Antagonistic Crowd Simulation Model Integrating Emotion Contagion and Deep Reinforcement Learning

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Abstract—The antagonistic behavior of the crowd often exacerbates the seriousness of the situation in sudden riots, where the spreading of antagonistic emotion and behavioral decision making in the crowd play very important roles. However, the mechanism of complex emotion influencing decision making, especially in the environment of sudden confrontation, has not yet been explored clearly. In this paper, we propose one new antagonistic crowd simulation model by combing emotional contagion and deep reinforcement learning (ACSED). Firstly, we build a group emotional contagion model based on the improved SIS contagion disease model, and estimate the emotional state of the group at each time step during the simulation. Then, the tendency of group antagonistic behavior is modeled based on Deep Q Network (DQN), where the agent can learn the combat behavior autonomously, and leverages the mean field theory to quickly calculate the influence of other surrounding individuals on the central one. Finally, the rationality of the predicted behaviors by the DQN is further analyzed in combination with group emotion, and the final combat behavior of the agent is determined. The method proposed in this paper is verified through several different settings of experiments. The results prove that emotions have a vital impact on the group combat, and positive emotional states are more conducive to combat. Moreover, by comparing the simulation results with real scenes, the feasibility of the method is further verified, which can provide good reference for formulating battle plans and improving the winning rate of righteous groups battles in a variety of situations.

Index Terms—Emergencies, Crowd Simulation, Contagion model, Emotional Contagion, Deep reinforcement learning.

1 INTRODUCTION

With the rapid development of the global economy and the growth of urban population, the frequency and severity of emergencies continue to rise. These emergencies have the characteristics of uncertainty, suddenness, and harmfulness. Once the event occurs, it may cause serious harm to society and citizens, and even irreversible consequences, e.g. the crowd riots. For example, in August 2011, a demonstration in London suddenly turned into a violent confrontation [1]. Criminals attacked the police, innocent people, and destroyed public property. In September 2020, in Kentucky, the United States, due to conflicts between demonstrators from two different camps, the two sides gathered in public venue to confront and provoked each other, which aroused social concern. There are many similar sudden crowd incidents, and the harm and losses caused by each incident are incalculable and shocking.

How to enable relevant departments to efficiently resolve such incidents has become a matter of great concern to all the society, and it is also one key issue that many scholars have devoted themselves to research. Traditional solutions mainly include manual exercises and learning from previous examples in similar incidents, which have certain feasibility. However, carrying out manual exercises will consume a lot of manpower and corresponding resources, and each emergency has distinctive conditions. It is difficult to obtain truly useful and general information from past incidents.

As an important research direction in the field of computer graphics, crowd simulation is widely used in many fields such as security management and control, military exercises, and traffic planning. Especially in the face of sudden riots, crowd simulation methods are often used to help simulate this kind of process, which will save a lot of public resources compared to traditional solutions. By modeling and simulating the evolution process of group behavior, it is possible to have a more detailed understanding of the crowd riots and the trend of group movement under emergencies, to truly reproduce such crowd behavior. Then, we can quickly analyze and formulate effective decisions to quell the incident and reduce the loss caused by the incident. In the military headquarters, researchers often use this method to deploy combat decisions [2] [3] [4]. However, in sudden riots, on the one hand, there are many factors playing different roles when the crowd fights, and the emotions affect the group’s antagonistic behavior to a large extent [5] through determining the decision-making of group behavior [6]. When planning group antagonistic behaviors, emotional factors need to be incorporated into the crowd simulation model carefully. On the other hand, individuals need to quickly make decision-making behaviors in a complex and changeable environment, and it is difficult for individuals to gain effective experience from similar events in the past. Although the existing crowd simulation model have considered the emotional factors when planning group behaviors, it is not so reasonable to design the overall movement trend and specific behaviors of
the agent in advance at the same time, and the formulated combat behaviors may deviate from the real cases.

Recently, deep reinforcement learning that combines the perception capabilities of deep learning and decision-making capabilities of enhanced learning have been widely explored. Many researchers try to use this novel technique to study the decision-making behavior of the crowd to better plan the decision-making path \[7\] \[8\]. However, when using this method to model the crowd behavior, the attributes of agent, such as the inherent group emotions, are not considered fully.

To solve the above problems, this paper proposes an antagonistic crowd behavior simulation model (ACSED) that combines emotional contagion and deep reinforcement learning. First of all, this work fully considers the key role of emotions on group antagonistic behaviors. We build an emotional contagion model based on the improved SIS model and combine with specific combat situations to estimate individual emotions. Then, we use deep reinforcement learning to build the simulation model of group behavior, allowing agent to learn decision-making behavior efficiently and autonomously, and using mean field theory to simplify the calculation complexity when modeling. Finally, we combine with the agent emotion to judge whether the learned behavior is reasonable, and the final battle is determined according to the rules of agent behavior under different emotional states. The simulation experiments prove that the proposed method is helpful for studying the antagonistic behaviors in the riots, and can formulate more realistic and reasonable combat plan for the righteous group and finally improve the victory rate of the combat.

The main contributions of this paper is as following:

1) This paper proposes one new crowd antagonistic behavior simulation model by combining emotional contagion and deep reinforcement learning technology. The DQN and mean field theory are introduced to predict the tendency of the combat behavior of the agent. The proposed model can provide the agents with more reasonable and effective combat behaviors.

2) This paper introduces one new emotional contagion mechanism based on the improved SIS model, which helps to determine the combatting state of individuals. This mechanism analyzes whether the behavior predicted by DQN is reasonable, and determines the final combat behavior according to the behavioral rules of the agent under different emotional states.

