6

*Simulation of Collective Crowd Behavior with Psychological Parameters**

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6.1 Introduction

Simulating the behavior of human crowds requires an understanding of the interaction between individuals, which may be complex and unpredictable. Crowds sometimes display spontaneous collective behavior, the emergence of which is formulated by social scientists using different theories such as contagion models or predisposition hypotheses. Crowd simulation research as well as industrial applications have also gained a new direction of modeling and visualizing different categories of collective crowd behavior [1–5].

Crowds are categorized in terms of their dominant behavior according to a taxonomy defined by Brown [6]. The main categories of this taxonomy are audiences and mobs. Both audiences and mobs are composed of individuals with common purposes. However, audiences are passive crowds whereas mobs are active. Examples of audiences include students in a classroom and pedestrians who are polarized around a street player. Mobs are classified into four groups: aggressive, escaping, acquisitive, and expressive mobs. Aggressive

* This chapter is mostly based on our article describing the system that enables the specification of different crowd types ranging from audiences to mobs [2].

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. Mobs are discriminated from audiences by 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 [7].

We provide animators/designers with a tool to easily simulate the behavior of different crowd types, especially mobs, according to the described taxonomy [2]. 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. We follow the OCEAN (openness, conscientiousness, extroversion, agreeableness, neuroticism) personality mapping approach presented in Reference 8. 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 and 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 [9] to simulate cognitive appraisal and emotions.

In addition to emotionality, mental homogeneity is attributed to collective behavior, where mental states of individuals are mirrored by others and these states are disseminated within the crowd. Gustav Le Bon explains mental homogeneity as a product of emotional contagion [10], 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 formulate an emotion contagion model.

We suggest 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 [11] 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. Personality, environmental stimuli, and agent roles contribute to the heterogeneity of the simulated crowds. We use the Unity [12] artificial intelligence (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 (cf. Figure 6.1).

(a)

(b)

FIGURE 6.1
Still frames from two crowd scenarios representing expressive and acquisitive mobs: (a) protest and (b) sales.

6.2 System

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 Figure 6.2.

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 are short term and elicited from events, other agents, and objects [9]. They influence memory, decision-making, and other cognitive capabilities [13,14].

Intrinsic, long-term personality traits and short-term emotions 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.

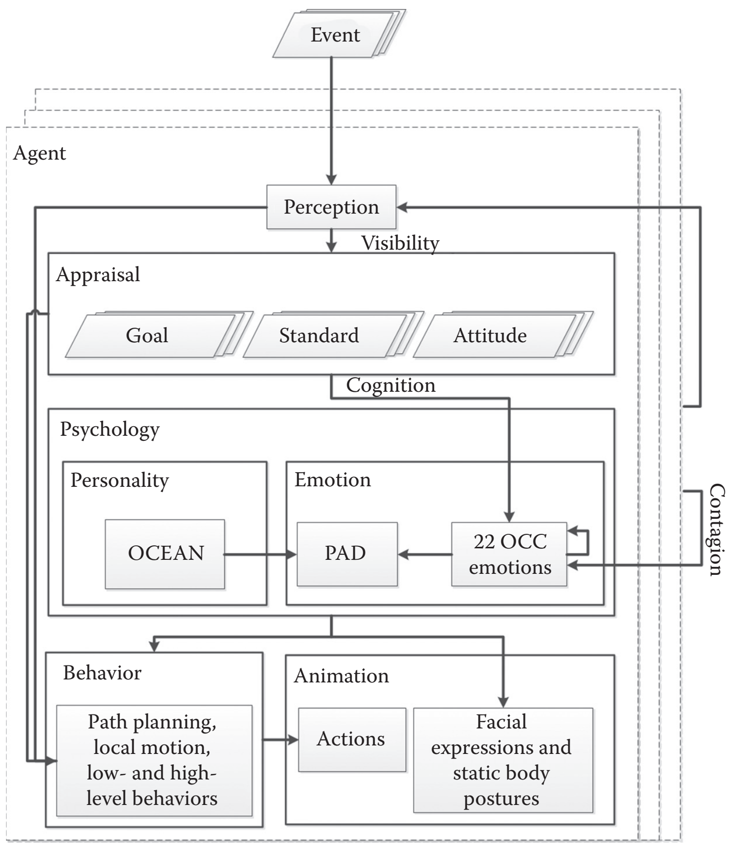

FIGURE 6.2
Framework of agent psychology. (F. Durupınar et al. Psychological parameters for crowd simulation: From audiences to mobs. *IEEE Transactions on Visualization and Computer Graphics*. In press. © 2015, IEEE.)

6.2.1 Personality

Personality is a pattern of behavioral, temperamental, emotional, and mental traits, which defines an individual. It defines a disposition to emotions. 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 [15], which has gained recognition in computer graphics and virtual world 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 $\langle \psi^O, \psi^C, \psi^E, \psi^A, \psi^N \rangle$ 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 Reference 8. 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. Aside from its function in determining the values of steering parameters, personality affects the tendency of the emotional state, for which we are going to give examples in the next section.

6.2.2 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 (cf. Figure 6.3).

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.

$$e_t = f(\text{goals, standards, attitudes}) + \lambda_t(\varepsilon), \tag{6.1}$$

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 [16]. 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:

$$\varepsilon_j = 0.354\ \psi_j^O + 0.177\ \psi_j^C + 0.135\ \psi_j^E + 0.312\ \psi_j^A + 0.021\ \psi_j^N \tag{6.2}$$

