Eurographics/ ACM SIGGRAPH Symposium on Computer Animation (2011)
A. Bargteil and M. van de Panne (Editors)

Simulating Heterogeneous Crowd Behaviors Using Personality Trait Theory

Stephen J. Guy[†], Sujeong Kim, Ming C. Lin, Dinesh Manocha

Department of Computer Science, UNC - Chapel Hill

Abstract

We present a new technique to generate heterogeneous crowd behaviors using personality trait theory. Our formulation is based on adopting results of a user study to derive a mapping from crowd simulation parameters to the perceived behaviors of agents in computer-generated crowd simulations. We also derive a linear mapping between simulation parameters and personality descriptors corresponding to the well-established Eysenck Three-factor personality model. Furthermore, we propose a novel two-dimensional factorization of perceived personality in crowds based on a statistical analysis of the user study results. Finally, we demonstrate that our mappings and factorizations can be used to generate heterogeneous crowd behaviors in different settings.

Categories and Subject Descriptors (according to ACM CCS): I.2.11 [Computer Graphics]: Distributed Artificial Intelligence—Multiagent systems

1. Introduction

Modeling the behavior of large, heterogeneous crowds is important in various domains including psychology, robotics, transport engineering and virtual environments. Heterogeneous crowds consist of dissimilar types of groups, each with potentially independent behavior characteristics and goals [LB97]. According to *Convergence Theory*, crowd behavior is not a product of the crowd itself, rather it is carried into the crowd by the individuals [TK87]. As a result, it is important to accurately model the behavior and interactions among the individuals to generate realistic, heterogeneous crowd behaviors.

In terms of modeling the behavior of individuals within a crowd, even simple tasks, such as walking toward a given destination, involve several complex decisions such as what route to take and the various ways to avoid collisions with obstacles and other individuals. As a result, different people will achieve the same goal in different manners. While there are many factors that govern people's overall behaviors, such as biological and developmental variations, we focus on capturing the portion of these variations that are due to differences in underlying personality.

In general, categorizing the variety of personalities that humans exhibit is a difficult and multifaceted task. While many psychologists have proposed different models to organize this variation in personality, there are limitations in their ability to capturing all types of human personality using a single classifying model [HMS95, RWC00]. In fact, personality can be defined as the interplay between maintaining goal-directness while responding to the demands of the current situation [Per03]. Rather than trying to directly encode this complex interplay by hand, we attempt to characterize these personalities based on data from our user study which asked participants to describe the perceived behaviors of individual agents in computer-generated crowds.

In this paper, we focus on the problem of generating heterogeneous crowd behaviors by adjusting the simulation parameters to emulate personality traits of individuals within a crowd and evaluate the effects of individual personalities on the overall crowd simulation. Our approach is based on Personality Trait Theory, which proposes that complex variations in behavior are primarily the result of a small number of underlying traits. We draw on established models from Trait Theory to specify these variations for each individual. We use the well-known Eysenck 3-Factor personality model [EE85] to establish the range of personality variation. This is a biologically-based model of three independent factors of personality: Psychoticism, Extraversion, and Neuroticism. This so-called PEN model has inspired other similar personality models, most famously the Big-5 or OCEAN personality model [CM92], which proposes five independent axes of personality based on a factor analysis of user responses. The

† contact: sjguy@cs.unc.edu
http://gamma.cs.unc.edu/personality/

OCEAN model has been previously used as framework for exploring variations in crowd simulations [DAPB08].

Our main result is an efficient approach to create and control the perceived personalities of agents in a crowd simulation. We present a mapping between the low-level simulation parameters and high level behavior descriptors. This mapping is used to control the extent that agents exhibit various degrees of aggressive, shy, tense, assertive, active, and impulsive behaviors. We also place these parameters in the context of the PEN personality model. Additionally, we propose a novel two-dimensional factorization of personality traits derived from our empirical study results on perceived personalities in computer-generated crowds. These mappings are used to generate heterogeneous crowd simulations with different, predictable perceived agent personalities.

The rest of the paper is organized as follows. In Section 2 we highlight related work in crowd simulation and behavior modeling. Section 3 gives a brief overview of established personality models and Trait Theory. We describe our user study on perceived personalities in Sec. 4, and Sec. 5 uses the results to compute the mappings. Section 6 demonstrates the resulting behavior of agents simulated using our approach.

