Psychological Parameters for Crowd Simulation: From Audiences to Mobs

Funda Durupınar, Uğur Güdükbay, Aytek Aman, Norman I. Badler

(a) protest (b) sales

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

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 parameterize 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. We demonstrate and evaluate two scenarios that realize the behavior of distinct mob types.

Index Terms—Crowd simulation, autonomous agents, simulation of affect, crowd taxonomy, mob behavior.

1 Introduction

Crowd simulation continually interests the computer graphics and visualization community as well as cognitive science and artificial intelligence researchers. According to the Gestalt principle, which states that the whole is bigger than the sum of its parts, masses of human beings must be more complicated to study than a single human. 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, R. W. Brown uses the term “collectivity” for two or more people who can be described as a category [7]. He defines crowds as collectivities that congregate on a temporary basis. Since the reasons that bring crowd members together are varied, Brown classifies them in terms of the crowd’s dominant behavior. He gives a detailed taxonomy of crowds, but basically classifies them into two categories: 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. 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.

Our main goal is to simulate the behavior of different crowd types, especially mobs, as described by Brown. At this point, let us note that the focus of our study extends beyond crowds that belong to neither of these categories, that is people without a common interest, such as pedestrians who happen to be in close proximity just by chance. 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. Most of the emphasis in this field is put on individual agents, usually conversational, interacting with a human user [15]. Crowd simulation systems that include personality have also been introduced [11, 17]. However, personality alone is not sufficient to represent the emotionality that characterizes a mob. Therefore, a full-fledged psychological model is crucial for the sake of creating realistic crowd behaviors.

In this study, we incorporate a psychological component into the virtual agents of a crowd in order to simulate the emotional nature of mobs. For this purpose, we provide the agents with the three basic constituents of affect: personality, emotion and mood. Each of these

- *F. Durupınar, U. Güdükbay and A. Aman are with the Department of Computer Engineering, Bilkent University, Bilkent 06800, Ankara, Turkey; e-mails: fundad@cs.bilkent.edu.tr, gudukbay@cs.bilkent.edu.tr, aytek.aman@cs.bilkent.edu.tr.*
- *N.I. Badler is with the Department of Computer and Information Science, University of Pennsylvania, 3330 Walnut Street, Philadelphia, PA 19104-6389, USA; e-mail: badler@seas.upenn.edu.*

elements contributes varyingly to the emergence of different aspects of behavior. In addition, agents have an appraisal module, which enables them to assess their surroundings and trigger appropriate emotions. We also represent another central feature of collective behavior, mental homogeneity, with an emotional contagion model.

Our system provides the animator with the functionality to author various scenarios, initializing each agent with different roles and personality traits. The 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 navigation mechanism of the Unity Game Engine as the underlying crowd simulator.

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 (cf. Figure 1). We then present the results of a user study that we conducted to evaluate whether the conveyed emotions were accurately perceived.

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 implementation details of the two scenarios mentioned. Section 5 describes the user study and the evaluation results. Finally, Section 6 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 [35], in which animation is developed as a distributed global motion with a local tendency. Since then, social forces models [19], continuum dynamics techniques [38] and hybrid methods combining Lagrangian and Eulerian models [31] have been introduced. In addition to these methods, cognitive models that use reasoning and planning to accomplish long-term tasks [14] and hierarchical models that organize the agents into virtual crowds, groups and individuals [30] have been developed.

Several studies integrate emotion, personality models and roles into the simulation of autonomous agents, thus representing individual differences through psychological states [1], [33], [34]. Shao and Terzopoulos introduce the autonomous pedestrians model, which incorporates perceptual, behavioral and cognitive control components [36]. 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 [40]. The agents in that system 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 [3]. 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 [15], 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. in [12] 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 [39] and the OCC model of emotions [32] to define and formulate a pedagogical agent in a social learning environment [23]. A later study presents a model that visualizes the affective state of virtual agents by their personality and emotions [2]. 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. We simply perform a one-to-one mapping between the most intense emotion and the facial expression of an agent.

Systems with multiple agents using formal psychological models have also been introduced. These include crowd simulation frameworks incorporating personality models [10], [11], [17]. A multi-agent system incorporating emotions is SIMPLEX, which stands for simulation of personal emotion experience [22]. 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.

The Massive system, which is a commercial software, generates and visualizes realistic crowds consisting of thousands or even millions of agents [24]. 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 [4]. 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 incorporate a social contagion model into our system in order to simulate the spread of emotions. A computational model of emotion contagion has also been implemented by Bosse et al. [5]. 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 epidemiological model, Bosse et al. describe a contagion model based on social psychology. In that sense, this model could have been another option for us.

3 System

3.1 System Overview

The mind of a virtual agent consists of several components 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 Figure 2.

The cognitive unit of an agent's mind is the appraisal component. Appraisal determines how agents assess events, other agents, themselves and objects. Their assessment is processed according to decision-making strategies and produces an emotional outcome. Emotions and intrinsic personality traits affect mood. All these psychological components explicitly or implicitly determine the 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 appraisal.