Emotions decay over time toward a neutral state. At each time step, t, the value of an emotion is decreased as

$$e_t = e_{t-1} - \beta e_{t-1} dt \tag{6.3}$$

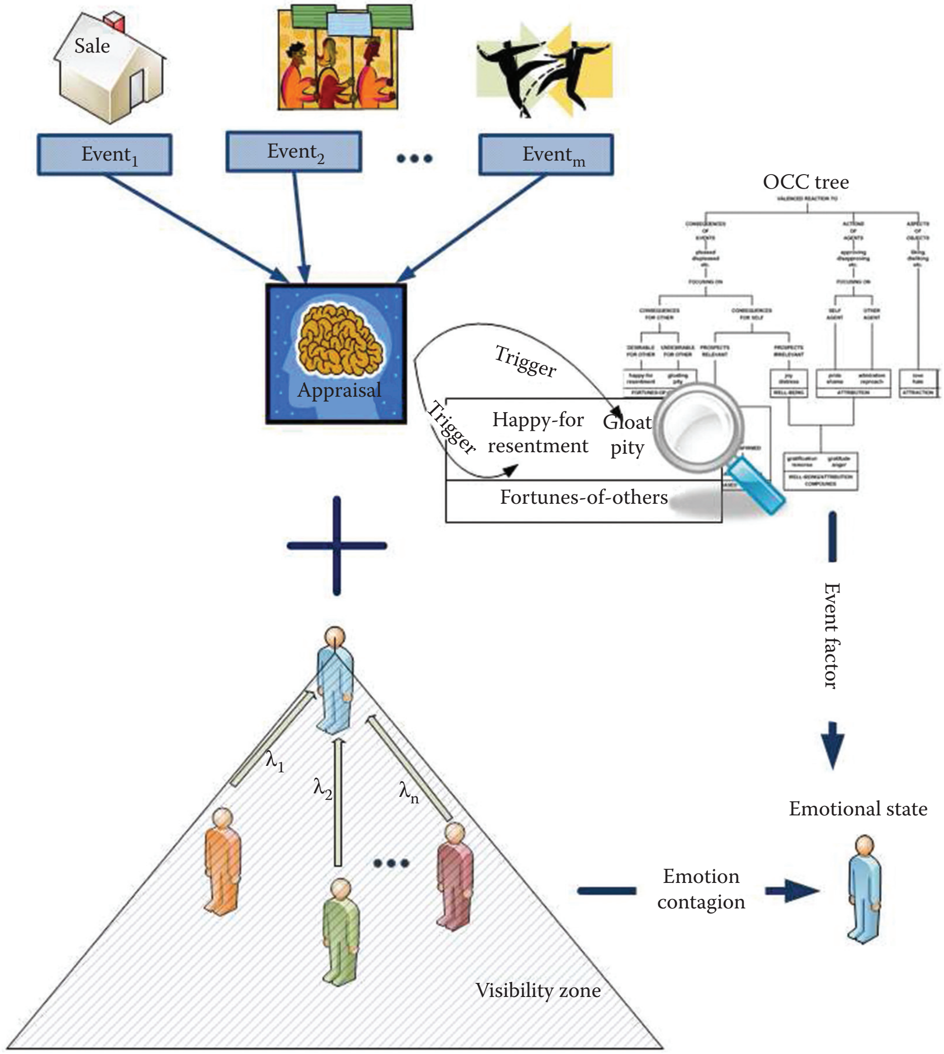

FIGURE 6.3
The emotional state update of an agent. (F. Durupınar et al. Psychological parameters for crowd simulation: From audiences to mobs. *IEEE Transactions on Visualization and Computer Graphics*. In press. © 2015, IEEE.)

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

6.2.2.1 Appraisal

As a widely acknowledged model of emotion synthesis, we employ the OCC model. The OCC model is based on the appraisal concept [9], 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 toward aspects of objects. Using these three stimuli as the main branches, the OCC model describes a hierarchy that classifies 22 emotions. Figure 6.4 shows details of this hierarchy. For instance, pity is elicited when an individual is displeased about an undesirable event for other people and joy is elicited when a person is pleased about a desirable event for himself/herself; admiration is the approving of another person's praiseworthy action and shame is the disapproving of one's own 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 surrounding events and relationships with other agents, it provides a suitable basis for crowd simulation applications.

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

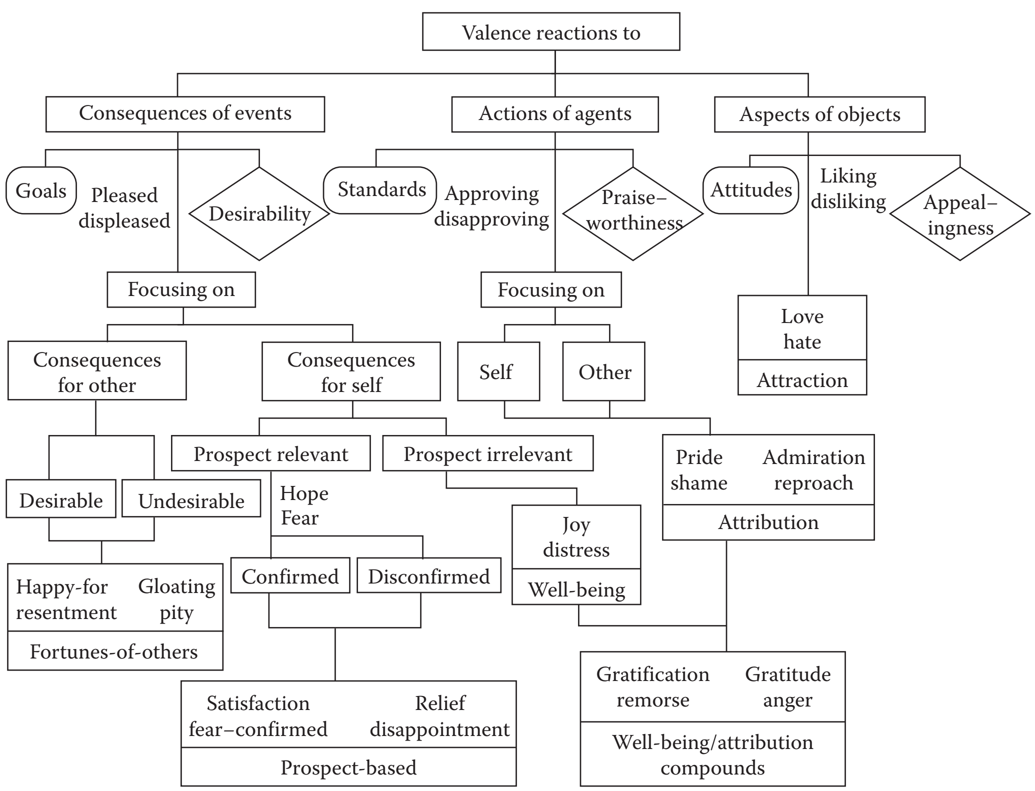

FIGURE 6.4
The OCC model of emotions. (F. Durupınar et al. Psychological parameters for crowd simulation: From audiences to mobs. *IEEE Transactions on Visualization and Computer Graphics*. In press. © 2015, IEEE.)

