Psychological Parameters for Crowd Simulation: From Audiences to Mobs

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Abstract—In the social psychology literature, crowds are classified as audiences and mobs. Audiences are passive crowds, whereas mobs are active crowds with emotional, irrational and seemingly homogeneous behavior. In this study, we aim to create a system that enables the specification of different crowd types ranging from audiences to mobs. In order to achieve this goal we parametrize the common properties of mobs to create collective misbehavior. Because mobs are characterized by emotionality, we describe a framework that associates psychological components with individual agents comprising a crowd and yields emergent behaviors in the crowd as a whole. To explore the effectiveness of our framework we demonstrate two scenarios simulating the behavior of distinct mob types.

Index Terms—Crowd simulation, autonomous agents, simulation of affect, crowd taxonomy, mob behavior, OCEAN personality model, OCC model, PAD model

1 Introduction

Crowd simulation continually interests the computer graphics and visualization community as well as cognitive science and artificial intelligence researchers. When humans form groups, interaction becomes an essential part of the overall group behavior. In some cases, individuality is lost and collective behavior emerges. Crowd psychology has been widely investigated by social psychologists, and researchers have come up with different theories to explain collective behavior. These theories range from formulating this phenomenon through the loss of individuality by contagion to predisposition hypotheses. Crowd simulation research has recently gained a new direction of modeling the psychological structure of individuals to generate believable, heterogeneous crowd behaviors.

In his prominent article, Brown [1] gives a taxonomy of crowds in terms of their dominant behavior. The two basic categories of this taxonomy are audiences and mobs. Audiences are passive crowds, who congregate in order to be affected or directed, not to act. Mobs, on the other hand, are active crowds, and they are classified into four groups: aggressive, escaping, acquisitive or expressive mobs. Aggressive mobs are defined by anger, whereas escaping mobs are defined by fear. Acquisitive mobs are centripetal and they converge upon a desired object. For example, hunger riots and looting of shops and houses are performed by acquisitive mobs. Finally, expressive mobs congregate for expressing a purpose, such as in strikes, rallies, or parades.

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What discriminates mobs from audiences is their emotionality, irrationality and mental homogeneity. So, an expressive mob differs from an audience by its ease of bending social norms and proneness to violence. When mob behavior emerges, feelings preponderate reason. Thus, affective reasoning dominates the decision-making process [2].

Our main goal is to provide animators/designers with a tool to easily simulate the behavior of different crowd types, especially mobs, as described by Brown. We use "behavior" as a generic term that spans all levels of agent actions, from low-level steering responses including local directional choices, velocities, to high-level activities like shopping. At this point, let us note that the focus of our study extends beyond crowds that cannot be categorized as mobs or audiences, that is people without a common interest, such as pedestrians who happen to be in close proximity just by coincidence. Because the defining trait of mobs is their emotionality, we aim to build a system based on a psychological model that effectively represents emotions and emotional interactions between agents. There has been extensive research on incorporating psychological models into the simulation of autonomous agents. Some emphasis has been put on individual agents, usually conversational, interacting with a human user [3]. Crowd simulation systems that include personality have also been introduced ([4], [5]), and we follow the OCEAN (openness, conscientiousness, extroversion, agreeableness, neuroticism) personality mapping approach presented in [4]. Personality is valuable for designing heterogeneous crowd behavior. However, with its static nature, personality alone is not sufficient to represent an impulsive mob agent. Therefore, we introduce an emotion component that modulates agents' decision making processes, superimposed on their personalities. Based on this strategy, agents' personalities, their appraisal of the environment and each other dynamically update their emotions leading to different emergent behaviors. We employ the widely recognized OCC (Ortony, Clore, Collins) model [6] to simulate cognitive appraisal and emotions.

(a) protest (b) sales

Fig. 1. Still frames from two crowd scenarios representing expressive and acquisitive mobs: (a) protest and (b) sales.

In addition to emotionality, an important tendency attributed to collective behavior is mental homogeneity, where mental states of individuals are mirrored by others and these states are disseminated within the crowd. Le Bon explains mental homogeneity as a product of emotional contagion [7], which emphasizes a disease-like spreading of emotions. Serious implications of emotional contagion within crowds include panic, stampedes, lynchings—characteristic mob behaviors that result from widespread fear, anxiety and anger. In light of these, in order to activate irrational behavior due to mental homogeneity, we define an emotion contagion model and integrate it in our psychology component. We employ a threshold model as it successfully represents the loss of responsibility due to increasing anonymity. The cost of an individual to join a riot decreases as the riot size increases [8]. In addition, threshold models are effective at capturing individual differences.

We propose that using a parametric psychology component with emotion contagion facilitates the simulation of mob behavior as it requires minimal user expertise and provides scalability. Instead of defining probability functions over state transitions, we consult the affective state of the agent to determine which action to take in a specific situation; thus, different behaviors can be combined easily. The internal mechanisms of the psychology module are abstracted: the only information that a user needs to provide is the personality distribution of the crowd. With a simple adjustment of personality parameters, a regular calm crowd can transform into an emotional mob. The benefit of using a personality model as input lies in its ability to provide the animator with an intuitive and principled way to produce a range of different behaviors. Because our mapping is deep (a small input set fans out to control many more internal parameters), identifying input with personality parameters maintains interface simplicity over larger, cumbersome, interacting, parametric control sets.

In order to control the mapping from personality distribution to emotional crowd behaviors we use a decision making strategy also based on psychology literature. We utilize the Pleasure-Arousal-Dominance (PAD) model [9] to determine the current emotional state and thus select relevant behaviors. Because the PAD model is associated with consistent mappings to the OCC emotions as well as the OCEAN personality traits, it provides a convenient medium between these two models.

Our system enables the authoring of various scenarios, where the animator can initialize agent groups with different roles and personality traits. Agents then act according to the scenario, exhibiting various behaviors based on their affective states triggered by interactions with each other and the environment. As well as high-level behaviors, such as fighting, they respond with facial and bodily expressions, such as changing their posture. We use the Unity [10] AI path-finding system for crowd simulation.

We demonstrate the performance of our framework on two cases: a protest scenario with protesters and police and a sales scenario similar to a Black Friday event, where agents rush into a computer store selling items with low prices (Fig. 1).

The contributions of this paper can be summarized as follows:

- Description of a parametric psychology framework for simulating different types of crowds. Individual components of this framework, while known, have not *all* been integrated into any crowd simulation system before.
- An easy-to-use integrated system in order to create specific crowd simulation scenarios.
- Introduction of an emotion contagion model, including empathy and expressiveness parameters that are based on OCEAN personality factors.
- Application of the OCC emotion model in multi-agent interactions.
- Application of the PAD model for decision making such as emotion expression and behavior selection.

The rest of the paper is organized as follows. Section 2 presents related work. Section 3 gives a conceptual system representation followed by the description of the psychology component. Section 4 explains the behavior selection process based on the psychological state of the crowd. Section 5 provides an evaluation of the system varying the personality distributions in the aforementioned scenarios. Section 6 presents discussions. Finally, Section 7 gives conclusions and future work.

2 Related Work

Crowd simulation has always attracted the interest of computer graphics researchers. The earliest models of crowd simulation include rule-based flocking systems [11], in which animation is developed as a distributed global motion with a local tendency. Since then, social forces models [12], continuum dynamics techniques [13] and hybrid methods combining Lagrangian and Eulerian models [14] have been introduced. In addition to these methods, cognitive models that use reasoning and planning to accomplish long-term tasks [15] and hierarchical models that organize the agents into virtual crowds, groups and individuals [16] have been developed.

Several studies integrate emotion, personality models and roles into the simulation of autonomous agents, thus representing individual differences through psychological states [17], [18]. Shao and Terzopoulos introduce the autonomous pedestrians model, which incorporates perceptual, behavioral and cognitive control components [19]. The pedestrians are also capable of demonstrating some minor psychological aspects, such as curiosity. Following the study, Yu and Terzopoulos build a behavioral model using decision networks upon the autonomous pedestrians model [20]. The agents are able to assess the behavioral interactions of social groups. Similar to our approach, that system incorporates personality traits as well as an emotional component. However, rather than using formal models of personality and emotions as we do, traits are represented as nodes of decision networks.