Clark McPhail explains a working definition of collective behavior in his book *The Myth of the Madding Crowd* [25]. Having observed many different collective gatherings, he formulates various elementary forms of collective behavior that groups have in common. These behaviors include collective orientation, such as clustering, arcing, ringing or vigiling; collective vertical locomotion such as sitting, jumping or standing; collective horizontal locomotion such as queuing, marching or running and collective manipulation such as applauding, waving or throwing objects. McPhail thus defines collective behavior as including two or more persons, engaged in one or more behaviors on

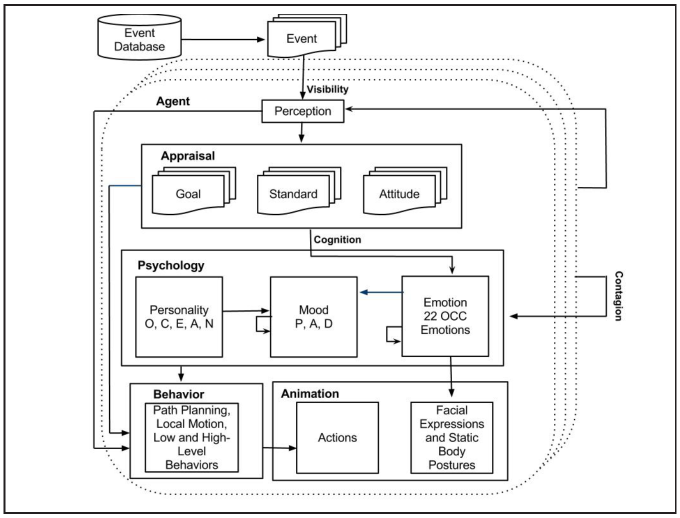


Fig. 2. The components that make up an agent

one or more dimensions. Following his descriptions, we designed 10 simple actions for the agents: *standing idly*, *walking*, *running*, *picking up an object*, *jumping*, *waving*, *applauding*, *fighting*, *sitting*, and *throwing*.

3.2 Psychological Model

In order to simulate human behavior we must first examine its psychological foundations. In this section, we explain our computational psychology model and formulate affect from its three basic aspects. A person's psychological state is composed of three basic constituents of affect: personality, mood, and emotion.

Personality, mood and emotion differ according to their temporal characteristics. Personality is a long-term affect; it is intrinsic and it usually does not change over time. Emotions are short-term and elicited from events, other agents and objects [32]. They influence memory, decision making and other cognitive capabilities [6], [20]. Mood is a medium-term affect. Moods last longer than emotions; however they are not as stable as personality. Research shows that moods also have a major impact on cognitive functioning [29].

3.2.1 Personality

Personality is a pattern of behavioral, temperamental, emotional, and mental traits, which defines an individual. Personality is one of the two causes of heterogeneity in a crowd, the other one being environmental stimuli. Initially, the animator creates groups with different personality traits. The 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 and moods of individuals will emerge depending on the events they face in addition to their intrinsic traits .

There is still considerable controversy in personality research over how many personality traits there are, but the Five Factor, or OCEAN model [39] is popular and it is the one we have chosen for our work. The five factors, orthogonal dimensions of the personality space, are openness, conscientiousness, extroversion, agreeableness and neuroticism. We define low-level behaviors such as walking speed or pushing, as functions of personality, and perform personality-to-behavior mapping following the approach given in [11]. The OCEAN model enables a one-to-one mapping between these low-level parameters and personality traits. Low-level steering parameters such as walking speed or agent radius are defined as part of the Unity Game Engine's navigation feature.

3.2.2 Emotion

We use the OCC model of emotions, which is based on the appraisal theory of emotions [32]. The model derives its name from the initial letters of the developers' names: Ortony, Clore and Collins. Despite some recent criticisms regarding the ambiguity of the model [37], it has been widely used in AI applications because of its structural, rule-based form. It also offers a sufficient level of detail to capture the emotional differences between virtual characters.

The OCC model suggests that all emotions have a cognitive basis and it formulates the steps that activate each emotion. It ignores internal events such as physiological responses. For instance, it does not include "surprise" since that emotion is not triggered through cognitive processes. The model consists of 18 basic emotions and four compound emotions; in total, a 22-dimensional space. It suggests that individuals have goals regarding consequences of events, standards regarding actions of other individuals and attitudes towards aspects of objects. There are also three more variables, which determine the strength of emotions, i.e., *desirability* of goals, *praiseworthiness* of actions and *appealingness* of objects.

Emotions take values between 0 and 1. An emotion is active if it has a value different from 0. As the OCC model suggests, activation of an emotion depends on the context. In our simulations, environmental stimuli activate different emotions. For instance, descending the branches of the OCC tree, if an agent has an unpleasant goal with consequences for self that is prospect relevant and unconfirmed, the triggered emotion will be fear. The intensity of the fear will depend on the (un)desirability of the goal. For example, a fear-inducing goal could be running away from an enemy. As we will explain in Section 4, emotions are activated as a part of an event factor, i.e., by observing the events (or the agents) around them.