virtual character. In order to overcome the complexity of the OCC model, we use the following five phases that split the emotion process, as described by Bartneck [17]:

- *Classification*, where an event, action, or an object is evaluated by the agent and the emotional categories that will be triggered are determined. The OCC hierarchy determines which emotion is going to be triggered (cf. Figure 6.4). For example, if an agent has approving standards about another agent's actions, the triggered emotion will be admiration.
- *Quantification*, where the agent calculates the intensities of the emotional categories. For instance, the intensity of admiration will depend on the (un)praiseworthiness of the agent's standard. As an example, Algorithm 6.1 shows the computation of the contribution of an agent's standards on the emotion's appraisal factor. The contributions of goals and attributes are computed in the same manner.

Algorithm 6.1: Update Standard Contribution

```
for i ⟵ 0 to 22 do
    appraisalFactor[i] ⟵ 0;
foreach s ∈ Standards do
    if s.Approving then
        if s.Self then
            appraisalFactor[Pride]+ = s.praiseworthiness;
        else
            //Others appraisalFactor[Admiration]+ = s.praiseworthiness;
    else
        //Disapproving
        if s.Self then
            appraisalFactor[Shame]+ = s.praiseworthiness;
        else
            //Others
            appraisalFactor[Reproach]+ = s.praiseworthiness;
```

- *Interaction*, where the interaction of the current emotional category with existing emotional categories is calculated. Algorithm 6.2 shows the interaction of emotional categories.

Algorithm 6.2: Update Compound Emotions

```
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;
```

- *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 this and to incorporate the impact of personality on emotion, we exploit the PAD model, which will be explained in Section 6.3.1.
- *Expression*, where the emotional state is expressed through the facial expression, static body posture [18], and behavior of the agent. For instance, happy people tend to have a straight posture with high shoulders and look more confident, whereas sad people have collapsed upper bodies with low shoulders, and generally look downwards.

6.2.2.2 Emotion Contagion

In order to simulate the propagation of emotions, we adopt a generalized contagion model that unifies existing models of social and biological contagion, following the approach proposed by Dodds and Watts [19]. 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. Throughout this chapter, 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 [20]. 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 m and viewing angle as 120°.

All individuals keep a memory of their previous k doses as

$$D_j(t) = \sum_{t'=t-k+1}^{t} \sum_{\substack{\forall i \mid i \in Visibility(j) \wedge \\ i \text{ is expressive}}} d_j(t')e_i(t') \tag{6.4}$$

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

$$\lambda_j(t,\varepsilon) = \begin{cases} D_j dt, & \text{if } D_j(t) > susT_j(t) \\ 0, & \text{otherwise} \end{cases} \tag{6.5}$$

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.

6.3 Decision-Making Based on the Psychological State

6.3.1 PAD Model Mapping

Agents experience a range of different emotions; they may even feel opposite emotions simultaneously. A strategy to determine which emotions affect the current behavior to what extent is therefore crucial. Because emotion intensities are prone to fluctuation, mapping the emotions directly to behaviors may cause erratic behaviors. For instance, consider 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 PAD model, which determines the average emotional state across a representative sample of life situations [11]. OCC emotions are consistently associated with the PAD state [21,22]. The PAD space enables such a mapping with its three orthogonal scales used to assess emotional predispositions [11]. 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 is able to influence factors in his/her own life versus feelings of being controlled by others.

TABLE 6.1
Correlation between OCC Emotions and PAD Space

Emotion	P	A	D	Emotion	P	A	D
Admiration	0.50	0.30	−0.20	Hope	0.20	0.20	−0.10
Anger	−0.51	0.59	0.25	Joy	0.40	0.20	0.10
Disappointment	−0.30	0.10	−0.40	Love	0.30	0.10	0.20
Distress	−0.40	−0.20	−0.50	Pity	−0.40	−0.20	−0.50
Fear	−0.64	0.60	−0.43	Pride	0.40	0.30	0.30
Fears-confirmed	−0.50	−0.30	−0.70	Relief	0.20	−0.30	0.40
Gloating	0.30	−0.30	−0.10	Remorse	−0.30	0.10	−0.60
Gratification	0.60	0.50	0.40	Reproach	−0.30	−0.10	0.40
Gratitude	0.40	0.20	−0.30	Resentment	−0.20	−0.30	−0.20
Happy-for	0.40	0.20	0.20	Satisfaction	0.30	−0.20	0.40
Hate	−0.60	0.60	0.30	Shame	−0.30	0.10	−0.60

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 [23]

$$\begin{aligned} PAD_0(P) &= 0.21\psi^E + 0.59\psi^A - 0.19\psi^N \\ PAD_0(A) &= 0.15\psi^O + 0.30\psi^A + 0.57\psi^N \\ PAD_0(D) &= 0.25\psi^O + 0.17\psi^C + 0.60\psi^E - 0.32\psi^A \end{aligned} \tag{6.6}$$

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 all emotions are 0.

Table 6.1 shows the correlation between OCC emotions and PAD space. These parameters have been defined in the ALMA system [21]. 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:

$$PAD_t = PAD_0 + \mathbf{C}\, e_t \tag{6.7}$$

The octants of the PAD space are individually named (cf. Table 6.2). These octants, along with their intensities, determine agents' behaviors in a specific context.

6.3.2 Emotion Expression

A recent study reports that humans express four different facial expressions related to emotion: happiness, sadness, anger, and fear [24]. We define a correspondence between the PAD octants and emotional expressions in Table 6.3.