Some studies focus on single agents instead of crowds. For instance, research on embodied conversational agents (ECAs) introduces agents within different contexts that can communicate with the user through various means. As well as being able to recognize social cues, these agents can present different expressions. Ball and Breese introduce an early work on the modeling of emotions and personality in conversational agents [21]. Virtual characters recognize the user's emotions and personality and give appropriate responses accordingly. As another example of conversational agents, Gebhard introduces ALMA - a layered model of affect [3], which represents the three distinct types of affect (personality, moods and emotions), each of which is related to different human tasks. We prefer the same model choices for affect simulation as ALMA, although the applications are entirely different. Except for the mood component, the system presented by Egges et al. [22] uses the same personality and emotion models as described in the psychology literature. This system also focuses on conversational agents by incorporating bodily gestures. Similarly, Li et al. propose a framework that uses the OCEAN model of personality [23] and the OCC model of emotions [6] to define and formulate a pedagogical agent in a social learning environment [24]. A later study presents a model that visualizes the affective state of virtual agents by their personality and emotions [25]. The novelty of this approach lies in the visualization of emotional states. Emotions are mapped to facial expressions as a function of their intensities. In contrast to our system, which aims to simulate multiple agents interacting with each other and performing different behaviors, their model focuses on the faces of agents for visual representation. Marsella and Gratch discuss a computational model of emotion using appraisal theory, how they address the arousal and evolution of emotions and their design principles within a cognitive architecture [26].

Systems with multiple agents using formal psychological models have also been introduced. These include crowd simulation frameworks incorporating personality models [27], [4], [5]. A multi-agent system incorporating emotions is SIMPLEX, which stands for simulation of personal emotion experience [28]. SIMPLEX is based on the appraisal theory of emotions and enables the control of multiple virtual agents. However, it does not include an animation component, as opposed to the other studies mentioned here. Carretero et al. [29] evaluate the effect of behaviors of a task-irrelevant crowd in the background (neutral, happy and sad) on the perception of emotion of task-relevant individuals in the foreground, showing the importance of context. Kim et al. [30] model dynamic crowd behaviors coupling personality attributes with situational stress factors, i.e., stressors. Stressors include temporal, spatial, positional and interpersonal sources of stress and they cause aggressive and impulsive agent behaviors. Certain mob behaviors can be implemented with this method. Their examples mostly show escape mobs; however scenarios can easily be extended to depict aggressive mobs. Expressive and acquisitive mobs, on the other hand, require activators different from stress factors.

Massive [31] generates and visualizes realistic crowds consisting of thousands or even millions of agents. The software uses fuzzy logic to create plausible character behaviors. Similar to our system, it animates different scenarios such as rioting, angry crowds or cheering stadium crowds. Also similarly, a scene editor allows one to control the parameters of agent placement and behavior of agents in the scene. The difference lies in the underlying techniques: Massive uses fuzzy logic, whereas we employ psychological models to update behaviors. The video game, Assassin's Creed, is another industrial solution that creates believable crowds [32]. The crowds in Assassin's Creed are composed of individuals with a variety of behaviors. Although the non-player characters in the game give realistic reactions with variable gestures, their behaviors do not have any psychological basis. We intend to base our model on scientific literature as much as possible in order to allow for refinement as our knowledge of human psychology increases. Without a well-defined emotional model, fuzzy logic rules mostly rely on intuition. In addition, decision-making with the PAD model has performance advantage since fuzzification/defuzzification processes are computationally more expensive than the computation of PAD values.

We incorporate a generalized model of contagion into our system in order to simulate the spread of emotions. Lhommet et al. [33] also propose a computational model of emotional contagion based on individual personality and relationships. Like our model, it is also based on a computational mapping from OCEAN personality traits to emotional contagion. The results of this system are yet to be explored.

Another emotion contagion model was introduced by Bosse et al. [34] as the ASCRIBE system. The authors use a multi-agent-based approach to define emotion contagion within groups. The study investigates emotions as a collective entity, rather than focusing on single agents. Unlike our model, which borrows from both social sciences and mathematical epidemiology, ASCRIBE describes a contagion model resembling dynamics properties as in thermodynamic systems.

Tsai et al. present an emotional contagion model that proposes the highest level of emotion to be spread to surrounding agents in their ESCAPES framework [35]. This model is baseline, so the paper does not mention any of the relevant parameters that we include in our model, such as emotion accumulation, decay, tipping point, proximity, visibility, expressiveness or empathy. Simply assigning the highest emotion of the neighboring agents causes discrete emotion levels in the group, neglecting in-between values. This may yield potentially unrealistic outcomes due to lack of heterogeneity. In order to control the spread of emotions, the ESCAPES model incorporates authority figures by removing their contagion feature and making them resistant to emotional contagion. These authority figures thus have a calming effect on the panicking agents. In our system, we can create emotionally resistant agents by assigning them personalities with low empathy so that they are not affected by others' emotions. In both ESCAPES [36] and ASCRIBE [34], an agent with a lower emotion level has the capability of reducing the higher emotion level of another agent. Our contagion method, on the other hand, amplifies emotions rather than absorbing them. Certain studies in psychology literature support this choice [37], [38] as expression of emotion causes emotion contagion among group members, causing some sort of a positive feedback loop. Our system does not entail permanent emotion amplification though. Emotions are subject to decay. In addition, agents can dampen the emotions of one another. This is similar to the case of authority figures with calming down effect, and achievable because the final behavior of agents is based on the combination of emotions via the PAD model. For instance, a solely less fearful agent is not able to soothe a highly fearful agent; however, "a relieved" agent is.

Tsai et al. compare a previous version of our contagion model [39] with the ASCRIBE system using ESCAPES as a testbed [35]. They evaluate these models by reproducing real scenes that display panicking crowd behavior. In this paper, we make certain improvements over our previous framework and clarify some misinterpretations made in [35]. For instance, our model proposes that when the amount of an emotion around a person exceeds a certain threshold, that person becomes capable of being affected directly by the surrounding individuals' emotions of that specific type. Then, contagion plays a contributing factor. Tsai et al. instead evaluate our model based on the assumption that the emotion level of the affected person simply peaks in that case, which clearly impairs the effectiveness of our model. They also ignore the empathy parameter in our contagion model, which is a function of personality and similar to the receiver openness in ASCRIBE. Different from the previous version of our model [39] we introduce expressiveness, which is also a function of personality, and corresponds to the sender expressiveness in ASCRIBE. Our previous framework included visibility and proximity; however they were not incorporated into the formal definition of the contagion model but into the behavior planning algorithms. We explicitly state their effect on emotion contagion in this paper. Visibility is important, since emotional contagion may occur as an outcome of visual observation [40]. Range of visibility is not explicitly defined in the original ASCRIBE model. Bosse et al. later specify channel strength as a function of the distance between two agents and sight reach as a global parameter in their extended system [41].

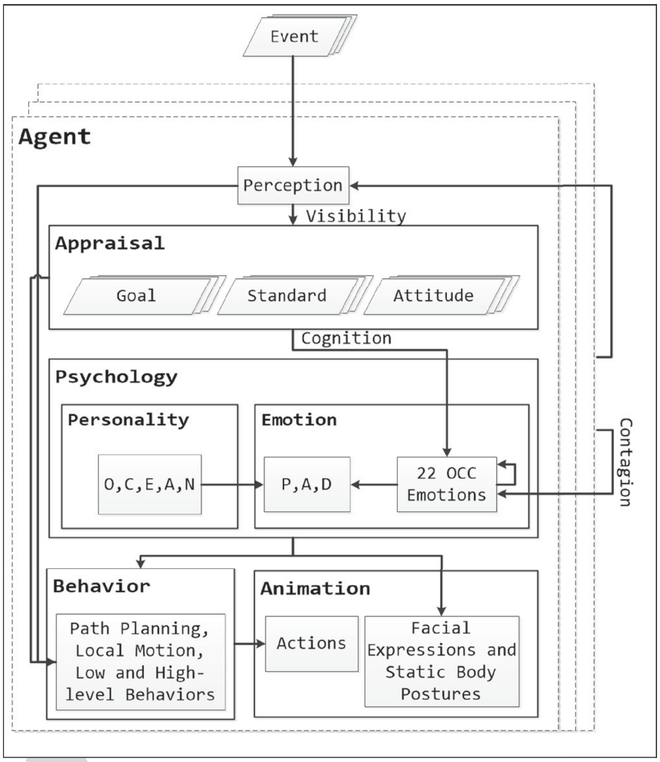


Fig. 2. The components that make up an agent.

3 SYSTEM

3.1 Agent Architecture

The mind of a virtual agent consists of several elements that determine cognitive, perceptual and psychological characteristics. The agent behaves according to the interaction of these features with environmental stimuli. The conceptual elements that comprise an agent are shown in Fig. 2.