2. Previous Work

2.1. Crowd Simulation

Several techniques have been proposed for local collision avoidance and interaction among various agents in crowd simulations. Boids, the seminal work of Reynolds [Rey87], provided a simple method based on forces that push individuals away from each other when they get too close, along with additional forces to provide cohesion in the crowd. The general Boids approach can be extended to simulate more complex crowd behaviors by adding more forces [Rey99].

Other techniques for local navigation also use force-based models, including the Social Force Model [HFV00] and HiDAC [PAB07]. These approaches use complex forces between agents to accurately model local interactions among the agents. Geometric formulations based on (Reciprocal) Velocity Obstacles (RVO) [vdBGLM09] have also been used to model local collision avoidance behavior and generate emergent crowd phenomena [GCC*10].

2.2. Human Behavior Modeling

Many researchers have proposed approaches to simulate crowds that can closely model human behavior. Funge et al. [FTT99] proposed using Cognitive Modeling to allow agents to plan and perform high level tasks. Shao and Terzopoulos [ST05] proposed an artificial life model with several components, that enabled agents to make decisions at both the reactive/behavioral and proactive/cognition levels of abstraction. Yu and Terzopoulos [YT07] introduced a decision network framework for behaviorally animated agents that was capable of simulating interactions between multiple agents and modeling the effect of different personalities.

Other approaches have directly incorporated personality models into crowd simulations. Durupinar et al. [DAPB08] suggested a method to vary the parameters of the HiDAC simulation model based on the OCEAN personality model by choosing a plausible mapping between OCEAN personality factors. Salvit and Sklar [SS11] created a testbed world based on termites collecting food where they demonstrated a variety of food-gathering patterns based on varying parameters of the MBTI personality model.

Perceptual or user studies have been used to improve crowd behaviors and rendering. McDonnell et al. [MLH*09] utilized perceptual saliency to identify important features that need to be varied to add visual variety to the appearance of avatars. McHugh et al. [MMON10] investigated the effect of an agent's body posture on their perceived emotional state. Durupinar et al. [DPA*11] evaluated their method to model the OCEAN personality with a user study.

2.3. Modeling Crowd Styles

Previous approaches have used data-driven methods to produce simulated crowds which behaved with a certain trait or “style". These methods commonly train models for crowd based on input video data. For example, Lee et al. [LCHL07] used data-driven methods to match recorded motion from videos by training a group behavior model. Ju et al. [JCP*10] also proposed a data-driven method which attempts to match the style of simulated crowds to those in a reference video.

3. Personality Models and Trait Theory

Psychologists have proposed various ways of characterizing the spectrum of personalities exhibited by humans. Several theories focus on aspects of personality that show cross-situational consistency, i.e. behavior aspects that are relatively consistent over time and across various situations. While there are many sources of variety in behavior, psychologists have proposed methods to categorize and organize these variations. Our work builds on Trait Theories of personality, a broad class of theories which categorizes people's behavior based on a small number of personality traits [Per03].

3.1. Trait Theory

A personality trait is an habitual pattern of behavior, thought or emotion. While humans display a vast number of different traits, a small number of these traits are believed to be central to an individual's basic personality. Trait theories identify these primary traits, which can be used to describe variations in personality; an individual's personality is described based on a score of how strongly or weakly they exhibit each of these primary traits.

One of the most well established trait theories is the Eysenck 3-factor model [EE85]. This model identifies three major factors which categorize personality: Psychoticism, Extraversion, and Neuroticism (commonly referred to as

PEN). An individual's personality is identified according to what extent they exhibit each of these three traits. The Psychoticism factor is a measure of a person's aggression and egocentricity. The Extraversion factor is a measure of social interest and higher levels of extroversion are associated with more active, assertive and daring behaviors. Finally, the Neuroticism factor is a measure of emotional instability which can correspond to shyness and anxiety [EE77]. Each of Eysenck's three PEN traits have been linked to biological basis, such as the levels of testosterone, serotonin and dopamine present in one's body.