TABLE 6.2

PAD Space Octants

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

TABLE 6.3

Expressions Related to PAD Space

Expression	Octants	P	A	D
Happy	Relaxed, dependent, exuberant, docile	+	+/−	+/−
Sad	Disdainful, bored	−	−	+/−
Angry	Hostile	−	+	+
Fearful	Anxious	−	+	−

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.

6.3.3 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 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 use 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 Reference 25.

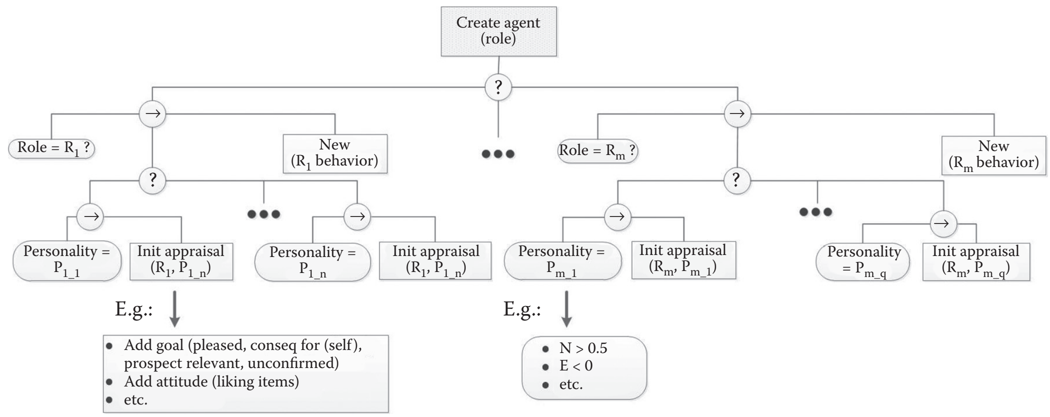

FIGURE 6.5
Behavior tree for initializing an agent in a crowd. (F. Durupınar et al. Psychological parameters for crowd simulation: From audiences to mobs. *IEEE Transactions on Visualization and Computer Graphics*. In press. © 2015, IEEE.)

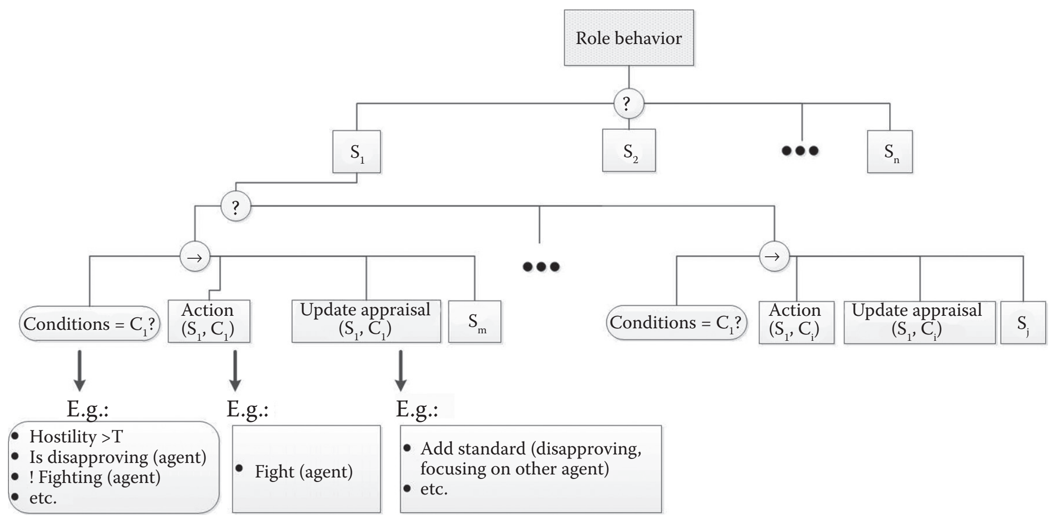

FIGURE 6.6
Behavior tree for roles. (F. Durupınar et al. Psychological parameters for crowd simulation: From audiences to mobs. *IEEE Transactions on Visualization and Computer Graphics*. In press. © 2015, IEEE.)

Figure 6.5 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. Figure 6.6 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.

6.4 Experimental Results

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.

6.4.1 Scenarios

Protest scenario: The scene consists of 200 protesters and 40 police officers. The protesters' initial appraisal states include general unpleasant goals causing "distress" and 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 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.

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 toward 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 toward 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 toward others such as "resentment," "reproach," and "gloating." "Satisfaction" and "confirmation of fears" emerge toward 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.

6.4.2 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). Figures 6.7 and 6.8 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 different PAD octants being 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.