An emotion is not forever active; it decays over time. At each time step, t, the value of an emotion is decreased as:

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

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

When an emotion is activated, it affects certain behaviors. Humans' emotions and attitudes can be inferred from nonverbal behaviors [16] such as postures, gestures and facial expressions. Inspired by Ekman's association of facial expressions with emotions [13] we devise the following correspondence between OCC emotions and facial expressions:

Happiness:	HappyFor, Gloating, Gratification, Joy, Pride, Admiration, Love, Satisfaction, Relief
Sadness:	Disappointment, Distress, Pity, Remorse, Resentment, Shame
Anger:	Anger, Hate
Fear:	Fear, FearsConfirmed
Disgust:	Reproach

Static body postures also depend on emotional state [8]. We apply the same mapping for the body postures. For instance, 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. We created the meshes for these postures and facial expressions offline.

3.2.3 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. 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 [18].

In order to simulate the spread of emotions, we adopt a social contagion model. For this purpose, we follow the approach proposed by Dodds and Watts [9]. The model is a threshold model, as opposed to an independent interaction model, where successive contacts may result in contagion with independent probability. Threshold models suggest that the probability of contracting infection increases as individuals become exposed to a greater number of infected individuals. The model by Dodds and Watts not only explains epidemiological contagion but also social contagion– an essential element of collective behavior. That the model also provides a formal mathematical definition, something the verbal descriptions in the psychology literature do not is another reason for us to utilize it in our system.

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 context. In terms of emotional responses, a susceptible individual can be "uninformed" about rumors, or a "non-adopter". Similarly, an infected individual relates to an "informed" individual, or an "adopter", one who adopts the emotional states of other individuals. When susceptible individuals come into contact with infected ones (determined by a certain physical proximity) they may become infected with some probability. The formal definition is as follows:

When an infected individual i makes contact with a susceptible individual j, j becomes exposed and may get infected with some probability. Making contact is determined by physical proximity. If i is within some threshold distance of j and j is in the visibility cone of i, i gets exposed. Here, visibility is important, since emotional contagion may occur as an outcome of visual observation, as suggested by Hatfield et al. [18]. The threshold distance is taken as 3 meters. Exposure means receiving a random dose d_j from a specified probability distribution. All individuals keep a memory of their previous k doses as:

$$D_j(t) = \sum_{t'=t-k+1}^{t} d_j(t') \tag{2}$$

If the cumulative dose $D_j(t)$ extends beyond a specified threshold T_j at any time of the simulation, then the individual j becomes infected. Both the dose and threshold distributions are log-normal distributions, $Log-\mathscr{N}$, with means $\mu_{d\,j}$ and$\mu_{T\,j}$, and standard deviations $\sigma_{d\,j}$ and $\sigma_{T\,j}$, respectively:

$$\begin{aligned} d_j &= \log - \mathscr{N}(\mu_{d\,j}, {\sigma_{d\,j}}^2) && (3) \\ T_j &= \log - \mathscr{N}(\mu_{T\,j}, {\sigma_{T\,j}}^2) && (4) \end{aligned}$$

The experience of another's emotions through emotional contagion is the basis of empathy and it leads to imitation of behavior. Empathy, ε, is another factor that, in addition to goals, standards and attitudes, affects the emotional state:

$$e_t = f(\text{goals, standards, attitudes}) + \lambda(\varepsilon), \tag{5}$$

where 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 [21]. According to the correlation values, empathy ε takes a value between 0 and 1 and it is computed for a male agent j as follows:

$$\varepsilon_j = 0.34\ \psi_j^O + 0.17\ \psi_j^C + 0.13\ \psi_j^E + 0.3\ \psi_j^A + 0.02\ \psi_j^N \tag{6}$$

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

$$\begin{aligned} T_j(t) &= \log - \mathscr{N}(\frac{1}{\varepsilon_j}, {\sigma_{T\,j}}^2) && (7) \\ \lambda_j(t) &= \begin{cases} 1 & \text{if } D_j(t) > T_j(t) \\ 0 & \text{otherwise} \end{cases} && (8) \end{aligned}$$

The dose threshold is a function of $\frac{1}{\varepsilon_j}$, because the more empathetic a person is the more susceptible s/he becomes to the emotions of other people. In order to provide heterogeneity within the crowd, each individual should be susceptible at different levels. These correlation values show us a way to determine the dose and threshold distribution values.

In our simulations, we take the time step as 200 milliseconds and the standard deviations for both the dose and threshold values as 0.5. Dose threshold mean is a function of empathy, whereas dose mean is taken as 1.

3.2.4 Mood

Mood acts as an intermediary between emotions and personality. The Pleasure-Arousal-Dominance (PAD) temperament model provides a computational link between these two structures. It refers to the three orthogonal scales used to assess emotional predispositions. We utilize the PAD model in our system [27]. Mehrabian defines temperament or mood as the average emotional state across a representative sample of life situations. The three traits of mood are found to be nearly orthogonal to each other. Three orthogonal axes ranging from -1 to 1 describe each mood state. 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.