Perceived stimuli are passed on to the cognitive component, where agents process incoming data to create appropriate responses. The cognitive unit of an agent's mind is the appraisal component. Appraisal determines how individuals assess events, other individuals, themselves and objects. Their evaluation produces an emotional outcome and aids decision-making. Emotions and intrinsic personality traits explicitly or implicitly determine an agent's behavior. For instance, facial expressions and static body postures depend on emotional state, whereas local motion choices such as collision avoidance or response to forces depend on personality and cognitive decisions.

In the following sections, we describe our computational psychology model and formulate affect from its basic constituents: *personality* and *emotion*. Personality is long-term; it is intrinsic and it usually does not change over time. Emotions are short-term and elicited from events, other agents and objects [6]. They influence memory, decision making and other cognitive capabilities [42], [43].

3.2 Personality

Personality is a pattern of behavioral, temperamental, emotional, and mental traits, which defines an individual. It defines a disposition to emotions. It is one of the three causes of heterogeneity in our crowds, the others being environmental stimuli and agent roles. Initially, the animator creates groups with different personality traits. Distribution of traits within a group is not uniform; Gaussian distribution is applied to create distinctions within each group. Thus, during a simulation, variations in the emotions of virtual humans will emerge depending on the events they face and their roles in these events in addition to their intrinsic traits.

We represent personality using the Five Factor, also known as the "OCEAN" personality model [23], which has gained recognition in computer graphics and virtual worlds research. The five factors—*openness*, *conscientiousness*, *extroversion*, *agreeableness* and *neuroticism*—are orthogonal dimensions of the personality space. Personality is represented as a five-dimensional vector $< \psi^O, \psi^C, \psi^E, \psi^A, \psi^N >$ where each dimension takes a value between -1 and 1. The only parameters that the animator needs to set are the mean and standard deviation of each personality dimension for a selected group of agents.

The orthogonality and continuity of these five factors allow a direct association with agent behaviors. We define local steering behaviors such as walking speed, pushing, or agent radius, as functions of personality, and perform personality-to-behavior mapping following the approach given in [4]. The OCEAN model enables a one-to-one mapping between these low-level parameters and personality traits. Local steering parameters are defined as part of the Unity Game Engine's navigation feature.

The main focus of this work is on the representation of dynamic affect components. Aside from its function in determining the values of steering parameters, personality affects the tendency of the emotional state. We are going to give examples of how personality affects certain emotions throughout the next section.

3.3 Emotion

We define an agent's emotional state as a combination of two components: the agent's cognitive appraisal of the environment and an instinctive, less conscious aspect–emotional contagion (Fig. 3).

Before explaining appraisal and contagion in detail, let us clarify how an emotion is updated in general. At each time step, t, we calculate the contribution of these two elements separately and clamp their sum between 0 and 1,

$$e_t = f(\text{goals, standards, attitudes}) + \lambda_t(\varepsilon), \tag{1}$$

where f is the appraisal contribution function and λ is the contagion contribution function. The experience of another's emotions through emotional contagion is the basis of empathy and it leads to imitation of behavior. Therefore, λ is a function of empathy, ε. Empathy is found to be positively correlated with all five factors of personality. Jolliffe and Farrington measured the correlation values between a basic empathy scale (BES) and personality factors [44]. We use these correlation values as coefficients of personality dimensions to define an empathy value ε between -1 and 1 for an agent j as follows:

$$\varepsilon_j = 0.354\ \psi_j^O + 0.177\ \psi_j^C + 0.135\ \psi_j^E + 0.312\ \psi_j^A + 0.021\ \psi_j^N. \tag{2}$$

An emotion is active if it has a value different from 0. However, emotions do not remain active forever; they decay over time towards a neutral state. At each time step, t, the value of an emotion is decreased as:

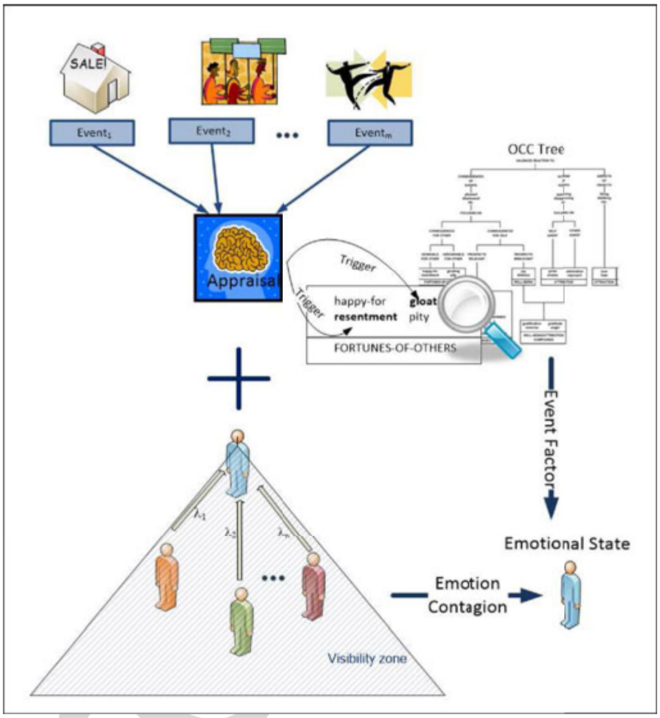


Fig. 3. The emotional state update of an agent.

$$e_t = e_{t-1} - \beta e_{t-1} dt. \tag{3}$$

The variable β determines the speed of emotional decay and it is proportional to neuroticism – the opposite of emotional stability.

3.3.1 Appraisal

As a widely acknowledged model of emotion synthesis, we employ the OCC (Ortony, Clore, Collins) model. The OCC model is based on the appraisal concept [6], which attributes emotion elicitation to the subjective interpretation of a person's environment. The OCC model suggests that emotions are positive or negative reactions to an individual's goals regarding consequences of events, standards regarding actions of other individuals and attitudes towards aspects of objects. Using these three stimuli as the main branches, the OCC model describes a hierarchy that classifies 22 emotions. Fig. 4 shows details of this hierarchy. For instance, fear is elicited when an individual is displeased about the prospect of an undesirable event and distress is elicited when an undesirable event is encountered; pride is the approving of one's own praiseworthy action and admiration is the approving of someone else's praiseworthy action; love is the liking of an appealing object and hate is the disliking of an unappealing object. *Desirability* of goals, *praiseworthiness* of actions and *appealingness* of objects determine the strength of emotions.

The OCC model has been widely used in AI applications because of its structural, rule-based form and the fact that it links emotions to a cognitive basis. It formulates the steps that activate each emotion and offers a sufficient level of detail to capture the emotional differences between virtual characters. The complexity of the OCC model ensures that most situations that an agent may encounter are covered, except internal events such as physiological responses. Because the OCC model enables us to formally define the rules that determine an agent's evaluation of its

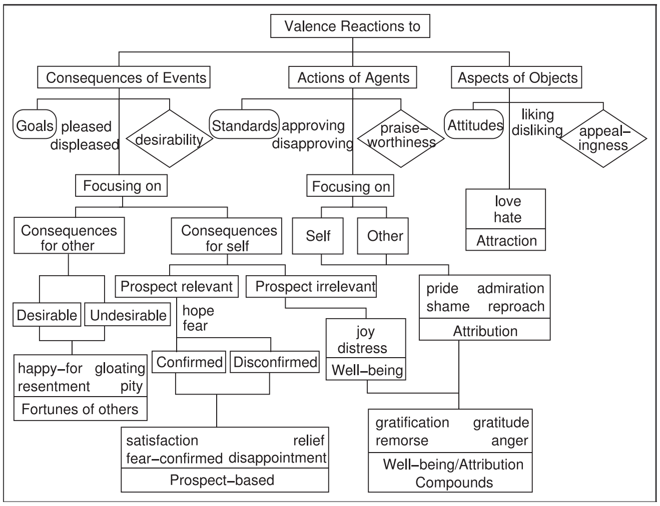


Fig. 4. The OCC model.

surrounding events and relationships with other agents, it provides a suitable basis for crowd simulation applications.

