) = e_o(t - 1) + \Delta e_o(t)
\]

(9)

### 4.4 Antagonistic evolutionary gaming module

In our model an agent establishes game play with all the agents from the opposing group within his or her perceived range, according to game theory. When agents confront different scenarios and situations, they adopt different strategies and get varying benefits. They aim to maximize their benefits and minimize casualties according to the current situation. In this subsection, we present the evolutionary game theoretic module of our model, which is used to analyze the strategies and benefits of agents.

At first, agents estimate surrounding situations based on the deterrent forces of the agents in their perceived range. Deterrent force is a kind of power by which an agent can beat his or her opponents and is closely related to the agent’s behavior. Emotion plays a crucial role in agents’ deterrent forces [70]. The deterrent force of agent \(i\) is defined in the following equation:

\[
f_i(t) = \sin \left( |e_i(t)| \cdot \frac{\pi}{2} \right)
\]

(10)

where \(e_i(t)\) is the emotion of agent \(i\) at time \(t\). The more positive or negative the emotion of an agent is, the greater the deterrent force the agent possesses [70]. The total deterrent forces are defined as follows:

\[
F_i(t) = \sum_{k \in A} f_k(t)
\]

(11)

\[
\hat{F}_i(t) = \sum_{k \in A} f_k(t)
\]

(12)

where the set \(A\) denotes agents of the same type in the perceived range of agent \(i\) and the set of the opposing agents in the perceived range of agent \(i\) is \(\hat{A}\).

The situation is defined according to the difference between the total deterrent forces of cops and activists perceived by agent \(i\), which is expressed in Equation [13] as follows.

\[
\Delta F_i = F_i(t) - \hat{F}_i(t)
\]

(13)

Under different situations, the benefits gained during the games are different. The benefit matrix is defined according to varying situations. In contrast, the benefit matrix defined in [12] is based on the number of cops and activists and assumes that the deterrent forces of all the agents are the same. Instead, we define the benefit matrix based on the deterrent forces of cops and activists. We fully account for the differences between the deterrent forces of all the agents, which conforms to real-world scenes. The benefit matrix corresponding to different situations is shown in Table 3.

| Situations | Benefit | Strategy of cops |
|------------|---------|-----------------|
| \(\Delta F > 0\) | Cooperation, Defection |
| \(\Delta F < 0\) | Cooperation, Defection |
| \(\Delta F = 0\) | Cooperation, Defection |

When the total deterrent force of the cops is higher than that of the activists (\(\Delta F > 0\)), if both groups adopt a strategy of cooperation, cops miss an opportunity to make arrests. Compared with activists, cops reap fewer benefits. If both groups defect, cops gain the upper hand because they have a higher total deterrent force and therefore reap more benefits. If cops cooperate and activists defect, both groups’
benefits remain relatively neutral. Cops should defect to confront activists while activists should cooperate to avoid challenging cops and inviting casualties. If cops defect and activists cooperate, cops exert dominance over activists and activists avoid direct conflict. Therefore, both groups obtain benefits. When the total deterrent force of cops is less than or equal to that of activists ($\Delta F < 0$ or $\Delta F = 0$), their benefits are defined similarly.

After a game, the strategies of cops and activists are updated according to the results of that game. Each agent is defined by a binary string. This string encodes the strategy bits in different situations. This string suggests the strategies an agent should adopt when $\Delta F = 0$, when $\Delta F > 0$, and when $\Delta F < 0$. Then the effectiveness or benefit of each strategy is calculated. The more beneficial strategy is chosen and it will be passed on to the offspring in an attempt to create a better strategy.

4.5 Behavior control module

The behavior control method of agents is determined by antagonistic emotional contagion and evolutionary game theoretic approaches. In this section, we present some rules about how agents determine their positions at the next time step and their living states.

Agents determine their positions at the next time step based on the cellular automaton model [15]. A cellular space of $M \times N$ cells is defined and each agent occupies one cell. At each time step, agents choose to move to their neighboring cells or stay still.