3.2. Factor Analysis

The Eysenck 3-factor model is one of several different trait theories. Other theories have used different methods for classifying the fundamental dimensions of human personality. A particularly successful method of identifying basic personality traits comes from applying *factor analysis* to various user studies where participants use common personality adjectives to describe the behaviors of themselves or others in various situations [CE72]. Factor analysis is the process for determining which small number of unobserved latent variables can describe the behavior of a large number of observed variables. In the context of personality trait theory, the observed variables are the many different adjectives that people use to describe personalities, while the latent variables are a smaller number of axes which explain the correlation in the way people use these personality describing adjectives. An example latent variable might be extraversion, which is associated with the uses of the adjectives outgoing, active, and assertive.

Costa & McCrae [CM92] applied factor analysis to data collected from various personality studies and suggested five primary factors of personality which they dubbed: "Openness to experience", "Conscientiousness", "Extraversion", "Agreeableness", and "Neuroticism" (commonly referred to as OCEAN). While the OCEAN model is very popular, other researches have applied factor analysis to similar user studies and found different factors or different numbers of factor (e.g. the 16 Personality Factor model [CE72]). Additionally, many studies have shown that the five OCEAN factors are not fully orthogonal (i.e. not independent from each other) [DK95]. Furthermore, OCEAN, along with other models such as PEN, deals with personality in the context of general human behaviors. In this work, we seek to study personality specifically within the context of crowd simulations. To that end, we apply a similar factor analysis technique to user responses about personalities perceived in our computer-generated crowds.

4. Behavior Perception User Study

Our goal is to understand how varying parameters in a crowd simulation affects the perceived behavior of agents in the crowd. To this end, we investigated several low-level parameters commonly used in crowd simulations: preferred speed, effective radius (how far away an agent stays from other agents), maximum number of neighbors affecting the local behavior of an agent, maximum distance of neighbors affecting the agent, and planning horizon (how far ahead the agent plans). Many agent-based crowd simulation methods use these or similar parameters to compute the mutual interaction between agents.

We adopt a data-driven approach and derive a mapping between simulation parameters and perceived agent behaviors based on the results of this perceptual study. Our approach has at least two advantages over trying to hand-tune a plausible mapping. First, it ensures that the perceived personality results are based on the input of a wide range of study participants. Second, it allows for richer, more complex mappings than would otherwise be possible with hand-tuning plausible parameters.

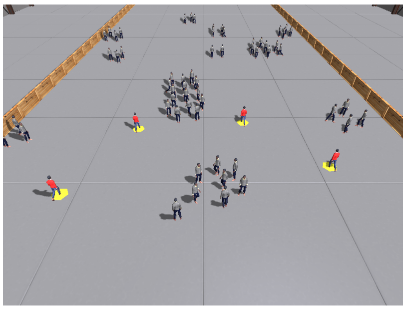
In designing the study, we developed an approach which would satisfy multiple goals. First, the ability to produce mappings to several common adjectives used to describe individuals in crowds, such as "shy", "assertive" and "aggressive". Second, the ability to produce a mapping from simulation parameters to an established psychological theory, such as the Eysenck's PEN model. Finally, the gathered data should be sufficiently rich enough to support a factor analysis that enables us to extract underlying latent variables describing the space of personality seen in crowd simulations.

4.1. Method

To achieve the above stated goals, we designed a user study, which allowed participants to describe behavior in crowd simulations using several adjectives. Our study involved 40 participants (40% female) between 24 and 64 years old, with an average age of 33 years (std. dev. of 12 years). In this study, participants were asked to view three different scenarios of computer generated crowds. In each video, several agents were highlighted to be the focus of user questions. Animations of these scenarios can be seen in the supplementary video. All simulations were created using the publicly available RVO2 Library for multi-agent simulation [vd-BGLM09].

Fig. 1 shows a still from each of the scenarios used in the study. The first scenario was the Pass-Through scenario, where four highlighted agents move through a cross-flow of 400 agents. Second was the Hallway scenario where four highlighted agents move through a hallway past 66 other agents, who are in several small groups. Lastly, was the Narrowing Passage scenario where 40 highlighted agents walk alongside 160 other agents towards a narrowing exit. In all cases, the non-highlighted agents were given the default parameters from the simulation library, which mostly results in homogeneous behaviors of the agents in the simulation. The highlighted agents all share the same simulation parameters, that are randomly chosen for each question given to the participants.