Algorithm 1. UpdateGoalContribution

```
for i ⟵ 0 to 22 do
  appraisalFactor[i] ⟵ 0;
foreach g ∈ Goals do
  if g.ConsequenceForSelf then
    if g.ProspectRelevant then
      if g.Unconfirmed then
        if g.Pleased then
          appraisalFactor[Hope] += g.desirability;
        else
          appraisalFactor[Fear] += g.desirability;
      else if g.Confirmed then
        if g.Pleased then
          appraisalFactor[Satisfaction] += g.desirability;
        else
          appraisalFactor[FearsConfirmed] += g.desirability;
      else if g.Disconfirmed then
        if g.Pleased then
          appraisalFactor[Disappointment] += g.desirability;
        else
          appraisalFactor[Relief] += g.desirability;
    else
      //Prospect irrelevant;
      if g.Pleased then
        appraisalFactor[Joy] += g.desirability;
      else
        appraisalFactor[Distress] += g.desirability;
  else
    //Consequence for others;
    if g.DesirableForOther then
    if g.Pleased then
    appraisalFactor[HappyFor] += g.desirability;
      else
        appraisalFactor[Resentment] += g.desirability;
    else
      //Undesirable for other;
    if g.Pleased then
      appraisalFactor[Gloating] += g.desirability;
    else
      appraisalFactor[Pity] += g.desirability;
```

The comprehensive structure of the OCC model is useful in implementing a wide range of scenarios. However, such precision may prove unnecessary to develop a believable virtual character. In order to overcome the complexity of the OCC model, we use the following five phases that splits the emotion process, as described by Bartneck [45].

- *Classification*, where an event, action or an object is evaluated by the agent and the emotional categories that will be triggered are determined. Descending the branches of the OCC hierarchy determines which emotion is going to be triggered. For example, if an agent has an unpleasant goal that has direct consequences for himself, and the goal is prospect relevant and unconfirmed, the triggered emotion will be fear.
- *Quantification*, where the agent calculates the intensities of the emotional categories. Continuing with the same example, the intensity of fear will depend on the (un)desirability of the goal. Intensity depends on both the emotion eliciting event itself and the agent's personality. When a certain goal is satisfied, it is removed from the agent's list of goals. As an example, Algorithm 1 shows the computation of the contribution of an agent's goals on the emotions' appraisal factor. The contributions of standards and attitudes are computed in the same manner.
- *Interaction*, where the interaction of the current emotional category with existing emotional categories is calculated. For example, when distress and reproach are combined, a third emotion "anger" is elicited. Algorithm 2 shows the interaction of emotional categories:
- *Mapping*, where the 22 emotional categories are mapped to a lower number of different emotional expressions as the OCC model is too complex for the development of believable emotional characters. In order to tackle with this and to incorporate the impact of personality on emotion, we exploit the "Pleasure-Arousal-Dominance Model", which will be explained in Section 4.1.
- *Expression*, where the emotional state is expressed through the facial expression, static body posture [46] and behavior of the agent. As an example posture, happy people tend to have a straight posture with high shoulders and look more confident. In contrast, sad people have collapsed upper bodies with low shoulders, and generally look downwards.

Algorithm 2. UpdateCompoundEmotions

```
if appraisalFactor[Admiration] > 0 ∧ appraisalFactor[Joy] > 0 then
    appraisalFactor[Gratification] ⟵
    (appraisalFactor[Admiration] + appraisalFactor[Joy])/2;
if appraisalFactor[Pride] > 0 ∧ appraisalFactor[Joy] > 0 then
    appraisalFactor[Gratitude] ⟵
    (appraisalFactor[Pride] + appraisalFactor[Joy])/2;
if appraisalFactor[Shame] > 0 ∧ appraisalFactor[Distress] > 0 then
    appraisalFactor[Remorse] ⟵
    (appraisalFactor[Shame] + appraisalFactor[Distress])/2;
if appraisalFactor[Reproach] > 0 ∧ appraisalFactor[Distress] > 0 then
    appraisalFactor[Anger] ⟵
    (appraisalFactor[Reproach] + appraisalFactor[Distress])/2;
```

3.3.2 Emotion Contagion

In its general sense, contagion means the communication of any influence between individuals. It can refer to biological contagion, such as contracting infectious diseases, or social contagion, which spans a wide range of areas from economic trends to rumor spreading and thereby results in collective behavior. Hatfield et al. [40] define emotional contagion as the tendency to automatically mimic and synchronize with another person's facial expressions, gestures, vocalizations, postures and movements and converge emotionally as a consequence.

In order to simulate the propagation of emotions, we adopt a generalized contagion model, following the approach proposed by Dodds and Watts [47]. This is a threshold model, as opposed to an independent interaction model, where successive contacts may result in contagion with independent probability. Speaking in biological terms, threshold models suggest that the probability of contracting infection increases as individuals become exposed to a greater number of infected individuals. Because threshold models imply the presence of memory, which is relevant to the adoption of social behaviors, the model by Dodds and Watts is able to explain not only epidemiological contagion but also social contagion – an essential element of collective behavior. Threshold and memory effects characterize individual differences in a social group. We introduce several augmentations to the model by Dodds and Watts to account for emotion contagion in a crowd.

The model states that in a population, individuals can be in one of the two states: susceptible or infected. These terms are derived from biological contagion; however, they are also meaningful in a social or emotional context. In terms of rumor spreading in a society, a susceptible individual is the equivalent of an "uninformed" person, who has not heard about the rumor yet. Similarly, an infected individual relates to an "informed" person. Throughout the paper, we will use the epidemiological terminology to refer to emotionally susceptible and emotion-contracted individuals. However, different from the epidemiological model, an emotionally infected individual is not necessarily capable of transmitting the contracted emotion. At this point, we introduce another condition: "expressiveness", which refers to the ability to spread an emotion. An agent is "expressive" of an emotion if the emotion's value exceeds a certain threshold, which is negatively correlated with extroversion [48]. The expressiveness threshold value $expT_j$ for an agent j is drawn from a normal distribution with mean $0.5 - 0.5\psi_j^E$ and a standard deviation $(0.5 - 0.5\psi_j^E)/10$.

When the amount of an emotion around a person exceeds a certain threshold, that person becomes infected. Here, infection means the individual is now affected directly by the surrounding individuals' emotions of that specific type. The value of the contracted emotions are then added up to the infected individual's existing emotion value. If the emotion intensity surpasses the expressiveness threshold, then that individual is capable of spreading that emotion to other people.

The formal definition is as follows: when a susceptible individual j sees an expressive individual i, j gets exposed by receiving a random dose d_j from a specified probability distribution multiplied by the emotion intensity of i. j sees i if i is within a certain proximity and the visibility cone of j. We take proximity as 4 meters and viewing angle as 120 degrees. Auditory information can also promote the perception of emotional cues, in which case the proximity is higher and the hearing angle is 360 degrees. However, for the sake of simplicity, we leave the incorporation of auditory perception as a future work.

All individuals keep a memory of their previous k doses as:

$$D_j(t) = \sum_{t'=t-k+1}^{t} \sum_{\substack{\forall i \mid i \in Visibility(j) \wedge \\ i \text{ } is \text{ } expressive}} d_j(t')e_i(t'). \tag{4}$$

The dose values are normally distributed with a mean value of 0.1 and a standard deviation of 0.01 so as to ensure variation. We take k as 10. These parameter values are adjusted empirically to ensure optimal results in our simulations.

If the cumulative dose $D_j(t)$ exceeds a specified susceptibility threshold $susT_j$ at any time of the simulation, then the individual j becomes infected. There is no complete recovery from emotion contagion. Therefore, we have not integrated the "recovered" state as found in several epidemiological models. However, once an individual's cumulative dose falls below the infection threshold, the individual becomes susceptible again with a higher threshold.

The $\lambda(\varepsilon)$ function, which determines how emotions are contracted among humans, is computed as:

$$\lambda_j(t) = \begin{cases} D_j dt, & \text{if } D_j(t) > susT_j(t) \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

The susceptibility threshold value $susT_j$ for an agent j is drawn from a normal distribution with mean $0.5 - 0.5\varepsilon_j$ and a standard deviation $(0.5 - 0.5\varepsilon_j)/10$. The susceptibility threshold is negatively correlated with ε_j, because the more empathetic a person is, the more susceptible s/he becomes to the emotions of other people.

We have expanded our previous contagion framework in [39] by incorporating an expressiveness parameter, increasing susceptibility threshold after "recovering", and revising the basis of parameters on certain personality factors. Expressiveness is the most important improvement over our previous model since it influences the strength of emotion communication and enhances heterogeneity due to its particular dependence on personality. We also explicitly formulate how visibility range and agent proximity affect the model update.