3) The proposed model can improve the victory rate of the battle when the two sides are fighting, and fully explore the advantages of the emotion to win more with less, which is more in line with the realistic cases.

The rest of this paper is organized as follows. The second chapter explain the related work of the technology involved in the work of this paper. The third chapter proposes a new antagonistic crowd behavior simulation model. The fourth chapter verifies the rationality of the proposed method through different experiments. The fifth chapter summarizes the work of the full text and discusses the research work to be carried out further.

2 RELATED WORK

This section will briefly describe the related work of crowd simulation, emotional contagion and deep reinforcement learning.

2.1 Crowd simulation

Crowd behavior simulation \[9\] becomes a hotspot technology researched by many scholars. The research of crowd behavior is of great significance to many fields and is widely used in different aspects such as social security, military training, and entertainment games \[10\]. Crowd behavior simulation is generally divided into macro models and micro models \[11\]. The macro model regards the crowd as a whole, focusing on the attributes and movement trends of the whole group, and the description of the details of individual movement is relatively rough. Representative models include fluid mechanics models \[12\], potential energy field models \[13\], and so on. The micro model pays attention to the concrete attributes of individuals in the group, studies the behavior rules and decision-making of individual movements, and can more realistically show the complex interactions between individuals. Classical microscopic models include cellular automata model \[14\], social force model \[15\], multi-agent model \[16\] and so on.

Spartalis et al. \[17\] and others used cellular automata to simulate pedestrian movement, and added crowd classification and guidance attributes to help study the influence of guidance on the process of crowd evacuation. Mao et al. \[18\] proposed a diverse crowd behavior model based on emotions, which uses the OCEAN personality model and the OCC emotion model, and combined the CA-SIRS emotional contagion model to simulate diverse crowd behaviors. Li et al. \[19\] proposed a crowd antagonistic behavior simulation model (ACSEE), which combined adversarial emotions and evolutionary game theory, based on cellular automata to determine the position of the agent, and simulated similar antagonistic crowd behavior in real scenes. Pax et al. \[20\] proposed a method based on agent modeling to build a decision support system, which has been applied to predict the state of large-scale crowd gathering in the future and potential dangerous areas in the scene. Pan and Han \[21\] simulated crowd competition, queuing and gathering behaviors based on multi-agent methods. Beltaief et al. \[22\] proposed a multi-agent simulation model based on psychological theory, which simulated the pedestrian crowding phenomenon more realistically and produced realistic and credible pedestrian behavior. With the gradual improvement which based on multi-agent methods and the gradual maturity of deep reinforcement learning technology, more and more researchers use deep reinforcement learning technology \[23\] to model crowd behavior based on multi-agent methods. Especially for emergencies, this method can calculate group behavior in a way that is closer to human thinking, which is more reasonable and reliable than previous methods. Gupta et al. \[24\] used multi-agent deep reinforcement technology to study the problem of the
complex and partly observable agents to learn cooperative strategies. By designing a set of experiments for cooperative control tasks, the effectiveness of this method was proved.

Although the theory and application of crowd behavior simulation have made good progress, they still face some challenges when using this technology to study emergent crowd incidents. The types of group violence and terrorism are complex and changeable, and it is difficult to plan group behavior in advance based on previous experience. Although the usage of multi-agent deep reinforcement learning allows agents to learn behavior inexperciendly, this technology used to model group behavior in current has not deeply studied individual attributes, and the authenticity of simulation still needs to be improved.

### 2.2 Emotional contagion

Emotion is a short-term psychological state produced by individuals based on subjective cognition, combining feelings, thoughts, and behaviors. When individuals receive external stimuli, they may change their own emotions, and emotions can easily cause changes in behavior. Therefore, individual emotions play a vital role in the process of their behavioral decision-making, and will have a great impact on their behaviors. Emotional cognitive evaluation theory believes that emotions arise from an individual’s evaluation of something that is beneficial or harmful to oneself. Group identity is the basis for the generation of group emotions. Intergroup emotion theory believes that if the individual classify themselves as part of a group, they will have a sense of identity and they belongs to this group, which called the group emotion. It will explain and evaluate events related to the group from the perspective of group members, and thus the emotional experience of the group. Group emotions are easily amplified and contagious, and different individuals may stimulate or change group behavior after mutual contagion, so many social problems and emergencies are caused by group emotions.

The main mechanism of group emotions in group incidents is emotional contagion. Therefore, when researching and solving emergencies, we should not only pay attention to the individual emotional state, but also need to study the process of emotional transmission in the crowd, that is, the problem of emotional contagion between groups. Hattflod gave a detailed explanation of the concept of emotional contagion in 1993, and it is currently widely accepted by the public. This statement means that when an individual comes into contact with other individuals with emotions, they first obtain the emotions of other people directly through the senses, and internally process the acquired information through their own brain and nervous system. After multiple intense processing, the individual will subconsciously submit to the emotions of others, and change his mental state to resonate with the emotions of others. Emotional contagion methods are mainly divided into two categories. One is based on thermodynamic methods and the other is based on epidemiological methods. The emotional contagion method based on thermodynamics is a kind of infection method similar to the dynamic characteristics in the thermodynamic system. The process of emotional contagion is similar to the heat dissipation phenomenon of thermodynamics. Based on epidemiological methods and the transmission mechanism of infectious diseases, emotional contagion are studied. Susceptible persons are at risk of being infected when they come into contact with infected persons. The more infected persons they contact, the greater the risk of infection. Hill et al. proved that the epidemic model can be used to study the problems related to emotional contagion in the population. This paper proposes SISa model based on SIS model, setting spontaneous infection factors, and susceptible persons may be infected after contacting with others, but also spontaneous infection. On the basis of this work, Liu et al. proposed SOSa-SPSa model, which divides crowd emotions into positive and negative states, and further studies the internal mechanism of emotional contagion. Nizamani et al. constructed an emotional contagion model based on the infectious disease theory, divided the population into five categories, and studied the spread of anger among groups.