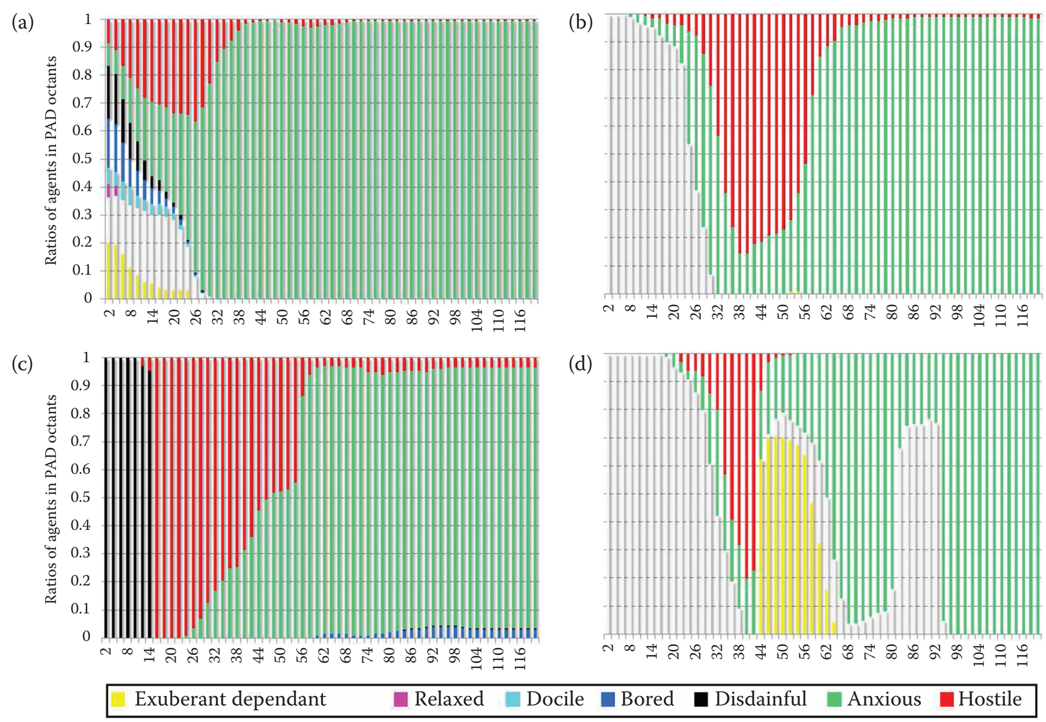

FIGURE 6.7
Ratios of agents in different PAD octants at each time step in the protest scenario: (a) random personalities, (b) all personalities equal to 0, (c) aggressive crowd with $\psi = \{0, -1, 0, -1, 0\}$, (d) peaceful crowd with $\psi = \{0, 1, 0, 1, 0\}$. (F. Durupınar et al. Psychological parameters for crowd simulation: From audiences to mobs. *IEEE Transactions on Visualization and Computer Graphics*. In press. © 2015, IEEE.)

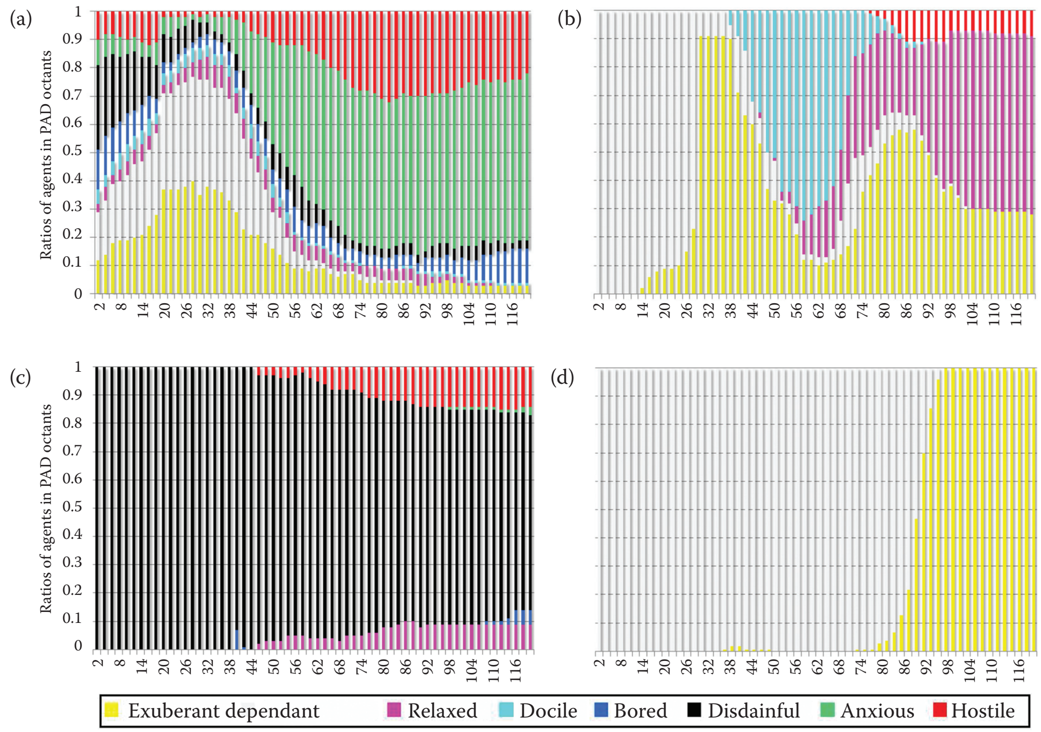

FIGURE 6.8
Ratios of agents in different PAD octants at each time step in the sales scenario: (a) random personalities, (b) all personalities equal to 0, (c) aggressive crowd with $\psi = \{0, -1, 0, -1, 0\}$, (d) peaceful crowd with $\psi = \{0, 1, 0, 1, 0\}$. (F. Durupınar et al. Psychological parameters for crowd simulation: From audiences to mobs. *IEEE Transactions on Visualization and Computer Graphics*. In press. © 2015, IEEE.)

6.4.3 Evaluation of the Contagion Model

We performed simulations to compare the influence of personality and threshold parameters on the outcome of emotion contagion. Figure 6.9 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 the 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% 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 with standard normal distribution. Anger spreads to part of the crowd and disappears after a certain time.