4 Decision-Making Based on the Psychological State

4.1 The Pleasure-Arousal-Dominance Model Mapping

Agents experience a range of different emotions; for that matter they may feel opposite emotions simultaneously. A strategy to determine which of the active emotions affect the current behavior is therefore crucial. Because emotion intensities change very quickly, mapping the emotions directly to behaviors is prone to erratic behaviors. For instance, consider

TABLE 1
Correlation between OCC Emotions and PAD Space

Emotion	P	A	D	Emotion	P	A	D
Admiration	0.5	0.3	−0.2	Hope	0.2	0.2	−0.1
Anger	−0.51	0.59	0.25	Joy	0.4	0.2	0.1
Disappoint.	−0.3	0.1	−0.4	Love	0.3	0.1	0.2
Distress	−0.4	−0.2	−0.5	Pity	−0.4	−0.2	−0.5
Fear	−0.64	0.60	−0.43	Pride	0.4	0.3	0.3
FearsConf.	−0.5	−0.3	−0.7	Relief	0.2	−0.3	0.4
Gloating	0.3	−0.3	−0.1	Remorse	−0.3	0.1	−0.6
Gratification	0.6	0.5	0.4	Reproach	−0.3	−0.1	0.4
Gratitude	0.4	0.2	−0.3	Resentment	−0.2	−0.3	−0.2
HappyFor	0.4	0.2	0.2	Satisfaction	0.3	−0.2	0.4
Hate	−0.6	0.6	0.3	Shame	−0.3	0.1	−0.6

TABLE 2
PAD Space Octants

Octant	P	A	D	Octant	P	A	D
Relaxed	+	−	+	Anxious	−	+	−
Dependent	+	+	−	Disdainful	−	−	+
Exuberant	+	+	+	Bored	−	−	−
Docile	+	−	−	Hostile	−	+	+

the simple decision of determining the facial expression of an agent having similar levels of joy and distress. One option would be to reflect the emotion with the highest value in the expression. However, this strategy could cause oscillating facial expressions. Another solution would be to add up these emotions considering joy positive and distress negative in the same dimension. However, this cannot be generalized to all the OCC emotions. Fortunately, the literature gives us a solution: the Pleasure-Arousal-Dominance model.

The PAD model determines the average emotional state across a representative sample of life situations as described by Mehrabian [9]. OCC emotions are consistently associated with the PAD state [3], [49]. The PAD space enables such a mapping with its three orthogonal scales used to assess emotional predispositions [9]. Pleasure defines the relative predominance of positive versus negative affective states. Arousal is a measure of how easily a person can be aroused by complex, changing or unexpected information. Finally, dominance assesses whether a person feels in control of and able to influence factors in his/her own life versus feelings of being controlled by others.

In addition to finding the dominant emotional state, we need to consider the impact of personality on behavior selection. Another advantage of the PAD model is that it constitutes a suitable link between the OCEAN personality factors and the OCC emotions. A direct mapping between the PAD space and the big five personality traits has been defined as [50]:

$$\begin{aligned} PAD_0(P) &= 0.21\psi^E + 0.59\psi^A - 0.19\psi^N, \\ PAD_0(A) &= 0.15\psi^O + 0.30\psi^A + 0.57\psi^N, \\ PAD_0(D) &= 0.25\psi^O + 0.17\psi^C + 0.60\psi^E - 0.32\psi^A. \end{aligned} \tag{6}$$

PAD_0 denotes a three-dimensional vector at time 0, where the three dimensions refer to P, A and D, respectively. This vector determines the default PAD value of an agent, PAD_0, where no emotions are active.

Table 1 shows the correlation between OCC emotions and PAD space. These parameters have been defined in the ALMA system [3]. We follow a similar approach to compute PAD values. However, unlike Gebhard, who uses the PAD model to denote mood, we utilize these values to determine the psychological tendency that regulates behaviors.

According to the table, $\mathbf{C}_{ij}$ for $i = 1, \ldots, 22$ and $j = 1, 2, 3$ give the emotion constants for the 22 OCC emotions with respect to P $(j = 1)$, A $(j = 2)$ and D $(j = 3)$ values, respectively. In the table "admiration" refers to $i = 1$, "anger" to $i = 2$, "disappointment" to $i = 3$, etc.

Incorporating the emotions, the PAD vector at time t is computed as follows:

$$PAD_t = PAD_0 + \mathbf{C}\, e_t. \tag{7}$$

The octants of the PAD space are individually named (Table 2). These octants, along with their intensities determine agents' behaviors in a specific context.

4.2 Emotion Expression

Ekman notes five universally recognized emotional expressions [51]. A recent study reports that humans express four different facial expressions related to emotion: happiness, sadness, anger and fear [52]. We define a correspondence between the PAD octants and emotional expressions in Table 3.

We store offline static postures for the emotional extremes (e.g., when anger is maximum and all other emotions are 0) as joint rotation angles for all happiness, sadness, anger, fear and neutral postures. At each time step t during the simulation, we perform spherical linear interpolation from the joint rotations of neutral posture to the posture of the predominant emotion using the emotion value at time t as the interpolation parameter. Similarly, we store the facial animations of emotional extremes and perform animation blending between neutral and emotional expressions for the faces of virtual characters (Fig. 5).

4.3 Behavior Update

An agent is controlled by different high-level behaviors running synchronously, each represented as a separate component attached to it. These components are both reusable and flexible, they can be easily added and removed when they are no longer required by the agent. The component-based agent architecture borrows from the component structure in Unity Game Engine, where components are the essentials of the objects and behaviors in a game. With this technique, authoring a new scenario simply consists of introducing

TABLE 3
Expressions related to PAD space

Expression	Octants	PAD Values
Happy	Relaxed, Dependent, Exuberant, Docile	$P+$
Sad	Disdainful, Bored	$P-A-$
Angry	Hostile	$P-A+D+$
Fearful	Anxious	$P-A+D-$

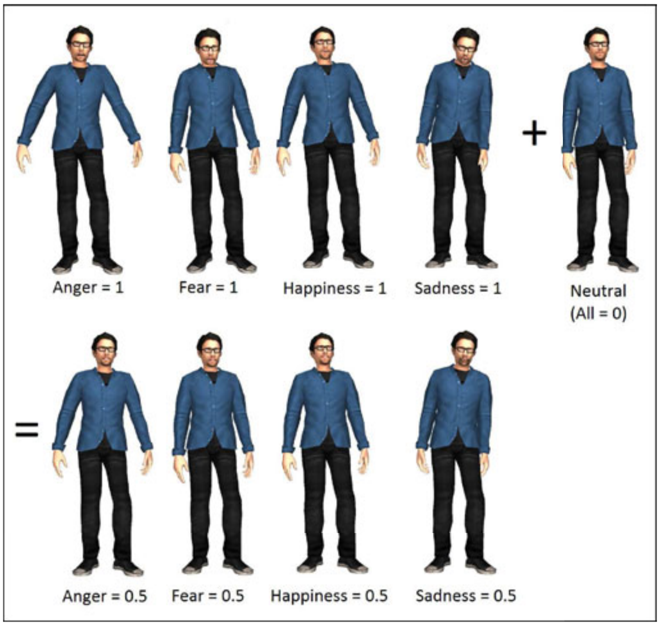


Fig. 5. Postures and expressions of characters showing maximum individual emotion values (top), blended with neutral posture and expression to get halfway emotion values (bottom).

new behavior components or modifying the existing ones without the need to be aware of the underlying mechanisms of the psychological model.

An existing scenario can be modified to observe different behaviors by changing the physical distribution, roles and personalities of agents in the crowd, and presenting external stimuli such as explosions. Physical distribution determines the location of different agent groups. Roles include "protester", "police", "shopper", "audience", etc. Roles are represented as behavior components so that an agent can adopt multiple roles or change its current one. Personality is edited through sliders in the user interface, selecting a group of agents and adjusting the corresponding mean and standard deviation of each personality trait. We deploy behavior trees for depicting the operation of different components. Behavior trees are efficient representation structures for controlling the goals and actions of agents. We follow a similar convention for the design and style of behavior trees given in [53].

Fig. 6 shows the behavior tree template for the initialization process of agents with different roles. Roles and personality determine the initial goals, standards and attitudes of agents. Fig. 7 displays the behavior tree template for state update of agents with different roles in different scenarios. Depending on local/global conditions and/or PAD values, agents perform actions and update their appraisal states.

5 Experimental Results

This section presents crowd scenarios to verify our proposed model and its components. Accompanying video shows these scenarios with different parameters.

5.1 Scenarios

We demonstrate our working system on two scenarios depicting a protest scene and a sales event, which correspond to expressive and acquisitive mobs, respectively. Different simulations are run by altering the personalities of the agents in the crowds. Varying the personalities changes the overall behavior of the crowds, sometimes leading to mob behavior.