(a) Pass-Through Scenario


(b) Hallway Scenario

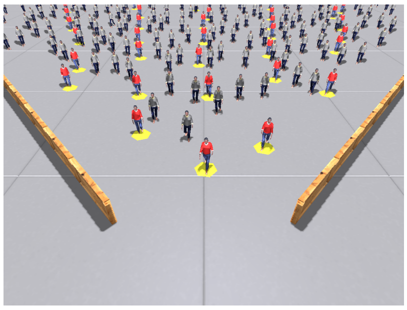

(c) Narrowing Passage Scenario

Figure 1: Three crowd simulation scenarios. (a) Four highlighted agents move through crowd. (b) Four highlighted individuals move through groups of still agents. (c) 20 highlighted individuals compete with others to exit through a narrowing passage.

In all scenarios, the highlighted agents are displayed wearing a red shirt with a yellow disc beneath them to allow them stand out in the crowd. Each participant was shown several videos for each scenario with randomly chosen simulation parameters for the highlighted agents. Each video was shown side-by-side with a reference video in which all the agents were simulated using the default set of parameters of the library. This "reference video" was the same for each question involving the same scenario to provide a consistent baseline for comparison.

The participants were asked to rate how the highlighted agents behaved in comparison to those in the reference video. Participants were asked to describe the differences in behavior as being more or less "Aggressive", "Shy", "Assertive", "Tense", "Impulsive" and "Active". These particular six adjectives were chosen both because they are useful in describing behaviors of individuals in crowds, and can span the space covered by the PEN model, with at least two adjectives for each PEN trait [Per03]. Participants then rated each crowd video in terms of all six personality adjectives on a scale from 1-9, with 9 meaning, for example, "much more assertive" than the references video, 5 meaning "about as assertive" and 1 meaning "much less assertive". The participants were allowed to re-watch the videos as many times as they felt necessary, and could go back and forth between questions within a section and revise their answers if desired.

To generate the highlighted agents in the question video the following simulation parameters were randomly chosen: maximum distance to avoid neighbors, maximum number of neighbors to avoid, planning horizon, agent radius, and preferred speed. The random parameter values were shared by all the highlighted agents in each video. The range of the sampled values is shown in Table 1.

For this study, approximately 100 videos were pre-generated for the 3 different scenarios with random values for each of the 5 simulation parameters. Each subject was asked to rate behaviors in several videos randomly chosen from this pool. To keep subjects engaged, the number of videos shown to each participant was limited to 6 randomly chosen clips from each of the 3 different scenarios (18 videos total); users were given the option to skip videos and watched an average of 15 video each. Each video was accompanied with 6 questions, which resulted in a total of approximately 3,600 data points mapping each set of input parameters to perceived levels of various personality traits.

Parameter	Min	Max	Unit
Max. neighbors dist.	3	30	m
Max. num. neighbors	1	100	(n/a)
Planning horizon	1	30	s
Agent radius	0.3	2.0	m
Preferred speed	1.2	2.2	m/s

Table 1: Range of simulation parameters.

5. Data Analysis

Given the large number of data points from the study, we are able to derive a mapping of the relationship between crowd simulation parameters and the perceived personality of the agents. We derive a linear model for the mapping, though other forms of regression are possible.

5.1. Mapping Perceived Behaviors

Using a QR decomposition with column pivoting, we found a linear regression between simulation parameters and perceived behaviors. As input to the regression, we use the difference between the given agents' parameters and those of the agents in the reference video. This removes the need to compute an offset as part of the regression. We also normalized the input by dividing each parameter by half of its min-to-max range to increase the numerical stability of the linear regression.