The PAD model 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 by Mehrabian [26]. In addition, OCC emotions are consistently associated with the update of the PAD mood state [15].

Mood is represented as a three-dimensional vector m_t, where the three dimensions refer to P, A and D, respectively. Mood is updated according to emotional state. We follow the ALMA [15] approach for human-like mood changes. Table 1 shows the mapping between OCC emotions and mood traits. According to the table, $\mathbf{C}_{ij}$ for $i = 1,\ldots,22$ and $j = 1,\ldots,3$ 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.

Table 1. Mapping 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

We first compute the P, A, D values that correspond to the emotions as the emotion center, ec_t by following Table 1 as:

$$ec_t = \frac{e_t\ \mathbf{C}}{\|e_t\|}, \tag{9}$$

where e_t is a 22-dimensional vector corresponding to the OCC emotions.

In order to update the mood, we first find where the current mood m_t stands considering the default mood m_0 and the emotion center ec_t. If it is between m_0 and ec_t, it is pulled towards ec_t. On the other hand, if it is beyond ec_t, it is pushed further from ec_t, meaning that the current mood is boosted by the experienced emotions.

$$m_t = \begin{cases} -c\,\frac{ec_t - m_t}{\|ec_t - m_t\|} & \text{if } (ec_t - m_t)\cdot(m_0 - m_t) > 0 \wedge \\ & \quad (m_t - ec_t)\cdot(m_0 - ec_t) < 0 \\ c\,\frac{ec_t - m_t}{\|ec_t - m_t\|} & \text{otherwise} \end{cases}, \quad (10)$$

where the constant c determines the speed of mood update. We compute the default mood m_0 according to personality, for which we use the mapping between the big five factors of personality and mood as given by Mehrabian [26].

$$m_0 = \mathbf{M}\,\pi^T, \quad (11)$$

where π is the personality vector $< \psi_O, \psi_C, \psi_E, \psi_A, \psi_N >$ and $\mathbf{M}$ is a constant matrix, as:

$$\mathbf{M} = \begin{bmatrix} 0.00 & 0.00 & 0.21 & 0.59 & 0.19 \\ 0.15 & 0.00 & 0.00 & 0.30 & -0.57 \\ 0.25 & 0.17 & 0.00 & -0.32 & 0.00 \end{bmatrix} \quad (12)$$

In humans, moods are more stable than emotions. However, they decay over a longer time. Mood decay is computed as:

$$m_t = m_{t-1} - \alpha(m_0 - m_{t-1}), \quad (13)$$

where α is a mood decay variable proportional to neuroticism, since neurotic people tend to experience frequent mood swings.

Moods are classified according to which octant they belong to. The mood names are given in Table 2.

Table 2. Mood Quadrants in PAD Space

Mood	P	A	D	Mood	P	A	D
Relaxed	+	-	+	Anxious	-	+	-
Dependent	+	+	-	Disdainful	-	-	+
Exuberant	+	+	+	Bored	-	-	-
Docile	+	-	-	Hostile	-	+	+

Due to the impact of moods on cognitive functioning and decision making, in a specific context, moods help agents to decide which behavior to perform. These behaviors are combinations of the simple actions that we mention in Section 3.

3.3 Psychological State Update

Algorithm 1 shows the psychological state update of an agent. The "ComputeEventFactor()" procedure simply walks down the branches of the OCC decision tree for emotions and updates the corresponding emotion value according to the active goals, standards and attitudes. Next, emotion contagion is computed by taking into account the emotions of the visible agents within a certain proximity. Then, emotional state and mood state are updated consecutively.

Algorithm 1: UpdateAffectiveState

```
appraisal.ComputeEventFactor();
ComputeEmotionContagion();
emotionModel.ComputeEmotionalState(appraisal.GetEventFactor());
emotionModel.ComputeMoodState(appraisal.GetEventFactor());
```

4 Implementation of Different Crowd Types

An agent is controlled by different high-level behaviors running synchronously, each represented as a separate component attached to that agent. 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, in which components are the essentials of the objects and behaviors in a game. 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 the behavior trees given in [28].

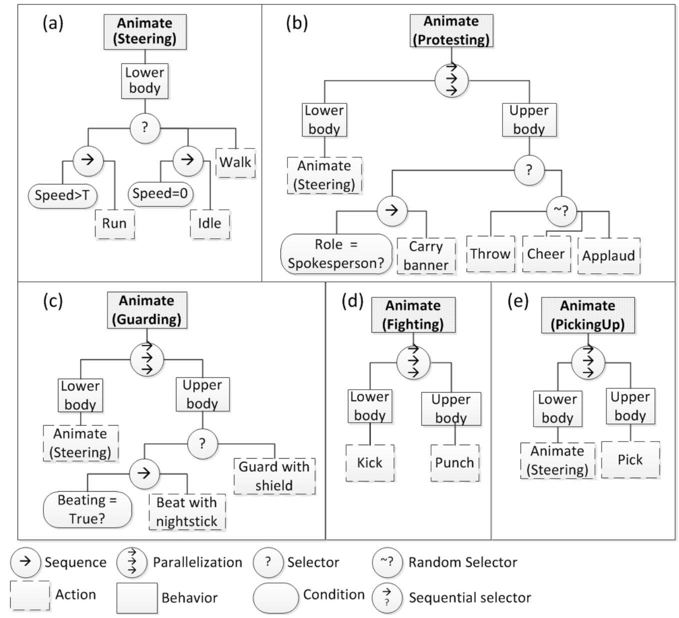


Fig. 3. Behavior trees for (a) steering, (b) protesting, (c) guarding, (d) fighting and (d) picking up.