Whether an agent moves or not depends on the deterrent forces exhibited by his or her neighboring agents. For a cop or an activist, this is divided into the following possible cases according to real-world videos:

- If the total deterrent force of agents in the opposing group is higher than that of agents of the same type in agent $i$’s neighboring cells, he or she has to move. The moving direction of agent $i$ is determined by the expected benefits of his or her neighboring cells. At first, the neighboring cells around agent $i$ will be checked to find the empty ones (an empty cell means that there is not an agent in it). Then the expected benefits of all the empty cells are calculated. The cell with the highest benefit is the position to which agent $i$ will move.

- Next we consider the situation where the total deterrent force of the opposing agents is less than that of agents of the same type in agent $i$’s neighboring cells. If agent $i$’s strategy is defection, he or she will move to the nearest opposing agent (i.e. attack the opposing agent). If agent $i$’s strategy is cooperation, he or she will stay away from opposing agents and move to the nearest civilian. If agent $i$ is a cop, he or she will protect the civilian. If agent $i$ is an activist, he or she will attack the civilian. In this case, agent $i$ may also choose to stay still.

- Agent $i$ with no neighbors chooses to move. The moving direction is the same as the situation where the total deterrent force of the opposing agents is less than that of agents of the same type.

- Civilians move to safer positions where there are more cops around them.

The agent with a defection strategy attacks his or her opponents. The agent may be dead. A dead agent in this case means being subdued by his or her opponents and therefore posing no threat to these opponents. It doesn’t mean real death. At each time step, the death probability of each agent is calculated and denoted as $P_{\text{die}}$. In contrast to the definition in [12], which is based on the number of cops and activists, we define $P_{\text{die}}$ based on the total deterrent forces of cops and activists.

$$P_{\text{die}} = 1 - \exp \left( \ln 0.1 \cdot \frac{\sum F_i}{\sum \frac{F_i}{20}} \right)$$  \hspace{1cm} (14)$$

where $\sum F_i$ represents the total deterrent force of agents of the same type, and $\sum \frac{F_i}{20}$ represents the total deterrent force of his or her opponents in the cells neighboring agent $i$. $\sum F_i$ denotes the total deterrent force of the cop-to-activist ratio within the perceived range of agent $i$. $\ln 0.1$ is set to ensure a plausible value ($P_{\text{die}} = 0.9$) when $\sum F_i = \sum \frac{F_i}{20}$.

Each agent has an early warning threshold $T_{\text{warn}}$. When the value of $P_{\text{die}}$ exceeds the threshold $T_{\text{warn}}$, the value of $\text{warn}_t$ increases by 1. When the value of $\text{warn}_t$ exceeds the threshold $T_{\text{warn}_t}$, the agent will die. Because the endurance of each agent is different, the values of the thresholds $T_{\text{warn}}$ and $T_{\text{warn}_t}$ are also different for each agent.

5 IMPLEMENTATION AND PERFORMANCE

We have implemented our model using Visual C++ to simulate antagonistic crowd behaviors based on Unity3D. The computing environment is a common PC with a quadcore 2.50 GHz CPU, 16 GB memory, and an Nvidia GeForce GTX 1080 Ti graphics card.

| Scenario | Number of agents | Size of 2-D Grid | $T_{\text{warn}}$ | $T_{\text{warn}_t}$ | Emotion |
|----------|------------------|-----------------|-----------------|-----------------|---------|
| No.1: Activists attack civilians | 80 | 50 | 40 | 20 x 20 squares | 0.1 | 0.5 | 0.5 | 0.5 |
| No.2: Rival stations | 80 | 50 | 70 | 20 x 20 squares | 0.1 | 0.5 | 0.5 | 0.5 |
| No.3: Cops encircling activists | 80 | 50 | 70 | 20 x 20 squares | 0.1 | 0.5 | 0.5 | 0.5 |
| No.4: Real-world 1 | 10 | 50 | 30 | 20 x 20 squares | 0.1 | 0.5 | 0.5 | 0.5 |
| No.5: Real-world 2 | 80 | 50 | 30 | 20 x 20 squares | 0.1 | 0.5 | 0.5 | 0.5 |
| No.6: Real-world 3 | 3 | 14 | 40 | 20 x 20 squares | 1 | -1 | 0 | 0.9 |
| No.7: Real-world 4 | 0 | 30 | 100 | 40 x 40 squares | 1 | -1 | 0 | 0.2 |
| No.8: Real-world 5 | 100 | 30 | 100 | 40 x 40 squares | 1 | -1 | 0 | 0.9 |
| No.9: ACEE vs. CVM | 80 | 50 | 30 | 20 x 20 squares | 0.1 | 0.5 | 0.5 | 0.5 |