Our mapping then takes the following form:

$$\begin{pmatrix} Aggressive \\ Assertive \\ Shy \\ Active \\ Tense \\ Impulsive \end{pmatrix} = A_{adj} \begin{pmatrix} \frac{1}{13.5}(Neighbor\ Dist - 15) \\ \frac{1}{49.5}(Max.\ Neighbors - 10) \\ \frac{1}{14.5}(Planning\ Horiz. - 30) \\ \frac{1}{0.85}(Radius - 0.8) \\ \frac{1}{0.5}(Pref.\ Speed - 1.4) \end{pmatrix}$$

Using a linear least-squares approach on the user study data we found the following 6-by-5 matrix A_{adj}:

$$A_{adj} = \begin{pmatrix} -0.02 & 0.32 & 0.13 & -0.41 & 1.02 \\ 0.03 & 0.22 & 0.11 & -0.28 & 1.05 \\ -0.04 & -0.08 & 0.02 & 0.58 & -0.88 \\ -0.06 & 0.04 & 0.04 & -0.16 & 1.07 \\ 0.10 & 0.07 & -0.08 & 0.19 & 0.15 \\ 0.03 & -0.15 & 0.03 & -0.23 & 0.23 \end{pmatrix}$$

Though A_{adj} is a not a square matrix, we can compute a mapping from high-level behaviors specified by the adjectives to simulation parameters by taking its pseudoinverse A^{+}_{adj}. In this way, we can predict the perceived change in behavior of an agent as we adjust the simulation parameters to achieve the desired behavior for each agent.

5.2. Mapping Parameters for the PEN Model

Rather than building a mapping for each of the six personality adjectives individually, we can use a similar procedure to build a mapping for the 3-factor PEN model. The adjectives from the user study can be mapped to the three PEN factors. We use the correspondence of adjective to PEN factors found in Pervin [Per03], summarized in Table 2.

Trait	Adjectives
Psychoticism	Aggressive, Impulsive
Extraversion	Assertive, Active
Neuroticism	Shy, Tense

Table 2: Excerpt from the mapping between adjectives and PEN factors given in [Per03] and used create A_{pen}.

Like the personality adjectives, we can determine a linear mapping for the PEN model, where:

$$\begin{pmatrix} Psychoticism \\ Extraversion \\ Neuroticism \end{pmatrix} = A_{pen} \begin{pmatrix} \frac{1}{13.5}(Neighbor\ Dist - 15) \\ \frac{1}{49.5}(Max.\ Neighbors - 10) \\ \frac{1}{14.5}(Planning\ Horiz. - 30) \\ \frac{1}{0.85}(Radius - 0.8) \\ \frac{1}{0.5}(Pref.\ Speed - 1.4) \end{pmatrix}$$

Based on a linear regression of the study data, A_{pen} was found to be

$$A_{pen} = \begin{pmatrix} 0.00 & 0.08 & 0.08 & -0.32 & 0.63 \\ -0.02 & 0.13 & 0.08 & -0.22 & 1.06 \\ 0.03 & -0.01 & -0.03 & 0.39 & -0.37 \end{pmatrix}$$

Again, this mapping lets us predict expected PEN values from any given simulation parameters.

5.3. Factor Analysis

Analyzing the various features of the A_{pen} matrix, we can observe the strong correlations between the different PEN factors. Psychoticism and Extraversion show a strong positive correlation with each other and both are negatively correlated with Neuroticism. Likewise in the A_{adj} matrix we see a correlation between several factors such as Aggressive and Assertive, which have a Pearson r-squared value of 0.45 in the data collected from our user study. These correlations suggest that a few underlying latent factors might be able to explain the perceived behaviors in the simulations.

Similar to the original OCEAN studies [CM92], we can find these few primary factors using factor analysis methods. By performing a Principal Component Analysis (PCA) on A_{adj}, we found two factors that can explain over 95% of the linear relationship between the simulation parameters and behaviors. This result suggests that low-dimension models such as the PEN model offers sufficiently rich dimensions to characterize personality traits in crowd navigation. The two Principal Component found through factor analysis on our user study data are:

$$\begin{pmatrix} PC1 \\ PC2 \end{pmatrix} = \begin{pmatrix} 0 & -0.04 & 0.04 & 0.75 & 0.66 \\ 0.14 & 0.5 & 0.8 & 0.15 & -0.19 \end{pmatrix}$$