Inspired by the above work, aiming at the spread of emotions between groups under sudden group violence incidents, this paper builds an emotional contagion model based on an improved SIS epidemic model, studies the influence of emotions on crowd antagonistic behavior, and formulates real combat behaviors for groups.

### 2.3 Deep reinforcement learning

The essence of reinforcement learning is continuous interaction-trial and error. Effective strategies are learned by interacting with the environment in a trial and error manner. Q-learning is a typical reinforcement learning algorithm, which executes a certain action according to a certain state in the Q table. The obtained Q value determines the next moment of action. However, reinforcement learning methods generally cannot solve the problem when the agents’ action and state dimensions are both in a high level. Therefore, if reinforcement learning is used to study crowd simulation, only a small number of people can be simulated, otherwise it may cause the problem of dimensional explosion due to the excessive amount of information. In recent years, one more successful method for this problem is to use deep neural network as the approximate function of reinforcement learning, that is, deep reinforcement learning. At present, deep reinforcement learning is an important research direction in the field of artificial intelligence. This type of method is widely used in many aspects such as robot control, parameter optimization, machine vision, group decision-making behavior, etc. This technology can be achieved through end-to-end learning. The direct control from the original input to the output has achieved substantial breakthroughs in many tasks that require the perception of high-dimensional original input data and decision control. DeepMind proposed the DQN algorithm, which combines Q-learning with deep learning. The state and action are regarded as the input of the neural network. After network processing, the Q value of the action is obtained, and the Q table is omitted. Wang et al.
proposed an improved multi-agent reinforcement learning method, combined with an improved social force model in crowd evacuation simulation. Toghiani-Rizi et al. [41] evaluated the ability of three deep reinforcement learning algorithms to learn tasks in simulated ground combat scenarios, proving that deep reinforcement learning has the potential to improve the practice and technology of combat behavior modeling. Yang et al. [8] combined Q-learning and MeanField Theory (Mean Field Theory, MFT) and proposed the MF-Q algorithm (Mean Field Q-learning), which is dedicated to solving the problem of interaction and calculation difficulties between large-scale agents. When calculating the influence of a certain agent, a mean value is used to replace the effect of all other agents, which greatly simplifies the problem of increasing the model space due to the increase in the number of agents. In a simple crowd antagonistic scenario, the effectiveness of the MF-Q algorithm is verified, which can guarantee the winning rate of group battles to a certain extent. However, this algorithm is not specifically proposed for group antagonistic events, and does not fully consider factors that affect individual combat behaviors, such as group emotions.

This paper will combine the advantages and disadvantages of the above technology, we will learn from and improve the work of [8]. In response to sudden crowd riots, we propose to integrate group emotions based on multi-agent deep reinforcement learning technology to build a simulation model of crowd antagonistic behavior, and plan more efficient combat behaviors for the group.

3 Antagonistic Crowd Behavior Simulation Model

This paper studies the sudden crowd riots and proposes an antagonistic crowd behavior simulation model that combines emotional contagion and deep reinforcement learning. We call the side that provoked the riot as the opposite, and the side that calmed the situation as the righteous. By studying the characteristics and laws of group movement behavior in riot scenes, we can formulate reasonable and efficient decision-making behaviors for the righteous group and improve the winning rate of group operations.

The framework of the antagonistic crowd behavior simulation model in this chapter is shown in Figure 1. Firstly, based on the improved SIS model, we combine with the group combat situation to build an emotional contagion model to calculate the group’s emotions in emergencies. Then, we model group behavior based on DQN and mean-field theory, and use neural network to reasonably analyze and predict group behavior. Finally, according to the emotion of agents, the combat behavior of the final agent is determined according to the behavior rules under different emotions. The method proposed in this paper helps to study the antagonistic behavior of the group under violent and terrorist incidents, so as to formulate more conducive behaviors for the justice group.

3.1 Antagonistic Emotional Contagion Model

When simulating crowd behaviors, we fully consider the influence of emotional factors on group antagonistic behaviors. Especially for group violence and terror incidents, where the incident involves a large area and a high density of people in the area, individual emotions will spread widely within the group, affecting the decision-making behavior of themselves and those around them. However, the current methods based on deep reinforcement learning to model group antagonistic behaviors do not fully consider the emotional factors of the individual and there are some disadvantages such as deviations between the simulation results and the truth, and the unsatisfactory combat behavior. To solve the above problems, we build an emotional contagion model suitable for confrontation scenarios. This model is based on the improved SIS model and combines with the combat situation, analyzes the specific effect of emotions on group antagonistic behavior. It can be more relevant when planning behaviors for combat groups under riots, then they can be more realistic, reasonable and credible.

We divide the emotions of agents into positive emotions and negative emotions. According to the warehouse model in the epidemic model, the population is divided into susceptible persons and infected persons. \( E_i \) represents the emotion of Agent\(_i\), the positive emotion value \( E_i \in (0, 1) \), the negative emotion value \( E_i \in (-1, 0) \). The greater the emotional value of the both groups, the more positive, the smaller the more negative. When it is closed to the median value of 0.5 or -0.5, it means that Agent\(_i\) is in a very peaceful state. For different types of agents, the more positive the emotional state of the righteous side, the more daring to take offensive behavior to subdue the opposite side. On the contrary, it will fear the opponent’s personnel and fight passively. The more negative the mood of the opposite side, the more inclined to challenge the righteous side and will actively attack them.