We run a series of experiments involving varying role number ratios in outdoor scenarios. The parameter values in different scenarios used in the simulation runs are listed in Table 4. The perceived range $PR$ of agents is 10, $T_{\text{warn}} \in [0.7, 0.9]$, and $T_{\text{warn}_t} \in [8, 20]$. Figures 3, 6
Fig. 3: The numbers of three types of agents at different time steps according to different initial $R_{ca}$ (the ratio of cops to activists): (a) $R_{ca}$ is 0 (0 cops), (b) $R_{ca}$ is 0.6 (30 cops), (c) $R_{ca}$ is 0.8 (40 cops), (d) $R_{ca}$ is 1 (50 cops), (e) $R_{ca}$ is 1.2 (60 cops), (f) $R_{ca}$ is 1.4 (70 cops), and (g) $R_{ca}$ is 1.6 (80 cops). (h) Active ratio curves for different initial $R_{ca}$s. (a) shows a steep drop in the number of civilians. The number of activists remains the same because there are no cops to fight with the activists. We can see from (a) to (g) that the number of dead activists increases as $R_{ca}$ increases. When $R_{ca}$ is 1.2, all the activists have been subdued by cops. The time required for all the activists to be subdued by cops decreases as $R_{ca}$ increases. The civilian survival time lengthens and there are more surviving civilians as $R_{ca}$ increases. We can see that there is an initial rise in the number of civilians in (f) and (g) because the total deterrent force of the cops is much higher than that of the activists. Some activists change their roles (from activist to civilian). (h) shows the overview of active ratios (ratios of the activists to the sum of the activists and civilians) corresponding to different $R_{ca}$s. An inverse relationship between the active ratio and the $R_{ca}$ is presented. Therefore, increasing the ratio of cops can help subdue activists.

We can learn from Figure 3 that the number of different kinds of agents determines the outcome of crowd violence to some extent. When we increase the ratio of cops, they can help subdue activists. 

Fig. 4: The positions of all the agents at the 168th frame ($R_{ca}$ is 1). The green, purple, and blue circles represent civilians, activists, and cops, respectively. The stronger the color intensity of a circle, the higher the deterrent force of the agent.

5.1 The impact of ratios of agents in different roles on the result of crowd violence

We investigate the effects of varying ratios of agents in different roles on the results of crowd violence. By analyzing a large number of real-world antagonistic videos, we select several representative values of $R_{ca}$ (the ratio of cops to activists). In this section the initial $R_{ca}$s are 0, 0.6, 0.8, 1, 1.2, 1.4, and 1.6. The initial numbers of civilians and activists are 80 and 50, respectively. The initial emotion values of all the activists and cops are -0.5 and 0.5, respectively.

We can learn from Figure 3 that the number of different kinds of agents determines the outcome of crowd violence to some extent. When we increase the ratio of cops, they can
Fig. 5: Some fascinating emergent phenomena our model uncovers. (a), (b), and (c) are the simulations of activists attacking civilians. (d), (e), and (f) are the simulations of role transitions. (g), (h), and (i) are the simulations of cops encircling activists. The green, purple, blue, and grey circles are civilians, activists, cops, and dead agents, respectively. The stronger the color intensity of a circle, the higher the deterrent force of the agent.