Behaviors are coordinated by a component manager. The author of a new scenario only needs to script necessary behavior components and organize their coordination by modifying the component manager. When working on an existing scenario, different behaviors can be observed by modifying 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", and "leader", which is also a "protester". 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 demonstrate our working system on two scenarios about expressive and acquisitive mobs. However, before moving on to the scenario descriptions, let us first explain the animation of agents, as visual representation of agents is crucial to the scenario simulations.

4.1 Animations

Bodily expressions are combined with other low-level behaviors in order to form higher level, more complex animations, including fighting, protesting, guarding, picking up and steering. Upper and lower body actions are controlled separately (Figure 3). For instance, a virtual protester marches to a predefined destination, and randomly performs one of three actions- cheer, applaud or throw- with equal probability.

4.2 Mob Scenarios

We have authored two scenarios depicting a protest scene and a sales event. In the simulations, personalities of the agents are assigned randomly with a Gaussian distribution of mean 0 and standard deviation 1, spanning the whole personality range.

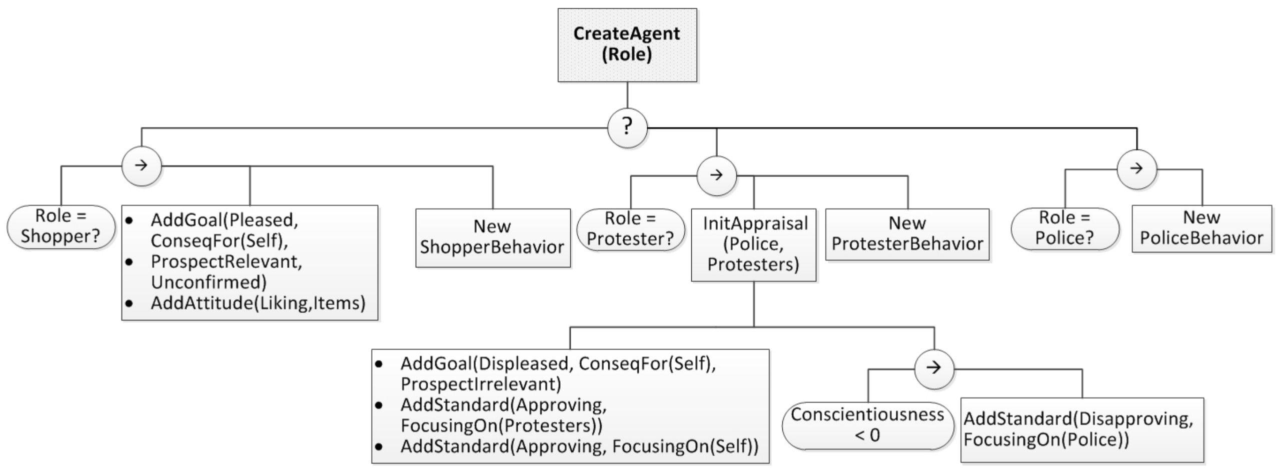


Fig. 4. Behavior tree for initializing an agent in a crowd.

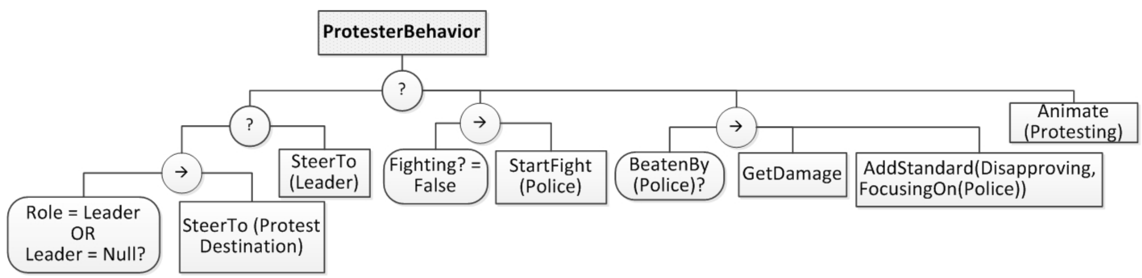


Fig. 5. Behavior tree for protester behavior.

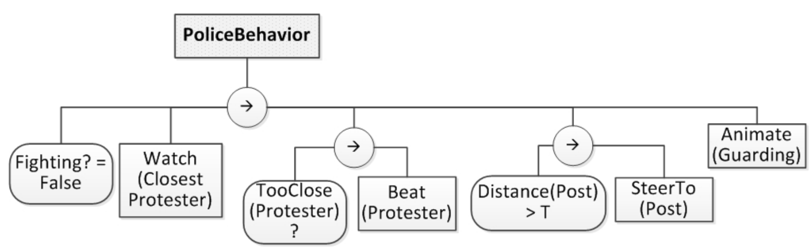


Fig. 6. Behavior tree for police behavior.