5.1.1 *Protest Scenario*

The protest scene consists of 200 protesters and 40 police officers. Protesters' initial appraisal states include general unpleasant goals causing "distress", approving standards about themselves and their group, leading to "pride" and "admiration" consequently. If they are not very conscientious (as opposed to yielding to authority) they have disapproving standards about the police. At the initialization, a *ProtesterBehavior* component is attached to a protester agent and a *PoliceBehavior* component is attached to a police agent. Protesters follow their leader if they have been assigned one, or they march directly to a predetermined destination. Meanwhile, if they are confronted by the police, they may get beaten causing some damage. In case a policeman becomes highly hostile and overwhelmed, he uses tear gas to scare the protesters. Then, an *ExplosionBehavior* component is

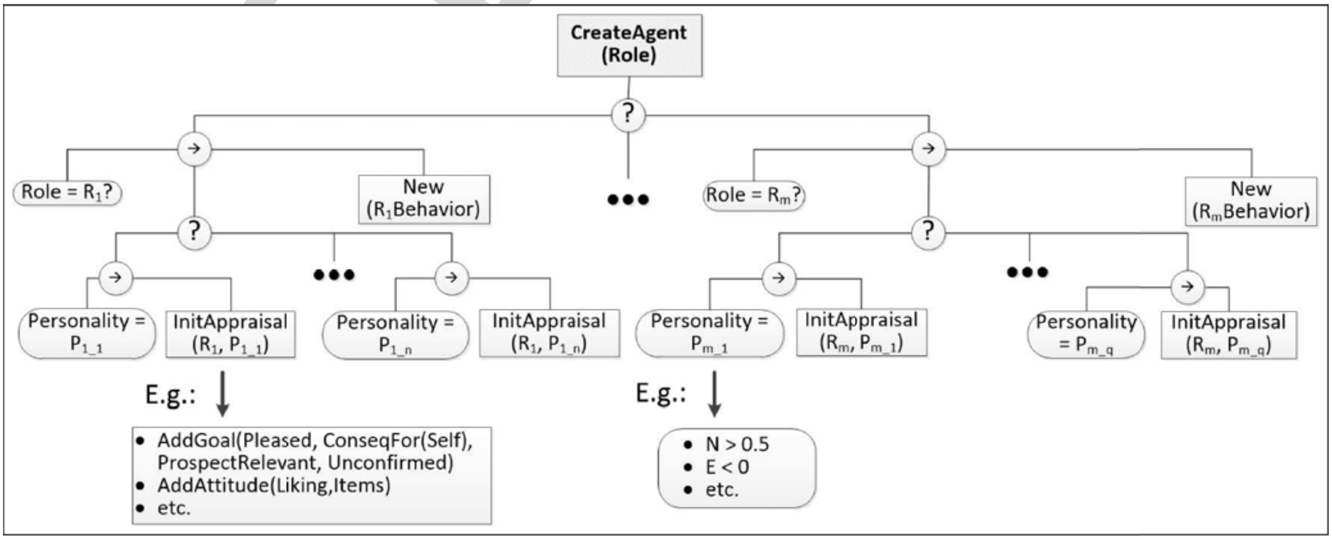


Fig. 6. Behavior tree for initializing an agent in a crowd.

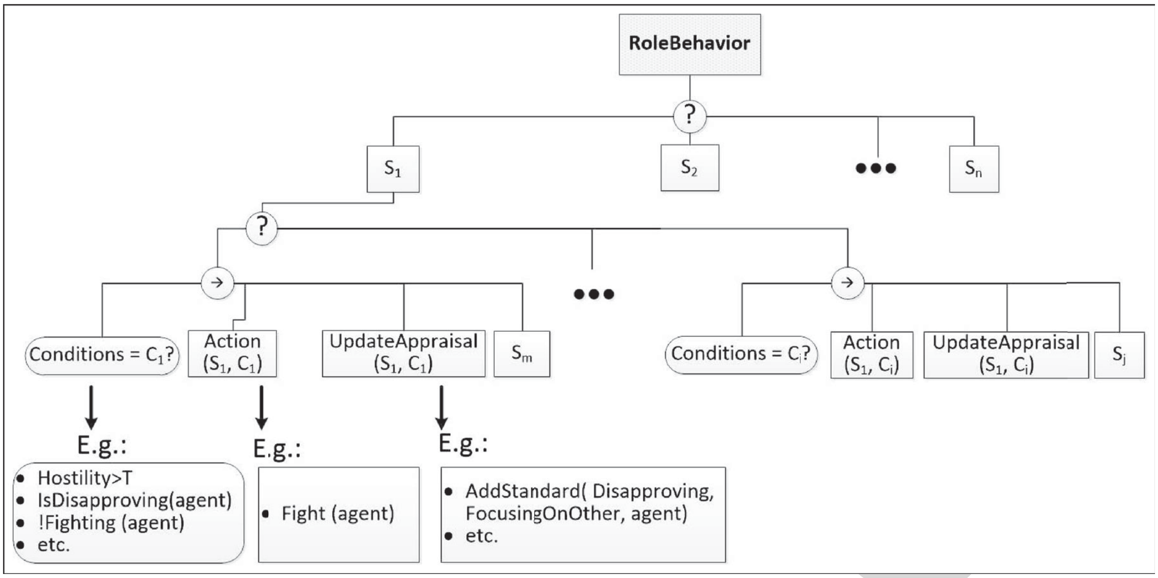


Fig. 7. Behavior tree for roles.

attached to the agents, causing protesters to become afraid and run away. The *ExplosionBehavior* component is removed once the gas diminishes.

If a protester is hostile and disapproving the police, s/he may start a fight with a nearby police officer. In that case, a *FightBehavior* component is attached to the protester and the policeman. The outcome of the fight determines the appraisal status of the agents. For instance, if wounded, unconfirmed, pleasant, prospect-relevant goals about self become disconfirmed, diminishing "hope" and eliciting "disappointment". In addition to the agents involving in the fight, agents witnessing the fight also update their appraisal states depending on whom they approve or disapprove of. When the fight is over, the *FightBehavior* component is destroyed.

5.1.2 Sales Scenario

Acquisitive mobs are simulated in a scenario that includes a sales event with 100 agents where customers rush into a store to get the items they desire. At the store's door, agents have pleasant goals regarding the sales event. Non-neurotic agents experience "hope". In addition, they have positive attitudes towards the discounted items leading to "love". On the other hand, neurotic agents are "distressed" and they experience "fear". Inside the store, agents disperse and rush to the closest item that they want. Sometimes more than one agent wants to get the same item. In that case, they develop disapproving standards towards each other. Depending on their anger level, they might start a fight with each other. Based on their neuroticism and disagreeableness levels, agents tend to experience negative feelings towards others such as "resentment", "reproach" and "gloating".

"Satisfaction" and "confirmation of fears" emerge towards the end of the simulation as they depend on whether agents achieve the desired items or not. Similarly, agents become "relieved" or "disappointed" at the end. After customers are finished in the store, they may either pay for the items they took or leave the store without paying depending on their conscientiousness.

5.2 Evaluation of the Scenarios

For each scenario, we display the results of four simulations for crowds in which: (a) personality is randomly distributed with a Gaussian distribution of mean 0 and standard deviation 0.25, spanning the whole personality range, (b) personality is set to 0 for all OCEAN dimensions (std = 0), (c) personality is set to -1 for agreeableness and conscientiousness with other dimensions set to 0 to simulate a crowd with aggressive tendencies (std = 0), and (d) personality is set to 1 for agreeableness and conscientiousness with other dimensions set to 0 to simulate a crowd with peaceful tendencies (std = 0). Figs. 8 and 9 show the ratios of agents in different PAD octants at each time step.

A quick look at the graphs shows us that emotions of crowds change based on the personality distributions of their members as well as the specific situation the crowds are placed into. For instance, in the protest case, despite

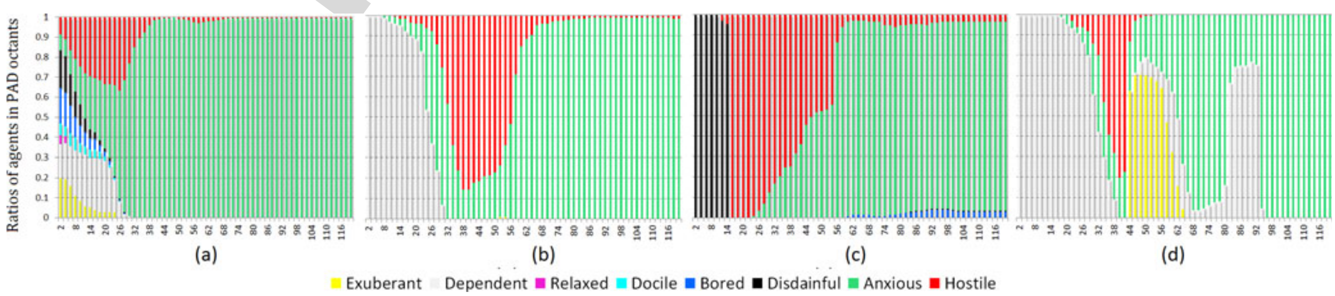


Fig. 8. Ratios of agents in different PAD octants at each timestep in the protest scenario: (a) random personalities, (b) all personalities equal to 0, (c) aggressive crowd with $\psi = \{0, -1, 0, -1, 0\}$, (d) peaceful crowd with $\psi = \{0, 1, 0, 1, 0\}$.