We learn from Figure 4 that activists participate in collective behavior to create regions of low cop-to-activist ratios, which reduces the chances of activist death. The conglomeration of scattered activists into small groups and the amalgamation of small groups into large ones make it difficult to wipe them out [71]. Although the number of agents determines the outcome of crowd violence to a certain extent, some take advantage of agents’ spatial distributions to affect the outcome of crowd violence.

5.2 The impact of agent parameters on the result of crowd violence

In this section we analyze the impact of agent parameters on the result of crowd violence. We choose two parameters which have great influences on the simulation results: PR (the radius of perceived range) and $A$ or $B$ in Equation 5. In Equation 5, $A_{j,i}$ is the strength attribute by which an emotion is received by $i$ from sender $j$ and $B_{i,j}$ is the strength attribute by which an emotion is sent from $i$ to receiver $j$. We discuss the relationship between active ratios (ratios of activists to the sum of the activists and civilians) and the parameters. The initial numbers of the civilians, activists, and cops are 80, 50, and 70, respectively. The initial emotions of the civilians, activists, and cops are 0.1, -0.5, and 0.5, respectively. The initial total deterrent force of the cops is higher than that of the activists.

We show active ratios according to various values of PR in Figure 6. We assume that all individuals have the same PR. When PR of agents are different, the results of active ratios are also different. With the increase of PR, agents can more accurately estimate the situations. Therefore, the high total deterrent force of cops plays a role in defeating the activists. The active ratio decreases with the increase of PR.

In addition, we also discuss the relationship between the values of $A$ or $B$ and active ratios in Figure 7. $A$ and
Fig. 6: Active ratios corresponding to different PRs (the radius of perceived range). The active ratio decreases with the increase of PR. When PR is greater than 10, the active ratio tends to be stable. We choose PR = 10 in this paper.

Fig. 7: Active ratios corresponding to different values of A. The active rate decreases with the increases of A. When A is greater than 0.8, the active ratio tends to be stable. We choose A = 0.8 in this paper.

B are very important parameters for emotional contagion in Equation 5. The values of them are positively correlated with the values of emotional contagion. We suppose all the strength attributes of A between any two individuals are the same and those of B between any two individuals are the same. The relationship between the active ratio and A is the same as that between the active ratio and B. We take A as an example to discuss this relationship. As the value of A increases, agents’ emotions also increase and the difference between the total deterrent forces of cops and activists is greater. Due to the high deterrent force of cops, more and more activists are subdued by cops. Therefore when the value of A increases, the active rate decreases.

5.3 Emergent phenomena uncovered by our model

Our model can simulate many emergent phenomena that conform to real-world scenes. Figures 5a, 5b, and 5c show that activists with strong deterrent forces attack civilians. At the top left corner of this scene, there are a lot of civilians. Many activists are at the lower right corner of Figure 5a. Agents of the same type gather together according to [72]. Therefore, it is reasonable that agents of the same type gather together. The number of activists is larger than that of the cops. We can see from Figure 5a that the total deterrent force of the activists is stronger than that of the cops. Activists attack civilians (Figure 5b) and more and more civilians die (Figures 5b and 5c).

At the lower right corner of Figure 5a, there are plenty of cops with high deterrent forces near the highlighted activist and his deterrent force is weak. If he continues to resist, he will die. He therefore transitions roles (from activist to civilian). When all the other activists die, he survives (Figure 5f). When the number of surrounding activists is large enough, it may impel civilians to become activists [73].

In Figure 5g, there are many more cops than activists. The total deterrent force of the cops is much stronger than that of the activists. At first, the cops divide the activists into two groups (Figure 5g) and prevent the activists from gathering together to form a larger group. Next, the cops eliminate these two groups of activists individually. There are some activists in the left side of the scene (the first group). Cops encircle these activists and more activists will die. When all the activists on the left side are eliminated, the cops return to the activists on the right side of the scene (the second group). These activists are encircled by the cops. Finally, all the activists are killed by the cops and the cops win.