We observe that PC1 primarily has the effect of increasing an agent's radius and speed. PC2 primarily makes agents plan further ahead and consider more agents for local avoidance. For these reasons, we suggestively refer to PC1 as "Extraversion" and PC2 as "Carefulness". Figure 2 shows which personality adjective is most affected, as PC1 and PC2 are jointly varied. The chart indicates that as "Extraverted" agents become more "Careful", they move from appearing Aggressive to Assertive to Active. Likewise, agents who are

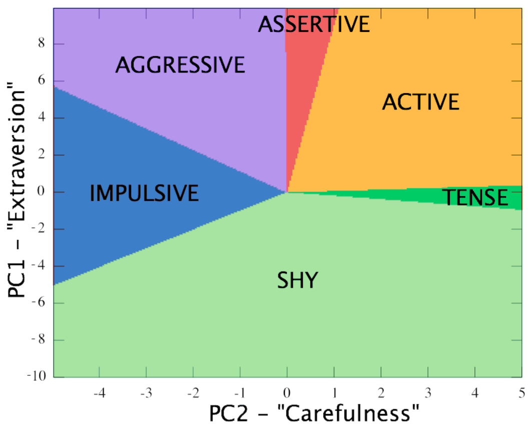
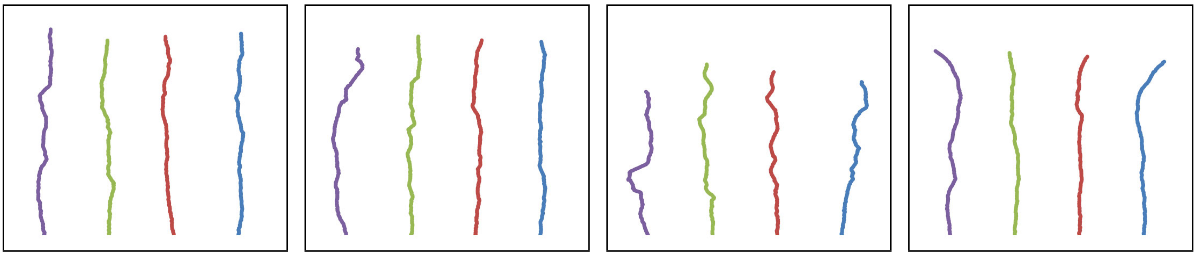


Figure 2: This chart shows which behavior adjective has the largest change as the two principal components are varied.



(a) Aggressive (b) Impulsive (c) Shy (d) Tense

Figure 3: **Pass-through Scenario.** Paths of agents trying to push through a crowd in various simulations. The agent's parameters correspond to various personalities. All paths are displayed for an equal length of time. (a) Aggressive agents make the most progress with the straightest paths. (b) Impulsive agents move quickly but take less direct routes. (c) Shy agents are diverted more easily in attempts to avoid others (d) Tense agents take less jittery paths, but are easily deflected by the motion of others.

not "Extraverted" appear Shy, as long as they are "Careful" enough to avoid looking impulsive. Furthermore, agents who are too "Careful" appear to be Tense. We believe these two principal components cover the personality space in an interesting and intuitive fashion.

6. Simulation Results and Validation Study

Using the above mappings of A_{pen} and A_{adj}, we are able to perform crowd simulations in which certain agents appear to exhibit high levels of the different PEN traits, or appear to display high levels of one or more of the studied personality adjectives. In this section, we show the resulting trajectory of agents displaying various personalities in several different scenarios. We also present the results of a second user study, designed to validate the ability of our approach to generate agents with a given personality using the derived mappings from the user study (see Sec. 5).

For the purpose of this validation study, we clamped the agents' preferred velocities to the range [1.35,1.55] m/s. We chose this range for two reasons. First, this is the range of normal walking velocities observed in crowds [Sti00], which focuses our study on normal behaviors rather than extreme ones. Second, inspecting the columns of A_{adj} and A_{pen} suggests that perceived personalities are most dependent on preferred velocities, by limiting this range we can better highlight the effect of other simulation parameters. Given these constraints on preferred velocity, we then used our mappings to find simulation parameters for various adjectives and traits covered in the user study. Again, to limit unnatural or extreme behaviors, we chose parameters that change behavior by only one "unit" (on the 1-9 scale described in Sec 4.1). The parameters used are summarized in Table 3.