4.2.1 Protest Scenario

The protest scene consists of 100 protesters and 40 police officers. Protester agents' initial appraisal states include general unpleasant goals causing "distress", approving standards about themselves and their group, leading to "pride" and "admiration" consequently (Figure 4). 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 (Figure 5), and a PoliceBehavior component is attached to a police agent (Figure 6). 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.

If a protester is in hostile mood and disapproving the police, s/he may start a fight with a nearby police officer (StartFight in Figure 8). In that case, a FightBehavior component is attached to the protester and the policeman (Figure 8). 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 FightBehavior component is destroyed.

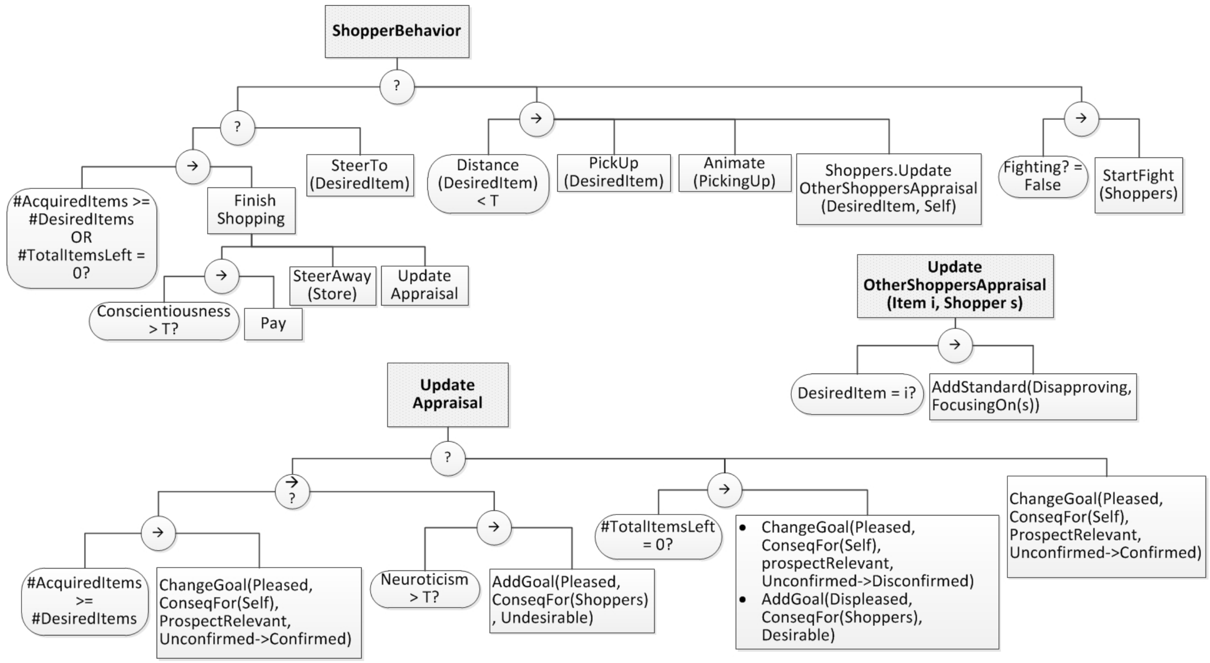


Fig. 7. Behavior trees for shopper behavior.