Figure 8 shows the simulation of antagonistic crowd behavior using 3D character models. The activists with high deterrent forces on the left of the scene are not afraid of the cops with low deterrent forces. In the upper left corner of the scene, the activists with high deterrent forces attack a civilian. The civilian runs away from the activists. In the middle and lower part of the scene, the cop with a high deterrent force attacks the activist and he runs away from the cop.

5.4 The impact of emotional contagion on the result of crowd violence

The impact of emotional contagion on the results of crowd violence is presented in Figure 9. The initial numbers of civilians, activists, and cops are 80, 50, and 40, respectively. In Figure 9a, the initial emotion values of the cops are higher than those of the activists. At the 53rd time step, the number
Fig. 9: The changes in the number of civilians, activists, and cops: (a) considering emotional contagion and (b) not considering emotional contagion.

Fig. 10: Simulation results (a) considering emotional contagion and (b) not considering emotional contagion. In (a) the deterrent forces of the agents are different and the same types of agents are more likely to gather together. In (b) the deterrent forces of all the agents are the same and the same type of agents are dispersed.

of activists is zero. All the activists have been wiped out by the cops. At first the number of civilians increases because the total deterrent force of the cops is much higher than that of the activists. Some activists change their role (from activist to civilian). In Figure 9b, all the agents without emotion have the same deterrent force. At the 41st time step, the number of cops is zero and the activists win.

We can learn from Figure 9 that the emotion module of our model can describe the differences observed between the agents. In our model, the deterrent forces of all the agents are different according to their emotions. The greater the absolute value of an agent’s emotion, the higher the deterrent force of that agent. Although the number of agents is small, it is still possible to overcome a larger group of opponents by improving the emotions and deterrent forces of them. Therefore, our model can simulate situations in which agents overcome their more numerous opponents.

Figure 10 shows simulation results with and without considering emotion. In Figure 10a the deterrent forces of the agents are different. The stronger the color intensity of a circle, the higher the deterrent force of the agent. Because of emotional contagion, the same types of agents are more likely to gather together, which is similar to what happens in real-world scenarios. In Figure 10b the deterrent forces of all the agents are the same and the same type of agents are dispersed.

Figure 11 shows the heat maps of antagonistic emotion.

Fig. 11: The heat maps of antagonistic emotion: (a) heat map at the 5th time step, (b) heat map at the 17th time step, (c) heat map at the 27th time step, and (d) heat map at the 42th time step. The red area represents the emotions of the cops. The blue area represents the emotions of the activists. The stronger the color intensity, the larger the value of the emotion.

Fig. 12: Cooperation ratios of cops and activists at different time steps: (a) when the total deterrent force of the activists is higher than that of the cops; (b) when the total deterrent force of the activists is equal to that of the cops; (c) when the total deterrent force of the activists is less than that of the cops.

Different colors represent different types of agents’ emotions. The stronger the color intensity, the larger the value of the emotion. At first, the emotions of the cops and the activists are very weak. Later, as a result of the confrontation between cops and activists, both types of emotions increase. Since the initial emotions of the cops are higher than those of activists, the overall emotional scope of the cops becomes wider and wider and that of the activists becomes smaller and smaller. Finally, all the activists are wiped out by the cops and there is no blue area on the map.

5.5 The influence of deterrent force on strategy selection

We present the relationship between deterrent force and strategy selection in this subsection. We analyze the strategy (cooperation or defection) adopted by each agent with respect to their different deterrent forces.

Figure 12 shows the overview of cooperation ratios (the ratio of the number of agents adopting a cooperation strategy to the total number of this type of agents) in relation to
different deterrent forces. When the total deterrent force of the activists is higher than that of the cops (Figure 12a), most of the cops adopt a cooperation strategy to avoid causalities and conserve their fighting forces. When the total deterrent force of the activists is equal to that of the cops, the cooperation ratios of cops and activists are almost the same from the 5th time step to the 45th time step. After the 45th time step, the cops defeat the activists. More and more cops adopt defection strategy, the cooperation ratio of the cops decreases, and the cooperation ratio of the activists increases. When the total deterrent force of the activists is less than that of the cops, the cooperation ratio of the activists is higher than that of the cops.