6.1. Simulation Results

We now show the results of agents with various personalities in different scenarios. Figure 3 shows paths taken by the highlighted agents in the Pass-Through scenario. The

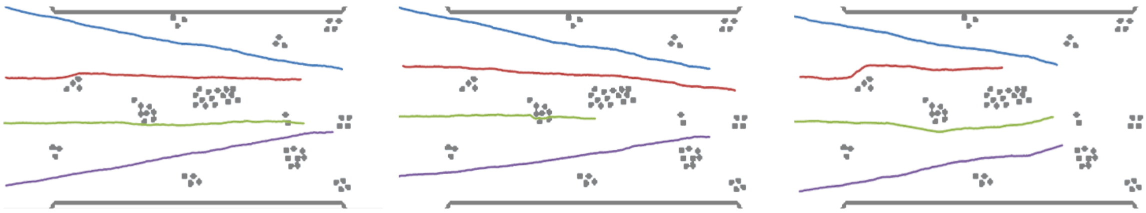
Trait	Neigh. Dist	Num. Neigh.	Plan. Horiz.	Radius	Speed
Psych.	15	40	38	0.4	1.55
Extrav.	15	23	32	0.4	1.55
Neuro.	15	9	29	1.6	1.25
Aggres.	15	20	31	0.6	1.55
Assert.	15	23	32	0.5	1.55
Shy	15	7	30	1.1	1.25
Active	13	17	40	0.4	1.55
Tense	29	63	12	1.6	1.55
Impul.	30	2	90	0.4	1.55

Table 3: Simulation parameters for various personality traits.

Aggressive agents can be seen to be taking fairly direct paths. The Impulsive agents still move quickly, but tend to take less direct routes. Shy agents avoid others more often, so progress more slowly. Tense agents take the least jittery paths, but are deflected by the crowds more than aggressive agents.

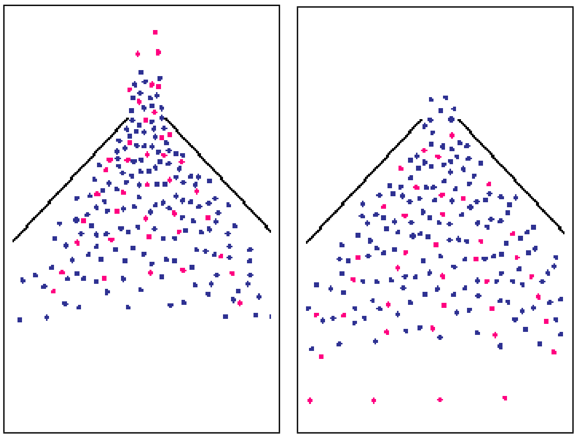
We can also choose agent behaviors based on the Eysnek 3-factor personality model by using A_{pen}. Figure 4 shows the Hallway scenario with agents that have a high level of "Psychoticism" (P-factor), agents with a high level of "Extraversion" (E-factor), and agents with a high level of "Neuroticism" (N-factor). The agents with a high level of Eysnek's P-factor take fast and direct paths coming close to other agents. The agents with a high level of Eynsek's E-factor also move quickly, but take more daring paths, sometimes attempting to weave through the other agents in the crowd. The agents with a high level of Eysnek's N-factor take slower less direct paths and move farther away to avoid the static gray agents.

In the Narrowing Passage scenario, agents also show a variety of behaviors for different personalities. Figure 5 shows the same time-step from two different simulations. In the left simulation, the light red agents are assigned a personality of



(a) High Psychoticism (P) (b) High Extraversion (E) (c) High Neuroticism (N)

Figure 4: **Hallway Scenario.** A comparison between (a) agents with high levels of "Psychoticism", (b) "Extraversion" and (c) "Neuroticism". Each of the four agents' paths is colored uniquely. The high P-factor agents repeatedly cut close to others taking the most direct paths. The high E-factor agents take faster and occasionally "daring" paths, the high N-factor agents take more indirect paths and keep their distance from others.



(a) Aggressive (b) Shy

Figure 5: **Narrowing Passage Scenario.** A comparison between dark-blue default agents and light-red Aggressive agents (a) and light-red Shy agents (b). The Aggressive agents exited more quickly, while several Shy agents stay back from the exit causing less congestion.