Emotional contagion between groups is similar to the spreading process of infectious diseases. Individual emotions will not only be affected by other people in the environment, but also self-infected by their own influence. Therefore, we calculate group emotions from the external environment and self-worth evaluation. The influence of the external environment includes the distance of other agents around Agent\(_i\) and the influence of their emotions on Agent\(_i\). The influence of self-worth evaluation indicates the influence of the behavioral value evaluation obtained by Agent\(_i\) on its own emotions. According to cognitive evaluation theory of emotion, emotions are generated from the evaluation of some specific aspects between the individual and the environment, thereby generating an adaptive response mechanism to the current situation. The calculation of emotional contagion is shown in formula (1):

\[
E_i = E_i^{es} + E_i^{en}
\]  

(1)

First, we calculate the amount of changes in the emotion of Agent\(_i\) after being affected by the external environment, that is, when Agent\(_i\) interacts with other agents around it, it is affected by other agents’ emotions. The method of calculating external emotions is inspired by the emotional contagion model in the literature [42]. The definition of the emotional contagion value of Agent\(_i\) is shown in formula (2):

\[
\Delta E_{i,j}^{es}(t) = \frac{1}{1 + E^{-\alpha}} \times E_i(t) \times A_{j,i} \times B_{i,j}
\]  

(2)
where, \( D \) represents the distance between \( Agent_i \) and other \( Agent_j \), \( E_i \) represents the emotion of \( Agent_i \), \( A_{j,i} \) is the intensity of emotion received by the affected person \( Agent_i \) from the influencer \( Agent_j \), and \( B_{j,i} \) refers to the emotional intensity sent from \( Agent_i \) to \( Agent_j \). The external emotional contagion value is the result of the contagion of the righteous and opposite people in the perception range on \( Agent_i \). People who belong to the same team as \( Agent_i \) have a positive effect on their emotions, otherwise they will have a reverse inhibitory effect. Formula (3) and formula (4) are used to calculate the external emotional contagion of the righteous and opposite at time \( t \), respectively:

\[
\Delta E_{p}^{cs} = \sum_{i=1}^{m} \Delta E_{p,p,i}^{cs}(t) + \sum_{j=1}^{m} \Delta E_{p,o,j}^{cs}(t) \tag{3}
\]

\[
\Delta E_{o}^{cs} = \sum_{i=1}^{m} \Delta E_{o,o,i}^{cs}(t) + \sum_{j=1}^{m} \Delta E_{o,p,j}^{cs}(t) \tag{4}
\]

When studying the emotional state of an agent, it is necessary to consider the emotional impact on the results produced by the agent after taking combat actions. In Section 3.4, deep reinforcement learning technology is used to model group behavior. During the battle between the two sides, the agent will obtain a reward value to evaluate whether the behavior is good or bad after taking behavior. The reward value is set based on the behavior taken by the agent in the current state and the impact on the current combat situation after executing the behavior. In this section, when calculating the influence of self-worth evaluation on the emotion of the agent, the calculation will be based on the reward value obtained by the agent after taking combat actions. The calculation method is as follows:

\[
\Delta E_{\text{reward}}^{r}(t) = 0.1 \times \left( \frac{1}{\gamma + \exp \left( \frac{\gamma}{r_i(t)} \right)} \right), r_i(t) \geq \gamma \tag{5}
\]

\[
\Delta E_{\text{reward}}^{r}(t) = -0.1 \times \left( \frac{1}{\gamma + \exp \left( \frac{r_i(t)}{\gamma} \right)} \right), r_i(t) \leq -\gamma \tag{6}
\]

Among them, \( r_i(t) \) represents the reward value, \( \delta \) is an empirical parameter. When \( r_i(t) \in (-\gamma, \gamma) \), the behavior of \( Agent_i \) has less effect on its emotions and can be ignored. When \( r_i(t) \geq \gamma \), it means that \( Agent_i \) performs the action to promote the result of the battle. If \( Agent_i \) is righteous, its emotions will become positive, and if it is opposite, it will become negative. We calculate the emotional contagion of \( Agent_i \) according to formula (5). When \( r_i(t) \leq -\gamma \) it means that the behavior performed by \( Agent_i \) is not conducive to the current combat situation. If \( Agent_i \) is positive, its emotions will become negative, and if it is negative, it will become positive. According to the formula (6), we calculate the amount of emotional contagion of \( Agent_i \):

\[
E(i,t) = E(i,t-1) + \Delta E_{\text{reward}}^{r}(t) + \Delta E_{\text{reward}}^{r}(t) \tag{7}
\]

At time \( t \), the emotional value of \( Agent_i \) at time \( t - 1 \) is summed with the increase in emotional contagion obtained by \( Agent_i \) at time \( t \).

### 3.2 Group behavior modeling by combining emotional contagion and deep reinforcement learning

In the event of sudden crowd riots, the combat behavior of individual is easily affected by the emotions of themselves...
and others, and individuals with different emotional states tend to adopt different antagonistic behaviors. Therefore, we will improve the work of Yang et al. [8], integrate emotional contagion and deep reinforcement learning to build an antagonistic crowd behavior simulation model. This model is to plan more favorable behaviors for combat groups in sudden riot scenarios, thereby improving the authenticity and practicability of the model. This section will introduce how to effectively integrate the two to determine the combat behavior of the Agent and improve the combat victory rate.