In summary, the agent with a higher deterrent force is more likely to adopt a defection strategy and the agent with a lower deterrent force is more likely to adopt a cooperation strategy.

5.6 Comparisons
To validate our approach, we compare our simulation results with those generated by the CVM [12] and ABEC [74] models and real-world videos. Main goal of our model is to predict trends of crowd movements in these situations without explicitly modeling the trajectory of a particular individual. Simulation results obtained by our model are closest to the real-world scenes in the overall trends of crowd movements.

The real scenes shown in Figures 13a and 13c are chosen from the public web dataset [75]. The real scenes of Figures 13e, 13g, and 13i are chosen from real antagonistic incidents on YouTube. For the real-world scenarios in Figure 13, we use different colors to distinguish different roles of individuals. The green, purple, and blue circles and cylinders represent civilians, activists, and cops, respectively. The red arrows are the dominant paths of crowd movements. Cops and activists in this case represent two opposing groups. Civilians in this case represent onlookers and neutrals. There are no deaths of activists or cops in these scenes.

The scenes can be simulated by increasing the values of the thresholds of $T_{warn}$ and $T_{warn\_time}$ for our model. The parameter values used in the simulation runs are listed in Table 4. More details can be seen in the supplementary video.

We use the dominant path and entropy metric to quantitatively evaluate our simulation results. Dominant path is defined based on collectiveness of crowd movements. Collectiveness, which indicates the degree to which individuals acting as a unit, is a fundamental and universal measurement for various crowd systems, including crowds in antagonistic scenes [76]. Individuals locally coordinate their movements and behaviors with their neighbors, and then the crowd is self-organized into collective movements without external control. The method proposed in [77] is used to calculate the collectiveness of our simulation results. When the collectiveness of individual movements in a certain area is significantly higher than that of surrounding area, a small group of agents with similar movements is formed. The center of the group is determined according to the average of the positions of all the agents in this group. The trajectory of the group center forms its dominant path and can be treated as the movement trend of the whole group. Using this method, we can get the dominant paths of the real-world videos. We use entropy metric [78], angular error (AE) [79], and inter-group distance metric (IDM) [80] to evaluate our crowd simulation results. They are used to evaluate the errors of trajectories, movement directions, and distances between each group, respectively. These three evaluation methods complement each other, which are used to evaluate our results more comprehensively.

An entropy metric [78] is adopted to evaluate the error between the dominant paths of simulation results and that of the real-world videos. A lower entropy value implies a higher similarity between the simulation results and the real-world scenarios. Table 5 shows the entropy metric of
the simulation results achieved by the CVM, ABEC, and ACSEE (ours) models on different scenarios in Figure 13. The simulation results obtained by our model conform to the real-world videos best.

The angular error (AE) \(^9\) between the movement direction of the simulation result \((V_x, V_y)\) and that of the ground-truth \((V_{xgt}, V_{ygt})\) is also used to evaluate our crowd simulation method. This AE is defined in Equation \(15\). The inter-group distance metric (IDM) \(^{80}\) compares the difference in the average distances between each pair of clustered agents. Tables 5 and 6 show the AE and IDM of our simulation results on different scenarios in Figure 13.

Tables 5, 6, and 7 show that our method consistently outperforms the CVM and ABEC models. Compared with the CVM model, our ACSEE model considers the agents’ antagonistic emotions and accurately describe the differences between agents’ deterrent forces. Compared with the ABEC model only considering emotional contagion in antagonistic scenarios, our method considers not only antagonistic emotion, but also the relationship between antagonistic emotion and evolutionary game theory. The agent is able to choose a more reasonable strategy according to the situation.

\[ AE = \cos^{-1}((V_x \cdot V_{xgt} + V_y \cdot V_{ygt})/\sqrt{V_x^2 + V_y^2} \sqrt{V_{xgt}^2 + V_{ygt}^2}) \]  