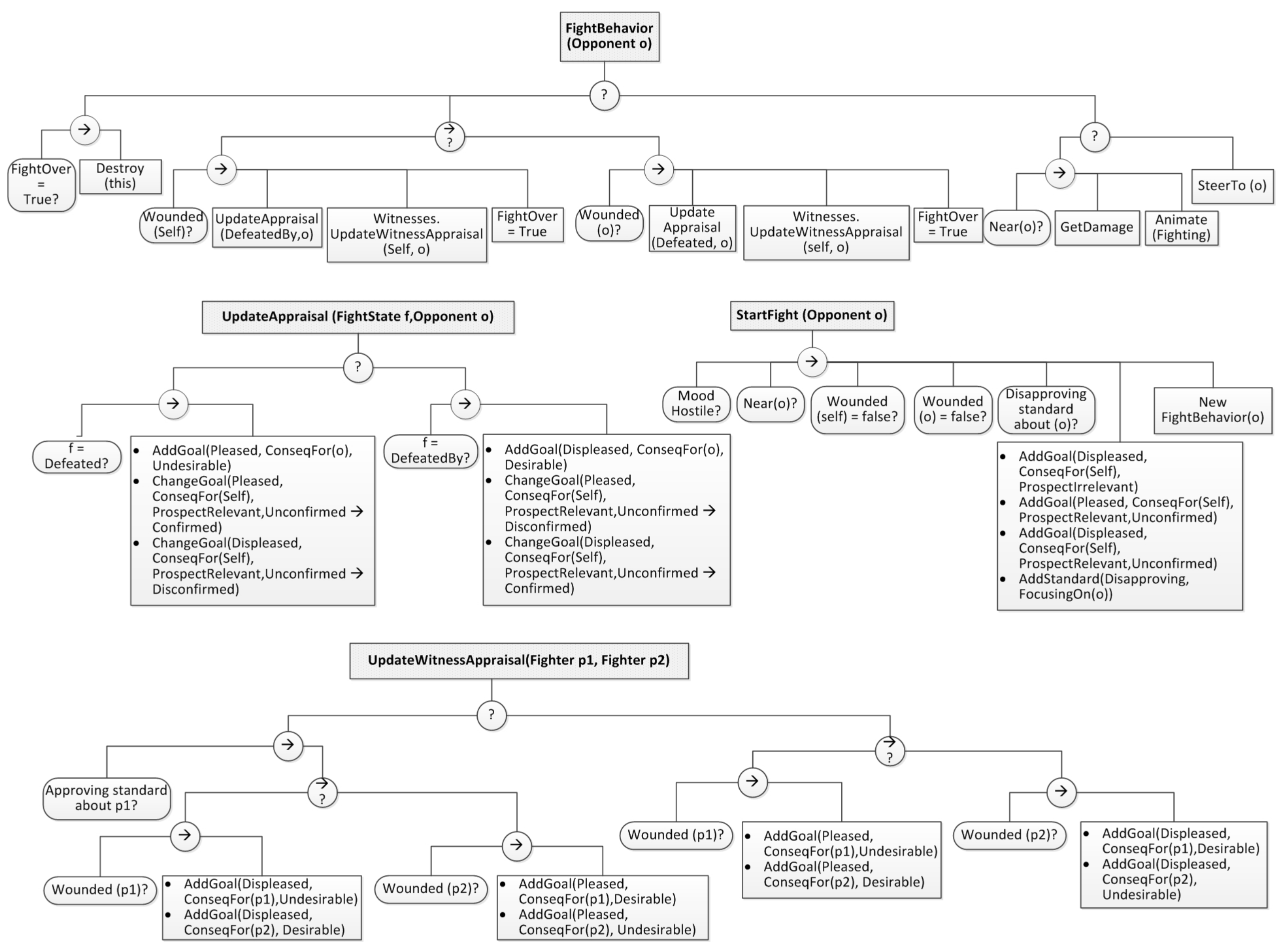


Fig. 8. Behavior trees for fight behavior.

4.2.2 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 (Figure 4). Therefore, they experience "hope". In addition, they have positive attitudes towards the discounted items leading to "love". Inside the store, an agent chooses the closest item (Figure 7). However, agents can become hostile and fight over the same item they want to achieve. This is an example of how we reuse the FightBehavior component. When another customer gets the item that an agent desires, the agent triggers a disapproving standard about that customer, which validates the condition in StartFight that checks whether there is a disapproving standard about the opponent. When a customer gets all the desired items, s/he may either pay for the items or leave the store without paying depending on her/his conscientiousness.

5 Evaluation

We conducted a user study to evaluate whether the emotions in the scenarios are perceived correctly. We showed two scenarios (protest and sales) to 33 participants, who were graduate students. The participants had no prior knowledge of the experiment. We gave them the names and definitions of the OCC emotions and asked them to identify which of these emotions they observed in the videos.

5.1 Analysis

After collecting participants' answers, we calculated the percentage of the responses for each emotion. For instance, if eight people marked an emotion in a video it means 24% of the participants observed that emotion. We organized the responses according to the emotions actually existing in the scenarios and the ones falsely recognized by the participants.

5.2 Results and Discussion

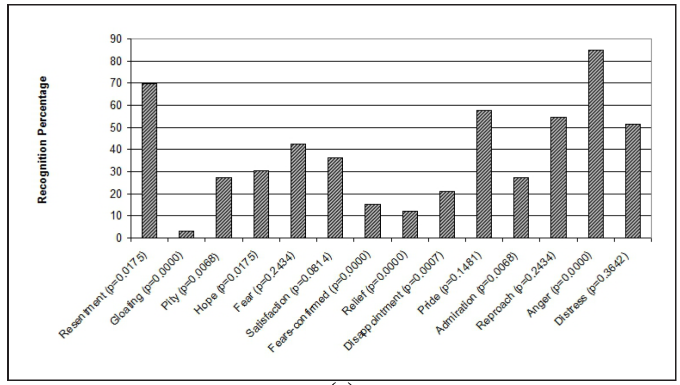
The results of the protest scenario are given in Figure 9, and the sales scenario in Figure 10. To estimate the probability of having obtained the results by chance we computed the p-values for each emotion as a cumulative binomial distribution.