Specifically, the proposed model algorithm is as follows:

**Algorithm 1** Antagonistic crowd behavior simulation algorithm integrating emotion contagion and deep reinforcement learning

**Input:** Agent attribute information  
**Output:** Agent combat behavior  
1: Set initial information for each Agent  
2: Get the emotional value and mean behavior of the agent;  
3: while step < 400 do  
4:   if one of the teams was subdued then  
5:     break  
6:   else  
7:     Enter the factors that affect group behavior into the network to calculate the $Q$ value;  
8:     Predict the combat behavior of the agent based on the maximum $Q$ value;  
9:     Update the agent information and calculate the profit value obtained;  
10:    Combine the agent’s current emotions to determine the combat state, and obtain the agent’s final decision-making behavior through specific behavior rules under different emotions;  
11:   Calculate the mean behavior at time $t$ according to the behavior of the agent at time $t$;  
12:   update the sentiment value of the agent at time $t$;  
13: end if  
14: end while

Step 1, we stipulate the attribute value range of the agents, randomly set the initial information of the agent, including ID information, position, emotional value, reward value, behavior and so on. Step 2, calculate the mean behavior according to the initial behavior of the group. Step 3, use the neural network to calculate the $Q$ value according to the input information, predict the combat behavior of the agent at time $t$. In addition to the basic elements of the input parameters, such as the position of the agent, the action, and the reward value obtained after performing the action, etc., two additional factors are added. One is the emotional value of the agent, which is calculated by the emotional contagion model based on the emotional value of the agent at $t-1$ and the surrounding environmental factors. The other is the mean behavior calculated based on the mean field theory. Step 4, update the reward value of the agent, calculate the accumulated reward value obtained by the groups in each group. Step 5, combine the emotion of the agent and the predicted combat behavior to plan the final combat behavior of the group. Step 6, calculate the mean behavior at time $t$ according to the combat behavior of the agent at time $t$, update the emotional value at time $t$, and repeat the above steps until one side wins the battle. The ACSED algorithm proposed in this chapter can be divided into two steps when calculating the combat behavior of the agent, as follows:

1) Preliminary prediction of combat behavior

We build a network model based on DQN and mean field theory to calculate the agent’s antagonistic behavior. There are two reasons for choosing DQN. On the one hand, DQN is suitable for solving such problems with less prior knowledge. Riot events are sudden and have different types, and it is difficult to accumulate experience from past events. On the other hand, DQN belongs to the off-policy model with experience playback pool, which can break the correlation between data and realize a more stable learning process. At the same time, the use of convolutional neural network as a value function can fit the $Q$ table in the $Q$-learning algorithm. This can well solve the problems of too large Q-table, difficulty in network convergence due to too many people in the study.

The network execution process in ACSED: firstly, experience is collected. The two combatants compete through the initial network, iterate several times, and store the data in the experience replay pool. Then, randomly sample data from the experience replay pool to train the network. After multiple iterations, the trained model is finally used to predict the combat behavior of the agent.

The specific network structure is shown in Figure 2. input_1 is used as the input of the first layer of convolution and contains information about the number of people. Then, the output of the two convolutional layers is transformed into a list and input to the first fully connected layer. input_2 is used as the input of the second fully connected layer, which contains information such as ID information, location, behavior, and emotional value. input_prob is the mean behavior, we input it into the fourth fully connected layer. The $Q$ value is obtained through the output layer, and the decision-making behavior of the agent at the next moment is determined according to the $Q$ value.

The above mean behavior is calculated using mean field theory. Due to the large number of people involved in sudden crowd riots, the calculation complexity can be simplified by combining this theory when constructing a
network model \[8\]. When we study the Agent in the scenario, all the influences of the agent from the neighboring agents are processed centrally to obtain the mean probability distribution which is input into the network. The agents behavior can be calculated through the network, which can reduce the dimensionality of complex problems. The behavior corresponding to the specific probability value is the mean behavior. We approximate the actions of all neighboring agents as one action, and the joint action of the Q function can be expressed as an action pair, as shown in formula \[8\]:

$$Q^i(s, a) = \frac{1}{M^i} \sum_{k \in m} Q^i_k(s, a^i, a^k) \quad (8)$$

Among them, \(M^i\) represents the index set of individuals in the neighborhood, referring to the joint action. \(a^i\) is the action taken by \(Agent_i\) in the state \(s\), and \(a^k\) represents the actions of other neighboring agents.

When calculating the crowd behavior at time \(t\), the agent behavior calculated by the neural network at time \(t - 1\) is counted. The action of \(Agent_i\) is a discrete action categorical variable represented by one-hot encoding. Through the behavior coding of the neighborhood agent, the mean behavior of the neighborhood agent is obtained, as shown in formula \[9\]:

$$a^k = a^{-i} + \delta a^{i,k}, \quad \text{where} \quad a^{-i} = \frac{1}{M^i} \sum a^k \quad (9)$$

Among them, \(a^{-i}\) represents the mean behavior. \(\delta a^{i,k}\) is a small fluctuation value. In this calculation method, the Q function of \(Agent_i\) can be as shown in formula \[10\]:

$$Q^i(s, a) = \frac{1}{M} \sum_{k \in m} Q^i_k(s, a^i, a^k) = Q^i(s, a^i, a^{-i}) \quad (10)$$

The mean probability distribution is taken as the key factor affecting the agent’s behavior. The action with the largest distribution value in this distribution is the action with the largest number of people. This factor is used as the input of the neural network to calculate the next action taken by the agent.

The way to update the Q value is as follows:

$$Q^i_t(s, a^i, a^{-i}) \leftarrow (1 - \alpha)Q^i_{t-1}(s, a^i, a^{-i}) + \alpha \left[ r^i + \gamma v^i_{t-1}(s') \right] \quad (11)$$

$$v^i_{t-1}(s') = \sum_a \pi^i_{t-1}(a^i | s', a^{-i}) \quad (12)$$

Among them, \(Q^i_t(s, a^i, a^{-i})\) is equal to the sum of the actual Q value obtained at time \(t - 1\) and the maximum actual value that can be obtained at time \(t\). \(\alpha\) represents the learning rate. \(\gamma \in (0, 1)\) represents the discount factor, which is used to balance the relationship between short-term \(v^i_{t-1}(s')\) is the mean field value function, and \(\pi\) represents a random strategy.