\( (15) \)

Table 5: Entropy metric for our simulation algorithms on different scenarios from Figure 13. A lower entropy value implies higher similarity between the simulation results and the real-world scenarios. Simulations with an entropy score less than 1.000 are considered very visually similar to the source data and those with a score greater than 6.000 are visually very different. Scene No. 2 (Figure 15) is too large and chaotic and the collectiveness of crowd movement is not so obvious. Therefore, the entropy value of Scene No. 2 is larger than 1.000, but this value is far less than 6.000.

| Scene No. | ACSEE | ABEC | CVM |
|-----------|-------|------|-----|
| 1         | 0.193 | 1.310| 0.255 |
| 2         | 1.310 | 0.255| 0.104 |
| 3         | 0.255 | 0.104| 0.117 |
| 4         | 0.104 | 0.117| 0.180 |
| 5         | 0.117 | 0.180| 0.187 |

Table 6: AE for the simulation algorithms on different scenes from Figure 13. A lower value for AE implies higher similarity with respect to the real-world crowd videos. We report mean and variance of AE at different time steps.

| Scene No. | ACSEE | ABEC | CVM |
|-----------|-------|------|-----|
| 1         | 0.132/0.159 | 0.205/0.329 | 0.210/0.399 |
| 2         | 0.205/0.329 | 0.210/0.399 | 0.100/0.038 |
| 3         | 0.210/0.399 | 0.100/0.038 | 0.060/0.003 |
| 4         | 0.100/0.038 | 0.060/0.003 | 0.090/0.003 |
| 5         | 0.060/0.003 | 0.090/0.003 | 0.090/0.003 |

The simulation result generated by our model is compared with those of the CVM \(^{12}\) and ABEC \(^{74}\) models in Figure 14. More details can be seen in the supplementary video. In contrast to the CVM and ABEC models, our method can better quantify the differences of the deterrent forces of all the agents. Besides, we also integrate antagonistic emotional contagion into evolutionary game theory to estimate situations of antagonistic scenes more accurately, which helps agents make reasonable strategies in the games. Therefore our simulation result is the most similar to the real-world scenario.

5.7 User Studies

In this section we describe user studies conducted to demonstrate the perceptual benefits of our ACSEE model compared to other models in simulating antagonistic crowd behaviors.

**Experiment Goals & Expectations**: Our main goal is to measure how close the crowd movement tendencies generated using different models are to those observed in real-world videos. We hypothesize that in both studies, agents simulated with our ACSEE model will exhibit overall more plausible antagonistic crowd movements than other models. Therefore, participants will strongly prefer our model to the other models.

**Experimental Design**: Two user studies were conducted based on a paired-comparison design. In each study, participants were shown pre-recorded videos in a side-by-side comparison of simulation results generated by different models and a real-world video. In particular, we asked the users to compare the crowd movement tendencies generated by different crowd simulation models with those observed in real-world videos. The studies had no time constraints and the participants were free to take breaks between the benchmarks. We encouraged the users to watch these videos as many times as they wanted and finally give a stable score.

**Comparison Methods**: The first study compares our ACSEE model considering emotion with our model that does not consider emotion. The second study compares our model with the CVM \(^{12}\) and ABEC \(^{74}\) models.

**Environments**: We use outdoor scenarios without obstacles. In these scenarios, the green, purple, blue, and grey circles are civilians, activists, cops, and dead agents, respectively.

**Metrics**: Participants were shown two pre-recorded videos in a side-by-side comparison of the simulation result and a real-world video. We asked the users to first watch the real-world video and then rate each simulation result on a scale of 1 – 5 in terms of the similarity of movement tendencies between the real-world video and the simulation result video. A score of 1 indicates most dissimilar and a score of 5 indicates most similar movement tendencies.