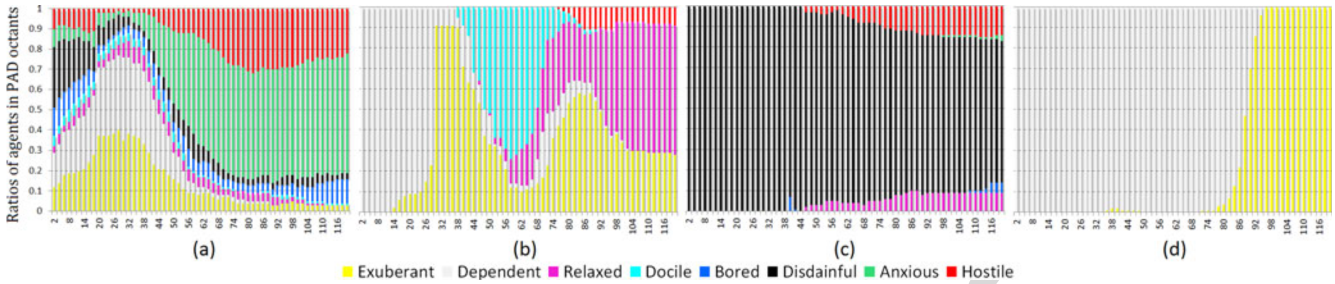


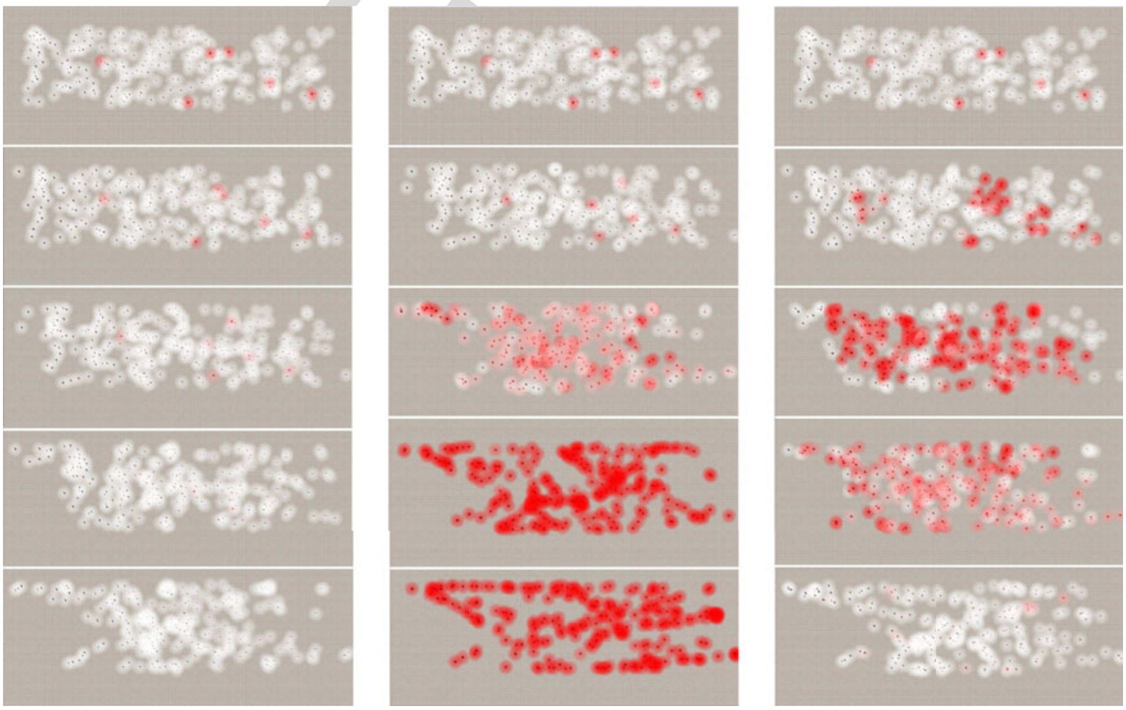
Fig. 9. Ratios of agents in different PAD octants at each timestep in the sales scenario: (a) random personalities, (b) all personalities equal to 0, (c) aggressive crowd with $\psi = \{0, -1, 0, -1, 0\}$, (d) peaceful crowd with $\psi = \{0, 1, 0, 1, 0\}$.

different PAD octants are observed in the beginning, the most dominant emotion turns out to be anxiety in the end. This is due to clashes with the police.

On the other hand, emotions are more varied in the sales scenario, and they are more affected by the personalities of agents. A sales crowd with random personalities displays all the emotions in the PAD space, whereas a crowd with disagreeable and unconscientious agents shows hostile and disdainful tendencies, turning into a mob. In contrast, crowds with neutral and peaceful personalities (agreeable and conscientious) exhibit mostly positive emotions. Personalities have impact on the emotions of the crowds in the protest scenario albeit with less effect. For example, aggressive and peaceful crowds display different emotion sets. However, the dominating emotion is always anxiety in the protest scenarios.

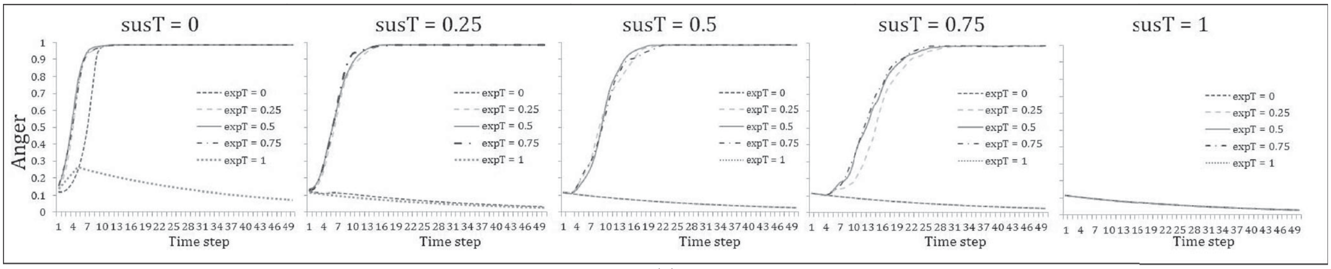
5.3 Evaluation of the Contagion Model

We performed simulations to compare the influence of personality and threshold parameters on the outcome of emotion contagion. Fig. 10 displays snapshots from these simulations, where the spread and decay of emotions are depicted in time. Individuals are shown as spheres, and time increases from top to the bottom. Emotions are color-coded, where zero emotion is white, maximum emotion is red and in-between values are interpolated between white and red. All the simulations start with 20 percent of the individuals initialized with "anger". Depending on the personality distribution of the crowd, expressiveness and empathy of agents are varied. This causes the difference in the emotion intensities captured at different times of the simulation. The images on the left show agents with all personality factors set to -1. Minimal empathy and expressiveness prevent the emotion from spreading before it disappears as a result of emotional decay. The middle images demonstrate the opposite case, where empathy and expressiveness take maximal values. In this case, anger spreads to the whole crowd before getting any chance to decay below the expression threshold. The images on the right show agents having personalities distributed

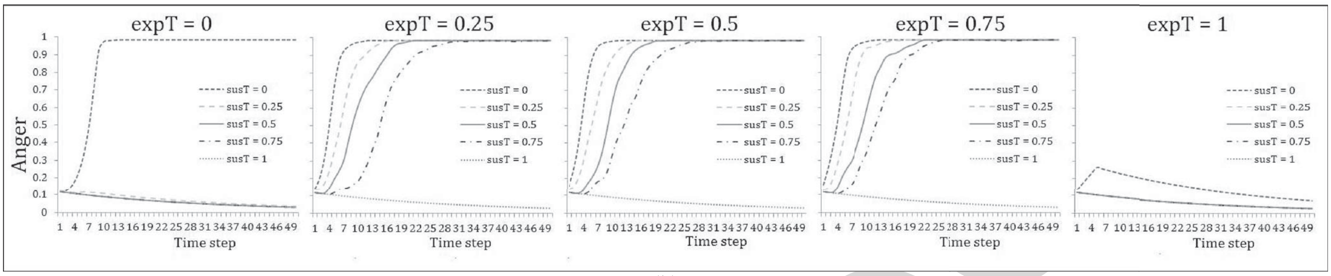


(a) (b) (c)

Fig. 10. Snapshots of emotion distribution taken at $t = \{40, 360, 1{,}060, 1{,}860, 3{,}840\}$ milliseconds of the simulations (from top to bottom), where (a) $\psi = \{-1, -1, -1, -1, -1\}$, expressiveness and empathy are 0; (b) $\psi = \{1, 1, 1, 1, 1\}$, expressiveness and empathy are 1; (c) personality is normally distributed with a mean value of 0 and standard deviation 1, expressiveness and empathy are 0.5. Intensity of emotion increases from white to red.