When training the network, we use the loss function to update the network parameters. The specific calculation formula is as follows:

$$y_i = r^i(s, a^i, a^{-i}) + \gamma v^i_{t}(s') \quad (13)$$

$$L(\theta^i) = \frac{1}{k} \sum (y_i - Q_{\phi^i}(s, a^i, a^{-i}))^2 \quad (14)$$

The gradient descent method is used to reduce the error between the estimation of the Q network and the target expected value. Then, the network parameters are updated backward through the parameter minimization loss value, and the original network is continuously improved and optimized. We save the trained model and apply it to the actual situation to predict the agent’s optimal combat behavior.

(2) Get the final combat action

In sudden crowd riots, group emotional factors play an important role in the evolution of events, and crowd behavior is easily affected by emotions. Under different emotional states, individuals in battle will often adopt different combat behaviors.

According to the behavioral tendency of agent and the type of behavior under different emotions, a critical value \(T\) is set, and the agent’s combat state is divided into two categories: radical and conservative. The behavioral tendency of agent in different situations is shown in Table \[1\].

If the agent is in an aggressive combat state, both the righteous and the opposite side will be more proactive in taking offensive behaviors and attacking the opponent. At this time, the righteous agent is active and will actively attack the opposing side, while the opposing agent will be negative and positive, and will attack the opposing side. The opposing agent is negative, and actively attacks the righteous. If the agent is in a conservative combat state, it means that the state is not active at this time, and there will be a defensive psychology, that is, simply adopting a defensive mentality, and more willing to adopt mobile-type behavior.

| Emotion   | Operational status | Agent behavior |
|-----------|--------------------|----------------|
| \(|E_i| > T\) | Aggressive offense  | Both righteous and opposite take actions that tend to take offensive types |
| \(|E_i| < T\) | Conservative defense | Both righteous and opposite take actions that tend to take the mobile type |

According to the emotional state of the Agent, we analyze whether the combat behavior predicted by the network is reasonable, so as to determine the final combat behavior of the agent. If the agent’s direct execution of the prediction behavior is unreasonable, it will have an adverse impact on its own combat situation, and then combine the agent’s combat status to re-plan the combat behavior that is more conducive to winning. The discussion will be divided into the following situations:

First, if the combat behavior predicted by the network for \(Agent_i\) belongs to the type of attack, it is necessary
to determine the rationality of the behavior based on the current combat status of Agent, and the target situation.

If Agent, is currently in a radical combat state:

1. If the target of Agent, is a blank location or wall, because attacking the blank position will get less reward than moving behavior. Therefore, Agent, should choose an agent in a conservative combat state to attack from the surrounding attackable targets. If there are multiple eligible agents, the agent with the closest distance is selected.

2. If the target of Agent, is the opposite member Agent, firstly, compare Agent, and the sentiment value of the target. If $|E_i| > |E_j|$ or $|E_i - E_j| < E_{-th}$ ($E_{-th}$ represents the emotional threshold), Agent, executes the aggressive behavior; if $|E_i| < |E_j|$ and $|E_i - E_j| > E_{-th}$, it needs to be determined to be within the perception range of Agent, If the number of your own party is smaller than the opponent, the behavior corresponding to the largest Q value in the movement type is selected. If the number of one’s own is greater than the opponent, the agent with the smallest absolute value of emotion in the opponent’s group will be attacked.

If Agent, is currently in a conservative combat state:

1. If the target of the Agent, attack is a blank location or a wall, the issue of reward is also considered, and the Agent, is to take the movement behavior corresponding to the largest Q value in the movement type.

2. If the target of Agent, is the opponent’s member, we compare the sentiment value of Agent, and the target of the attack. If $|E_i| > |E_j|$ or $|E_i - E_j| < E_{-th}$, then execute the attack behavior. If $|E_i| < \frac{1}{2} T$, the attack behavior corresponding to the second largest Q value in the attack type will be taken, and the attack target will be changed. If $|E_i| > \frac{1}{2} T$, the movement behavior corresponding to the largest Q value movement behavior type will be adopted.

Second, if the network predicts that the next behavior of Agent, belongs to the mobile type, it is necessary to discuss the rationality of the behavior based on the current combat status of Agent, and the surrounding environment.

1. If Agent, is currently in an aggressive combat state, we compare Agent, with the emotional value of all opponent members within its sensing range. If the combat state of all opponent members within the sensing range is more aggressive than Agent, (at the same agents in the aggressive state, the greater the absolute value of their emotions, the more aggressive they are), then they will execute the mobile behavior. If there are members in the opposing group who are in a conservative combat state, they will attack the agent. When there are multiple eligible agents, the agent with the most conservative combat state is selected to attack.