**Results**: There are 39 participants (20 female) with a mean age of 25.12 ± 3.26 years in these studies. We measure the mean and the variance of their scores and then compute the p-values using a two-tailed t-test. The means of their

| Scene No. | ACSEE | ABEC | CVM |
|-----------|-------|------|-----|
| 1         | 30    | 2    | 6   |
| 2         | 32    | 21   | 18  |
| 3         | 21    | 18   | 35  |
| 4         | 42    | 32   | 63  |
| 5         | 49    | 49   | 63  |
Our model gets higher scores than the CVM and ABEC models, as detailed in Figure 15b. Participants indicate their preference for our ACSEE model.

Fig. 14: Comparisons between the real scenario and simulation results of different crowd simulation models. The simulation result obtained by our model conform to the real-world video best.

Fig. 15: User evaluation of simulation scenes. (a) Comparison of simulation results considering emotion and without considering emotion. (b) Comparison of simulation results generated by the CVM, ABEC, and ACSEE models. Participants were asked to rate each simulation result on a scale of 1 - 5 in terms of the similarity of movement tendencies between the real-world videos and the simulation result videos. We can see from the results that our simulation results are most similar to real-world scenarios.

scores for our model without emotion and with emotion are $2.87 \pm 0.67$ and $3.73 \pm 0.93$, respectively. The means of their scores for the CVM, ABEC, and ACSEE models are $2.56 \pm 1.44$, $3.30 \pm 0.50$, and $3.70 \pm 0.90$, respectively. The p-value for Figure 15a comparison is $2.97e^{-26}$. The p-values for the comparison of the CVM and ACSEE models and that of the ABEC and ACSEE models in Figure 15b are $2.97e^{-26}$ and $1.05e^{-17}$, respectively. We observe that the antagonistic crowd behavior simulations generated by our ACSEE model score much higher than the other models at a statistically significant rate (p-value<0.05). The result indicates that the addition of antagonistic emotion and the integration of antagonistic emotion and evolutionary game theory improve the perceptual similarity of our simulations to the crowd movement tendencies in real-world scenes. Our model gets higher scores than the CVM and ABEC models, as detailed in Figure 15b. Participants indicate their preference for our ACSEE model.

6 Conclusion and Limitations

We present a new model for antagonistic crowd behavior simulation integrated with emotional contagion and evolutionary game theory. Our approach builds on well-known psychological theories to present a comprehensive and antagonistic emotional contagion model. Based on the emotional calculation method, we propose the deterrent force to determine the situation of cops and activists. According to the situation, an enhanced evolutionary game theoretic approach incorporated with antagonistic emotional contagion is determined. Finally, we present a behavior control decision method based on the antagonistic emotional contagion and evolutionary game theoretic approaches.

Our proposed model is verified by simulations. We investigate the impact of different factors (number of agents, emotion, strategy, etc.) on the outcome of crowd violence. Our model is compared with real-world videos and previous approaches. Results show that our proposed model can reliably generate realistic antagonistic crowd behaviors.

However, our model still has several limitations. Although our simulation results are closer to the real-world scenes in the overall trend of crowd movement, the antagonistic emotions in a crowd violent scene cannot be obtained directly or inferred accurately. One of the main reasons is that the quality of most of the real videos is poor, since they are often captured by moving phones. At present, there is no effective methods to identify and quantify the emotion values of all the individuals in such videos with poor quality. Thus, the initial state of our model is set empirically according to real-world videos, which is time-consuming and not very accurate. In the future, we plan to use the latest wearable equipment to collect these data and provide a new method that can quickly and accurately obtain the initial state. Moreover, the strategies and benefits calculated by our antagonistic evolutionary game theoretic approach are the ideal situations. Game theory assumes that all individuals are rational. However, some people in real scenes are irrational and extreme, which doesn’t fully satisfy the precondition of game theory. In practice, people do not necessarily adopt the optimal strategy because of the limitations of perception and other complex factors. Our current calculation result is optimal, which is only one of the possible results. In fact, it is impossible for all simulation results to be consistent with the real results. We will continue to improve our prediction results considering more actual situations of antagonistic crowds. At present, the behavior control in our model is proposed based on the cellular automata [15]. Other more complex behavioral control methods will be further considered.

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