Figure 6.10 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%

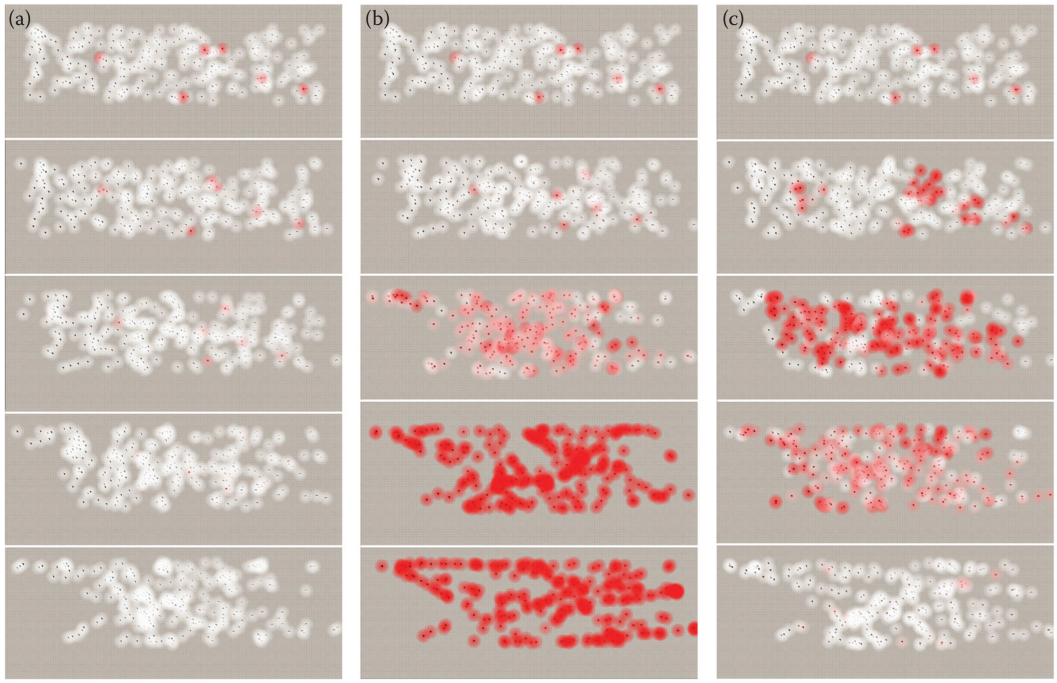

FIGURE 6.9
Snapshots of emotion distribution taken at $t = \{40, 360, 1060, 1860, 3840\}$ milliseconds of the simulations (from top to bottom), where (a) $\psi = \{-1, -1, -1, -1, -1\}$, expressiveness and empathy are 0; (b) $\psi = \{1, 1, 1, 1, 1\}$, expressiveness and empathy are 1; (c) personality 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. (F. Durupınar et al. Psychological parameters for crowd simulation: From audiences to mobs. *IEEE Transactions on Visualization and Computer Graphics*. In press. © 2015, IEEE.)

are assigned $anger = 0.9$ and 80% are assigned $anger = 0.1$. Agents randomly walk around and they perceive the emotions of other agents within 4 m and 120° 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. Figure 6.10a 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 Figure 6.10b, we can see that as susceptibility threshold decreases, population's average anger increase has a steeper slope.

Figure 6.11 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% of the individuals are assigned $anger = 0.9$ and 80% are assigned $anger = 0.1$. Agents randomly walk around and they perceive the emotions of other agents within 4 m and 120° 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

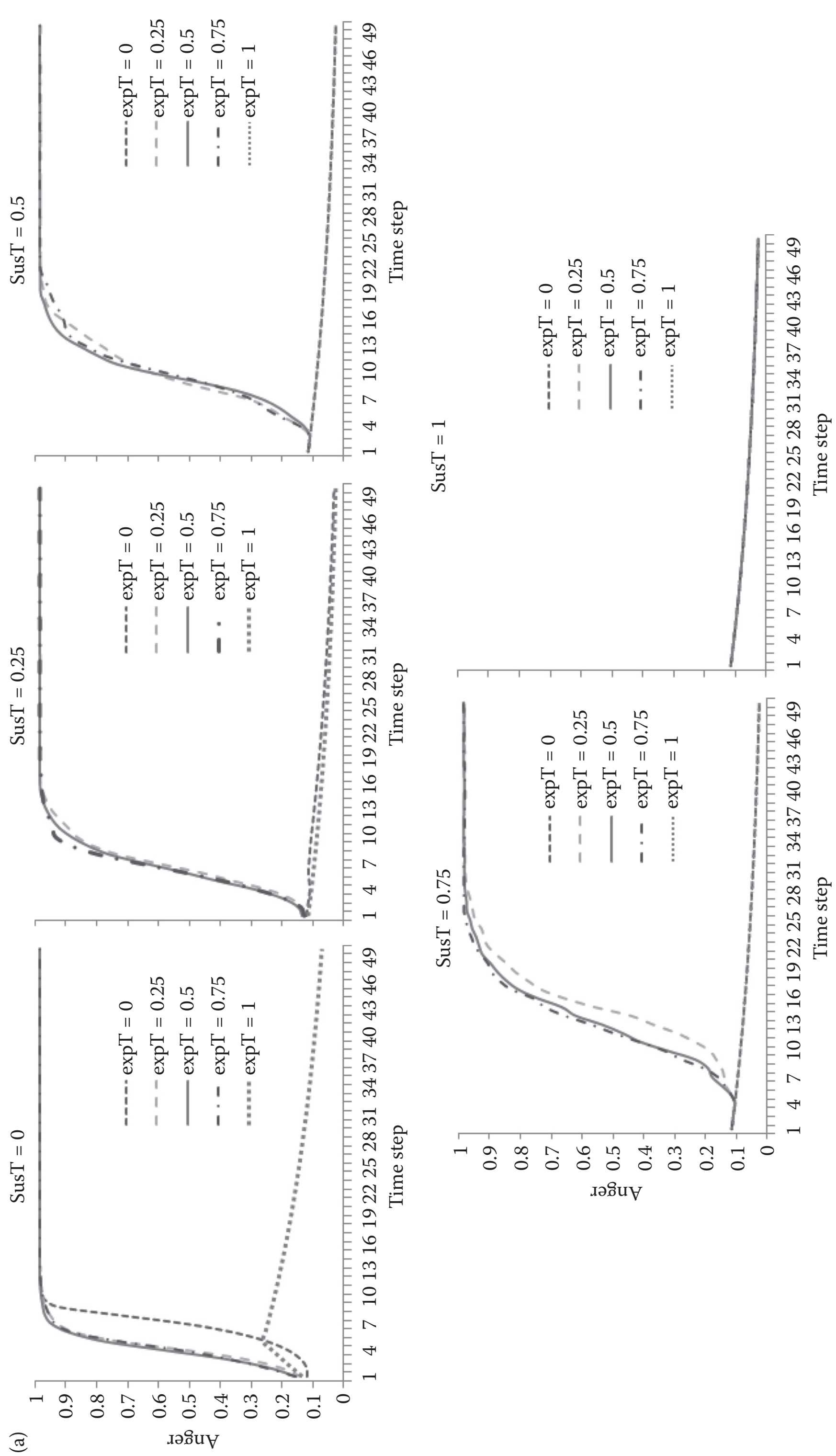

FIGURE 6.10
Average anger at each time step where (a) expressiveness thresholds are varied whereas susceptibility thresholds are kept constant. (F. Durupinar et al. Psychological parameters for crowd simulation: From audiences to mobs. *IEEE Transactions on Visualization and Computer Graphics*. In press. © 2015, IEEE.) *(Continued)*