2. If Agent, is currently in a conservative combat state, perform the predicted behavior.

In addition, we considers the influence of emotions on the harm suffered by the agent. When the agent takes offensive behavior, the emotional state is different, and the attack intensity is also different. The more aggressive the combat state, the stronger the attack, and the damage an agent takes after being attacked increases with the intensity of the attack. However, if the $Hp$ of the agent in the scene decreases by the same amount every time it is attacked, it obviously lacks certain rationality. Therefore, based on the above conclusions, we associates the agent’s emotion with the health value. When modeling group behavior, the attributes of the agent are set based on the actual situation to ensure that the calculation results are in line with reality and increase the practicability of the model. Specifically, according to the sentiment value when the agent takes the attack behavior, the damage to the attacked target is calculated, as shown in formula (15):

$$Hp_j(t) = Hp_j(t-1) - \beta \log \frac{1}{|E_i(t-1)|}$$

Among them, $E_i(t-1)$ represents the emotion of Agent, $\beta$ is an empirical coefficient, which is specifically set according to the experimental results. If Agent, is righteous, the more positive the emotion, the greater the intensity of the attack, and the more harm the attacked person will suffer. If Agent, is the opposite, the more negative the mood, the greater the intensity of the attack, and the more harm the attacked person will suffer. $Hp_j(t-1)$ represents the health value of Agent, at time $t-1$. When $Hp_j \leq 0$, the Agent, is subdued and does not have combat capability.

4 Experiment and analysis

The experiment is implemented on Intel Core, CPU i7-8700K, 3.70 GHz main frequency, 32GB memory, Linux operating system environment, using C++ and python language to realize the antagonistic crowd behavior simulation model. We verify the method proposed in this paper on MAgent, a multi-agent reinforcement learning platform that supports hundreds to millions of agents. The battle game in MAgent is a mixed cooperative competition scene. In a grid world, two groups of agents are fighting against each other, and provide combat behaviors for the agents in the two groups through the same or different algorithms. The goal of both parties is to defeat the other, and the group with the more remaining people wins. In each experiment, the two sides played against each other for 50 rounds, and the final outcome were determined based on the winning rate. The results of one of the rounds were randomly selected for visualization. Through multiple sets of different experiments, we evaluate and analyze the method proposed in this paper, explore the relationship between emotion and winning rate, and prove the effectiveness of the algorithm.

4.1 Comparison of the win rate of both side

4.1.1 Comparison of win rates between the two parties in different emotional states

The experiment in this section mainly analyzes the influence of agent emotion on the battle results of both sides. Both parties use the same proposed algorithm to provide combat behaviors, and the initial number is 256. We set up three sets of experiments to verify the results of the agent fighting under different emotions. The initial emotions of the opposite side are relatively peaceful, and the initial emotions of the righteous side are respectively peaceful, positive, and negative. Under different emotional states, we randomly assign initial emotional values to the agent.

Table 2 shows the battle results of the two sides in different emotional states. The first column in the table is the ratio of the number of people on the righteous side
to the number of people on the opposite side. According to the experimental results, in the first group, under the same other conditions, the winning rate is basically equal when the emotional state of both parties is the same. In the second group, since the emotional state of the righteous side is more active than the opposite side, the winning rate is 0.64, winning 32 rounds. In the third group, the opposing team wins with a winning rate of 0.42 : 0.58. The agents of the righteous have a negative emotional state and are afraid of the opponent and dare not attack. In this three sets of experiments, when the sum of the winning rates of both parties is not 1, it means that there is a tie.

From the second set of experiments, we randomly select a round of the battle process to simulate, as shown in Figure 3. The darker the color of the righteous indicates the more positive emotions, and the darker the color of the opposite indicates the more negative emotions. It can be seen that a small number of agents on the righteous side are negative in light blue, and some agents on the opposite side are negative in dark yellow. Agents with darker colors are in a state of aggressive combat and tend to attack the opponent, most of which are located in areas where the two sides fought fiercely. Agents with lighter colors are in a conservative combat state, fearing that the opponent is unwilling to attack them. Most of them are in a conservative combat state and mostly floating on the edge of the scene.

The experiment in this section proves that when the righteous is fighting the mob, it should have positive emotions and maintain the enthusiasm for combat. In an aggressive combat state, it will be more inclined to take offensive behaviors, have a greater probability of subduing the opponent, and improve the combat victory rate to a certain extent.

| Number of agent | Initial emotional state | Win rate |
|-----------------|-------------------------|----------|
| 256 : 256       | [0,0.4] : [-0.6,-0.4]   | 0.5 : 0.5|
| 256 : 256       | [0.4,0.6] : [-0.6,-0.4] | 0.54 : 0.46|
| 256 : 256       | [0.6,1] : [-0.6,-0.4]   | 0.64 : 0.32|
| 256 : 256       | [0.0,0.4] : [-0.6,-0.4] | 0.42 : 0.58|

### 4.1.2 Comparison of both sides win rate under different algorithms

This section compares the ACSED algorithm with the original MF-Q algorithm [8], and explores the two parties with different emotional states. When the other experimental conditions are the same, the team using which algorithm has a higher battle win rate. We set up three sets of experiments, the righteous side uses the algorithm proposed in this paper, the agent can perceive the emotions of itself and others, so as to can plan its own combat behavior based on the sensed information. The opposite side uses the MF-Q algorithm, when planning group behavior without considering individual emotional factors, the agent does not have emotional attributes and will not be able to perceive relevant information.

| Initial emotional state | ACSED : MF-Q |
|-------------------------|--------------|
| The same emotional state | 0.66 : 0.3   |
| Positive emotional state | 0.78 : 0.2   |
| Negative emotional state | 0.54 : 0.46  |

The results of the three groups of experiments are shown in Table 3. In the first group, the emotional state of both parties is the same. Three comparative experiments were conducted for three different emotional states of peace, positive and negative. The mean value of the three experimental results were calculated. The results showed that the algorithm proposed in this paper is better than the MF-Q algorithm. The winning rate is higher. In the second group, the emotional state of both parties is positive, and the results of the match are shown in the second row of the table. The righteous have a winning rate of 78%, winning 39 rounds, and surpassing the opponents. In the third group, the emotional state of both parties is negative, the righteous are afraid of the opposite, and the opponents tend to challenge and attack the righteous. In this case, the opponent can take advantage of the negative emotions and take advantage of the opponent’s low morale to attack and attack the righteous side. This will have a higher winning rate. However, as shown in the third row of the table, the winning rate of both parties is 0.54 : 0.46, the number of righteous wins is slightly more. This is because the opponent agent cannot perceive its own emotion and others, and cannot use the emotional advantage to plan favorable combat behaviors. When planning combat behaviors, the righteous can be combined with emotional information. When they perceive that the emotional state of opponent is negative and the combat state is aggressive, they will tend to adopt mobile-type behaviors to avoid blind attacks and protect themselves from harm. Therefore, the opposing team has a low win rate.