The results indicate that the highest recognition rates are for the emotions anger and resentment. Pride, distress, reproach and fear are also high compared to other emotions; however they also have high p-values. Except for pride, these are all negative emotions conveying the characteristic nature of a mob scene. These emotions were in fact the most dominant emotions in the scenario. Emotions regarding a fight, i.e., hope, fear, satisfaction, relief, fears-confirmed, disappointment and gloating were less successfully perceived. As for the false recognition, hate has the highest ratio. Within the OCC context, hate is directed towards objects. Although subjects were given the corresponding definitions of the emotions, we suppose that hate was confusing because of the everyday usage of the word, which is attributed towards people.

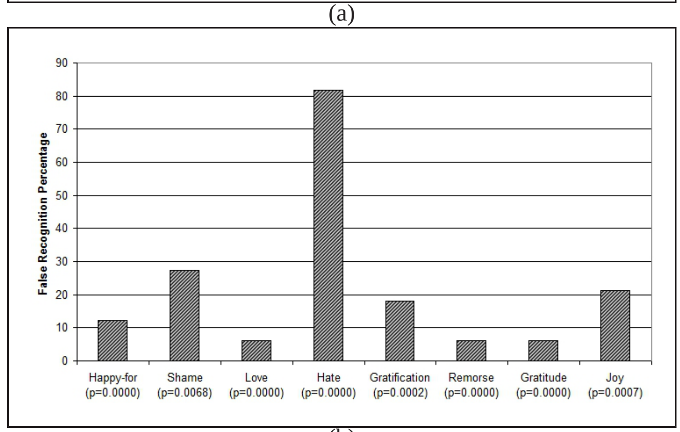
Similar to the protest scenario, negative emotions such as distress, anger, reproach, disappointment and resentment were more easily perceived than positive emotions such as hope, relief, love and satisfaction in the sales scenario. Again, hate is incorrectly perceived. Other false perceptions include pity, shame and remorse. Shame has the second highest false perception rate. However, significance of shame is low with a probability of 0.1481, implying being recognized by chance.

6 Conclusion

In this study we propose a crowd simulation system that incorporates a complex psychological component into the agents. In order to create a believable virtual human, different components comprising a real human must be considered. Representing intelligence on its own, for example, is not enough to reflect the complexity of a human's interaction with the environment. In particular, conversational agents should show human-like behavior by expressing their emotions. We integrated these facilities into a crowd simulation system. In our case, since there is a large number of virtual humans interacting with each

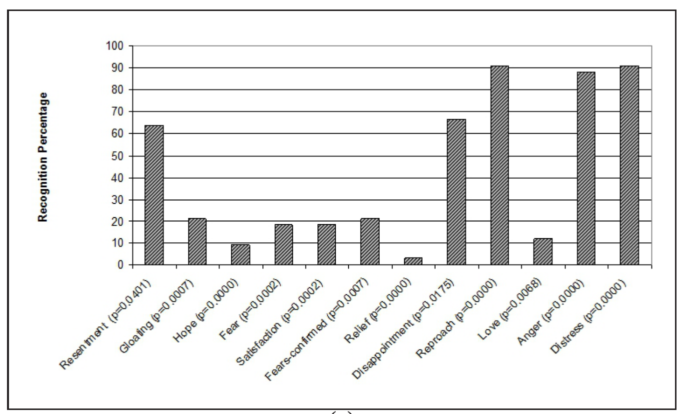


(a)

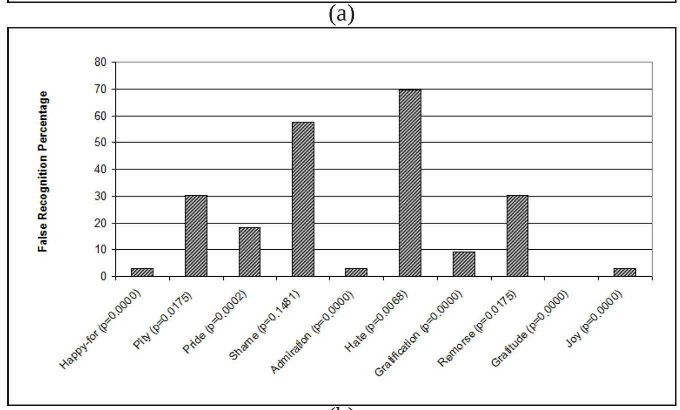


(b)

Fig. 9. (a) Correct, and (b) false recognition of emotions in a protest scene.



(a)



(b)

Fig. 10. (a) Correct, and (b) false recognition of emotions in a sales scene.

other, the psychological features of these humans become more significant. Furthermore, runtime results indicate that increasing the psychological complexity of agents does not greatly increase the overhead of the simulation performance, which is promising for our purposes.

We designed two scenarios representing expressive and acquisitive mobs (protest and sales) and evaluated whether the emotions in these scenarios were correctly perceived by conducting a user study. The results indicate that emotions related to aggression are better perceived than positive emotions within these settings. This is coherent with the fact that both scenarios are characterized by aggressive mob behavior.

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 the facial expressions of agents. The emotion 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.

Another future plan is to incorporate the intensity of emotions into the contagion model. Currently, we follow the social contagion model as proposed by Dodds and Watts. An augmentation idea is to use a probability distribution based on the intensity of emotions instead of a log-normal distribution.

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