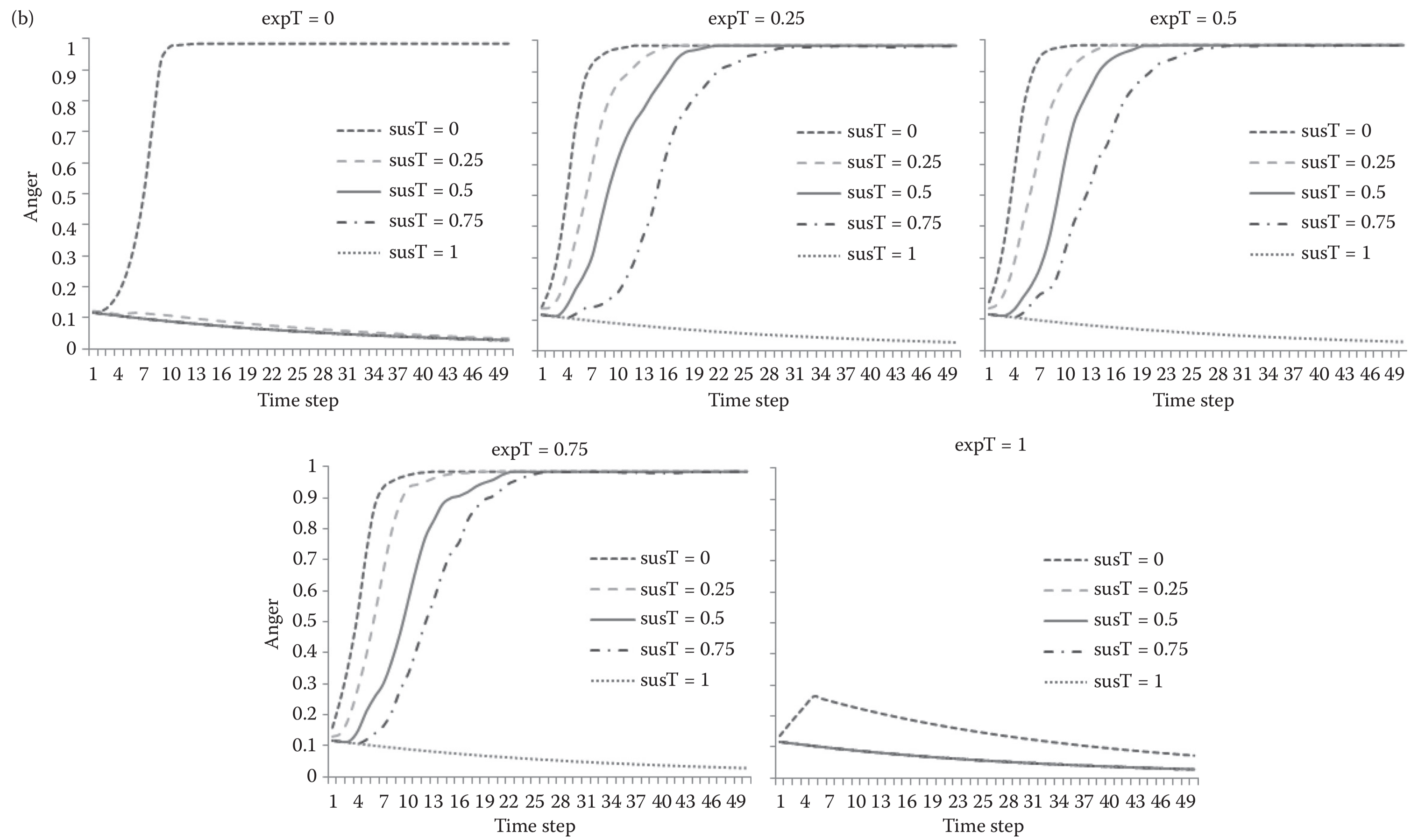

FIGURE 6.10 (Continued)
Average anger at each time step where (b) susceptibility thresholds are varied whereas expressiveness thresholds are kept constant. (F. Durupınar et al. Psychological parameters for crowd simulation: From audiences to mobs. *IEEE Transactions on Visualization and Computer Graphics*. In press. © 2015, IEEE.)