(a)



(b)

Fig. 11. Average anger at each timestep, where (a) expressiveness thresholds are varied whereas susceptibility thresholds are kept constant and (b) susceptibility thresholds are varied whereas expressiveness thresholds are kept constant.

with standard normal distribution. Anger spreads to part of the crowd and disappears after a certain time.

Fig. 11 shows the graphics of average emotion when expressiveness and susceptibility thresholds are varied. The simulations are run in a crowd of 200 individuals where 20 percent are assigned $anger = 0.9$ and 80 percent are assigned $anger = 0.1$. Agents randomly walk around and they perceive the emotions of other agents within 4 meters and 120 degrees around the viewing direction.

A susceptibility threshold of 0 implies that all agents can get infected at any time, whereas a susceptibility threshold of 1 rules out contagion. Fig. 11a indicates that expressiveness threshold does not have much effect on the slope of the average anger curve except when it is 0 or 1. Similar to susceptibility, an expressiveness threshold of 1 also prevents contagion because no individual is able to spread emotions. However, an expressiveness threshold of 0 where everyone is always expressive yields a different outcome of average emotion decrease over time. This is a result of calming down due to observing low anger. In Fig. 11b, we can see that as susceptibility threshold decreases, population's average anger increase has a steeper slope.

Fig. 12 shows how average emotion value of the crowd changes when dose mean (μ) and dose memory (k) values are varied. The initial setting is the same as before: a population where 20 percent of the individuals are assigned $anger = 0.9$ and 80 percent are assigned $anger = 0.1$. Agents randomly walk around and they perceive the emotions of other agents within 4 meters and 120 degrees around the viewing direction. Their personalities are all set to 0 in order to have both susceptibility and expressiveness thresholds equal to 0.5. A k value of 1 means that only the current dose is recorded as opposed to 10 and 100 previous doses for $k = 10$ and $k = 100$, respectively. The results indicate that anger is not diffused through the population with a small value of μ (0.01) unless k is big enough. On the other hand, a k value of 1 is not enough to trigger emotion contagion even if $\mu = 1$.

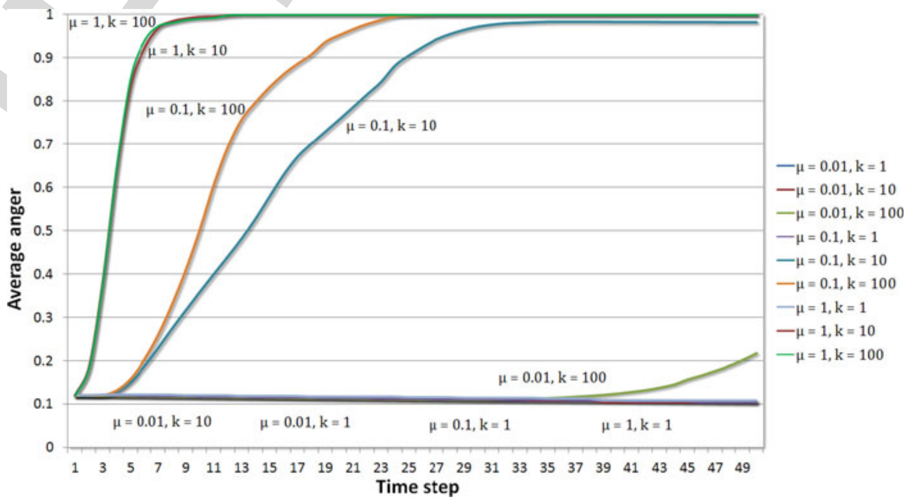
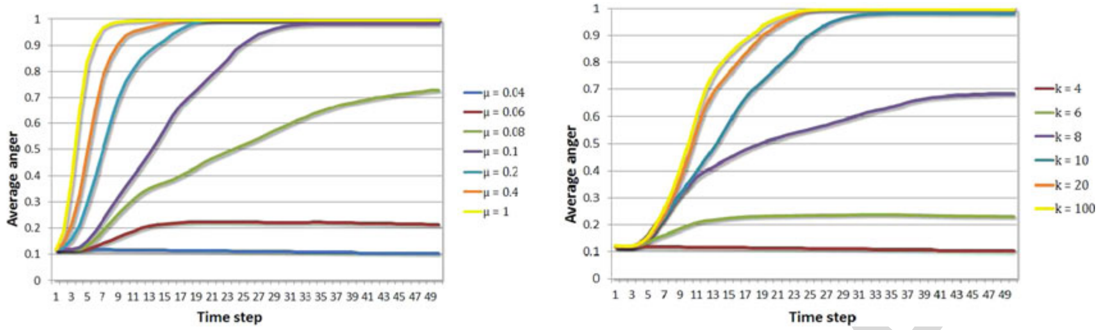


Fig. 12. Average anger with respect to various dose mean (μ) and dose memory (k) values.



(a) (b)

Fig. 13. Average anger at each time step, where (a) $k = 10$ and dose mean μ is varied, (b) $\mu = 0.1$ and k is varied.

We see that the difference between $\mu = 0.1$ and $\mu = 1$ is not as big as the difference between $\mu = 0.01$ and $\mu = 0.1$. Also, the difference between $k = 10$ and $k = 100$ is smaller than the difference between $k = 1$ and $k = 10$. Thus, we take $\mu = 0.1$ and $k = 10$ as baseline values. The model is sensitive to changes only at the extremes. It is robust as long as the values are kept within a certain threshold (Fig. 13). We get similar results with different population sizes.

6 Discussion

The main advantage of using emotions for decision making is the scalability that they provide for selecting new behaviors. The simulations show us that varying the personalities of the comprising agents leads to very different emotion distributions in time. Decision making based on emotions thus induces numerous emergent behaviors. A user only needs to tweak the personality parameters to achieve diversity. Animators could control every low level aspect of a crowd animation directly, but our approach gets the animation quite far along as is, on minimal and sensible inputs. Thus, reducing the procedural input space to fewer, more intuitive parameters provides a system that is easier to control.

Appraisal component enables agents to keep history of events that occurred in their environment, remember their foes, friends, attractive and repulsive objects around them. Consider a shopping scenario where we focus on the behavior of agent A after agent B gets an item that A was expecting to buy. This event is supposed to increase the reproach level of A, negatively correlated with A's agreeableness because A will develop a disapproving standard towards B's action. Depending on the value of aggressive emotions leading to angry behavior, A may fight with B or yell at B. However, if A is very happy at the moment, a calm behavior will emerge. In other words, history of events leading to this moment will determine A's next action; and the history of events is stored in memory in the form of goals, standards, attitudes enabling the computation of cumulative emotion values. Such behavior nuances are difficult to achieve by scripting or using probabilistic schemes.

Emotions are demonstrated in terms of facial expressions, postures and behavior selections such as yelling, fighting, applauding, making disappointed gestures and running away. The number and complexity of such behaviors can easily be extended in order to increase the realism of the scenario. However, please note that the main point in our study is not the diversity of behaviors but the variation of emotions to enable such diverse behaviors.

7 Conclusion

We propose a crowd simulation system that incorporates a complex, yet easy-to-use psychological component into the agents in order to simulate various crowd types. In our system, an animator can create crowds consisting of different groups with different personalities, roles and positions, add objects into the scene and author scenarios based on agent roles and objects in the setting. Designing new behaviors is easy, dependent on the appraisal update, agent roles, and low-level steering behaviors.

As a future work, we plan to show slight differences of emotions in facial expressions of agents. Currently, the PAD octant with the highest intensity determines the facial expression of the virtual character. However, in an ideal setting, the intensity and combination of emotions would be reflected in expressions and postures. In addition, we intend to increase the number of distinct behaviors and animations to distinguish the emotions of agents.

Another future plan is to incorporate the intensity of emotions into the contagion model. An augmentation idea is to use a probability distribution based on the intensity of emotions instead of a normal distribution. In addition, we would like to incorporate auditory information as well as visibility into the contagion model.

Acknowledgments

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