We randomly select a round of battles from the second and third experiments, as shown in Figures 4 and 5. The blue curve represents the righteous and the red curve represents the opposite. Figure 4(a) is the mean emotional value of both parties at each step. The initial emotional state of the righteous and the opposite are both positive. As the battle
Experiments have proved that only by fully considering the emotions of both sides can we truly grasp the current battle situation, understand the opponent’s combat state and the combat behaviors taken. It proves the rationality and necessity of considering emotional factors when planning the combat behavior of both sides. In the event of a sudden riot, using the algorithm proposed in this paper to provide a strategy for the righteous will have a better chance to subdue the opponent, thereby quelling the war and maintaining social security.

4.1.3 Comparison of the winning rate of the two sides under different proportions

The experiment in this section discusses the impact of different initial numbers on combat results when the positive and negative emotional states are both positive. We set up two sets of experiments: each set contains three comparative experiments, the number of combatants on the opposite side remains unchanged, and the number of combatants on the front side is changed. In the first group, both parties use the methods proposed in this paper to fight; in the second group, the righteous and opposite use the algorithms proposed in this chapter, and the opposing parties use the MF-Q algorithm.

Table 4 is the result of the first set of experiments. When the number of both parties is the same, the righteous wins. When the initial number of the righteous is reduced to 128, the righteous still wins. When the number is reduced to 128, the righteous loses. Experiments show that in battle, the righteous side can win more with less when it has positive emotions, but when the initial number of the two sides is large, the probability of winning will become small.

Table 5 is the result of the second set of experiments. When the initial number of the righteous is 256 and 192, the righteous wins. When the number is reduced to 128, the righteous loses. Experiments show that in battle, the righteous still wins. When the number is reduced to 128, the righteous loses. The algorithm proposed in this paper can still win more with less when playing against the MF-Q algorithm, and the two sides still can’t beat the other when the initial number of people gap is large. Moreover, in these two experiments where the righteous win, the winning rate is generally higher than that of the righteous in Table 4.

Experiments have proved that although the righteous side have a positive emotional state in combat can increase the victory rate, subject to objective conditions, if there is a large disparity between the two sides in the battle, it cannot rely solely on the positive emotional state to win. In the face of real group confrontation incidents, the experimental...
conclusions in this section have some reference value for formulating actual combat plans. When formulating plans, it is necessary to combine group emotions and reasonably arrange the number of participants in combat to have a greater certainty.

4.1.4 Comparison of simulation results with real scenes

The experiment in this section will use the proposed algorithm to simulate a real confrontation scene, compare the simulation results with the real scene, and verify the authenticity and practicability of our algorithm through group movement trends and position distribution. The simulated real scene in Figure 6(a) is selected from YouTube real confrontation events, and Figure 7 is selected from real exercise events.

Figure 6(a) is a real sudden riot. In this scenario, the purpose of the police is to control the riots provoked by criminals, and to subdue the criminals to maintain social order. In the video, the police actively fight against the lawless elements and take the initiative to attack the other side. The lawless elements are constantly moving and retreating in fear of the police; Figure 6(b) is a simulation scene, the green cylinder represents the police, and the purple cylinder represents the lawless elements. Figure 7(a) is a real confrontation exercise scenario, where the two sides are neck and neck, and both attack forward towards the other side. Figure 7(b) is a simulation scene. The green column represents the party wearing white clothes, and the purple column represents the party wearing dark clothes. By comparing the real scene and the simulation scene, we can see that the movement trend of the group in the simulation diagram is basically the same as that in the real scene. This shows that our algorithm is in line with reality and can simulate group confrontation incidents well, and in formulating a calming plan for such incidents can provide a reliable reference basis at the time.

5 Conclusion

This paper proposes an antagonistic crowd behavior simulation model that combines emotional contagion and deep reinforcement learning technology. In the case of sudden crowd riots in reality, this model provides strategies for defending justice and quelling wars, hoping to defeat the opponent as soon as possible and maintain social order. We build an emotional model based on the SIS epidemic model and the evaluation return value of the group combat situation. When modeling group behavior, deep reinforcement learning technology is used to predict the combat behavior of the agent more closely to human thinking, and the emotional behavior of the group is considered. According to the specific influence of the emotions, the individual combat state is determined, and the behavior of the agent is more conducive to combat according to the behavior rules under different emotions. Besides, the relationship between emotion and attack strength is considered, and the actual damage to the individual is calculated.

The method proposed in this paper is proved through a variety of experiments. For one thing, it can simulate the group’s antagonistic behavior more realistically and help to study group behavior under sudden riots. For another, it can provide a reference for the formulation of combat plans, thereby improve the victory rate of group operations.

Although our work can contribute to the control and calming of emergencies, there are still some shortcomings. For one thing, the initial emotion of the combat group is set based on real events. It is reasonable to set up after analysis. For another, individuals who provoke riots are often very irrational and extreme, and are uncontrollable compared to normal groups. In the future, we will deeply analyze the psychology of terrorist groups, improve the emotional model, and consider factors that affect crowd movement from multiple angles, so as to improve the accuracy of the model’s calculation results.

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