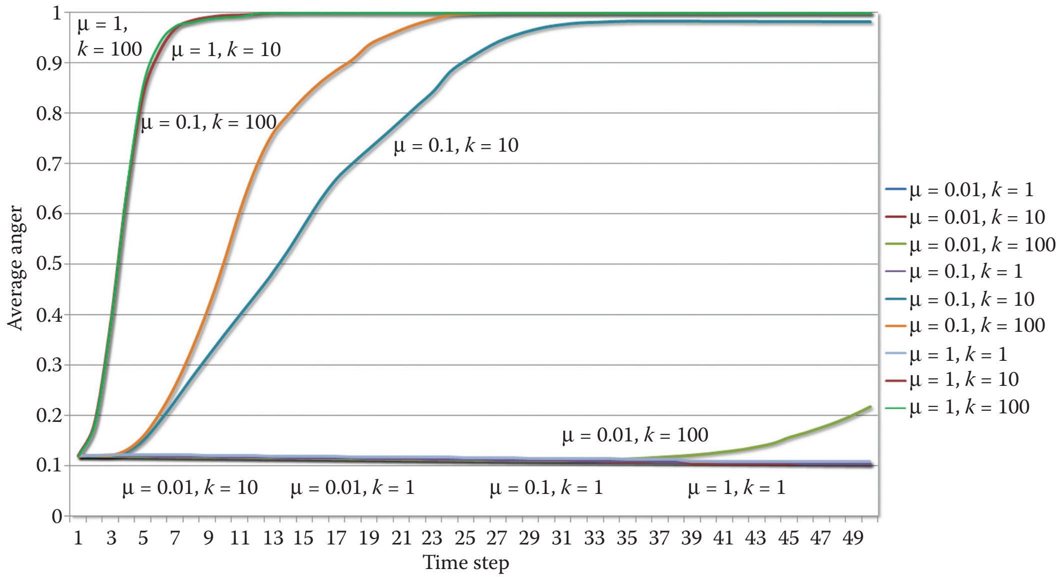

FIGURE 6.11
Average anger with respect to various dose mean (μ) and dose memory (k) values. (F. Durupınar et al. Psychological parameters for crowd simulation: From audiences to mobs. *IEEE Transactions on Visualization and Computer Graphics*. In press. © 2015, IEEE.)

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 $\mu = 1$.

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 (cf. Figure 6.12). We get similar results with different population sizes.

Glossary

Behavior tree: A well-defined visual representation tool for plan execution and decision making, which has become popular in game artificial intelligence development.

Emotion contagion: Synchronization of emotions within a group.

Five factor (OCEAN) personality model: A widely recognized personality model that categorizes personality into five orthogonal factors of (O)penness, (C)onscientiousness, (E)xtroversion, (A)greeableness, and (N)euroticism.

Ortony, Clore, Collins (OCC) model: An emotion model that suggests that emotions are triggered according to an individual's reactions to the consequences of events, actions of agents, and aspects of objects.

Pleasure–arousal–dominance (PAD): A three-dimensional emotion model that describes the average emotional state across a representative sample of life situations.

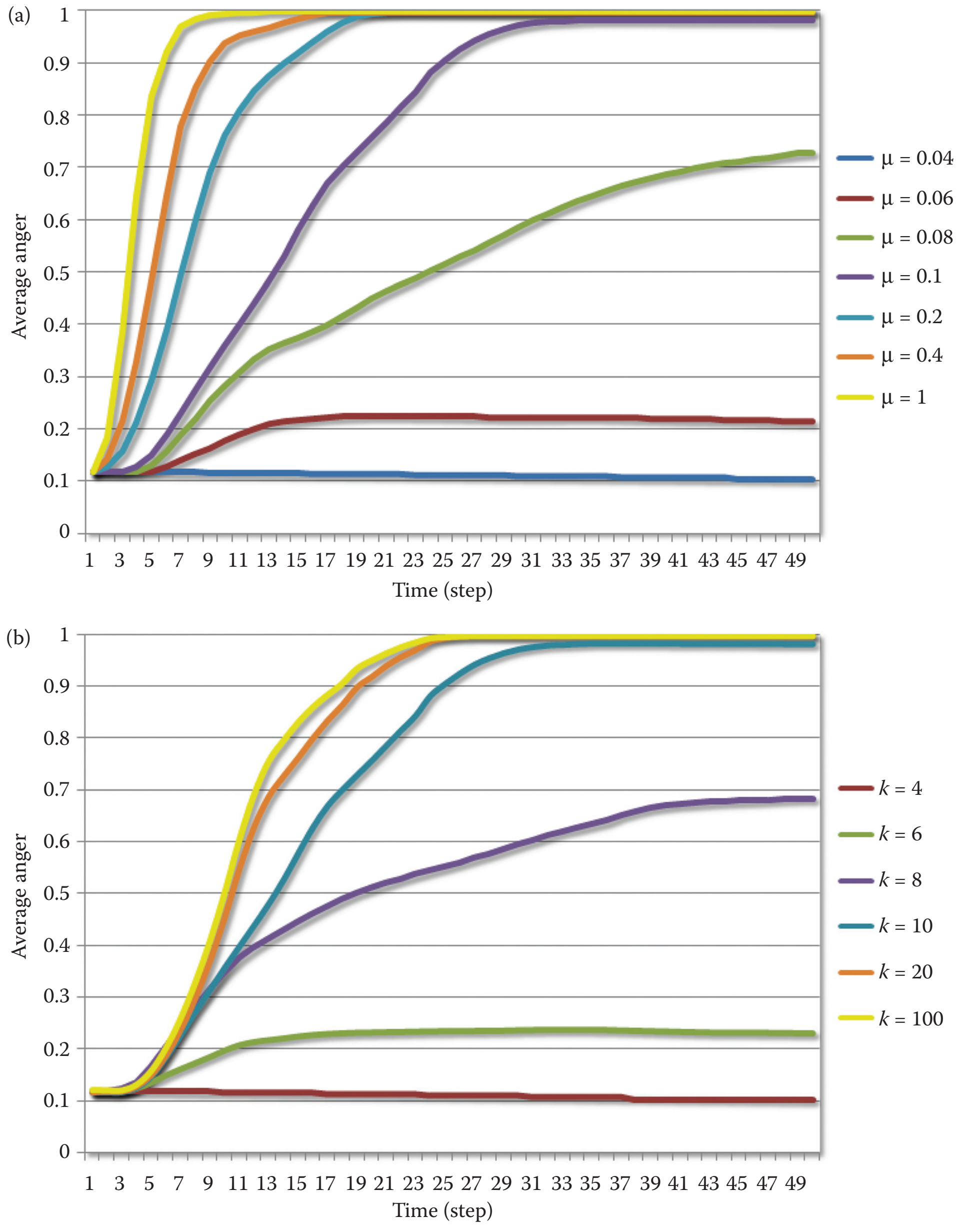

FIGURE 6.12
Average anger at each time step, where (a) $k = 10$ and dose mean μ is varied, (b) $\mu = 0.1$ and k is varied. (F. Durupınar et al. Psychological parameters for crowd simulation: From audiences to mobs. *IEEE Transactions on Visualization and Computer Graphics*. In press. © 2015, IEEE.)

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