Aggressive. In the right simulation, the light red agents are Shy. At this point, a few seconds into the simulation, many more Aggressive agents have moved through the exit than the Shy agents. Furthermore, several of the Shy agents can be seen to be holding back away from the exit causing less congestion.

A comparison of the rate at which the agents of various personalities passed through the exit is shown in Fig. 6. Shy and Tense agents were the slowest to pass through the exit, as they moved less quickly and packed in less tightly than the Aggressive and Assertive agents who made it out fastest.

The evacuation results change when too many of the agents are acting aggressively. Figure 7 shows how the average speed of the Aggressive agents in the scenario varies as the percent of Aggressive agents increases. As the graph shows, our Aggressive agents exhibit the well known "faster-is-slower" behavior associated with panic in crowds [HFV00]. Once a critical threshold of too many aggressive agents is reached, the aggressive agents actually exit the room slower than a non-aggressive agents would.

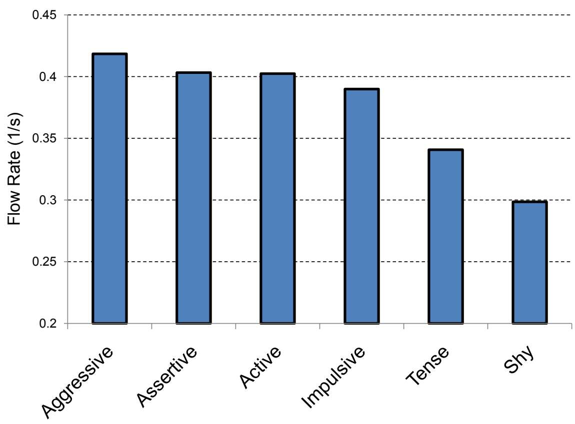


Figure 6: **Exit Rate.** Rate at which agents of various personalities exit in the Narrowing Passage scenario.

6.2. Heterogeneous Crowds

Using the mappings derived from experimental study, we can easily generate different simulations that map to different high-level personality specifications. We can use this capability to create interesting variations in complex, heterogeneous crowd simulations. Here, we chose an evacuation scene, where 215 agents simultaneously compete for space as they leave a room through the same exit. Using the personality-to-parameters mapping, our work can easily create a wide variety of specific behaviors during the evacuation, as shown in Fig. 8. We color code agents' shirts by their personalities, for example agents with red shirts are aggressive and those with brown shirts are shy. The agents behave as expected with aggressive ones exiting first, active agents

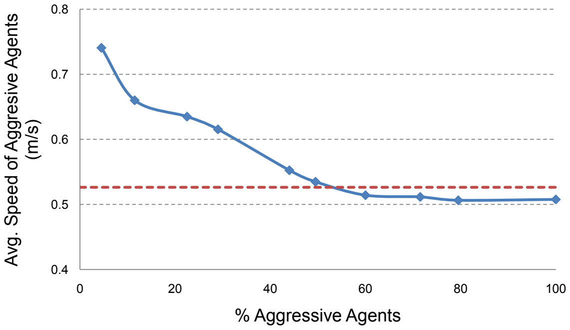


Figure 7: **Faster-is-slower behavior.** This graph shows the speed of Aggressive agents exiting in the Narrowing Passage scenario (solid blue line). As a larger percentage of agents become aggressive, their ability to exit quickly is reduced to the point where they exit more slowly than less Aggressive agents with the same preferred speed (dashed red line). This result is consistent with the well-known "faster-is-slower behavior" [HFV00].

(a) Initial Conditions

(b) Mid Simulation

Figure 8: **Evacuation Scenario.** 200 agents evacuating a building. Shy agents (brown shirts) hold back while Aggressive agents (red shirts) dart forward. The other personalities also display a variety of behaviors such as quick maneuvers, overtaking and pushing through.

darting around slow agents in front of them and shy agents hanging back. A rendering of this scenario can be seen in the supplementary video.

6.3. Timing Results

Because the behavior mapping can be computed as a preprocessing step, our method adds no overhead to the overall simulation runtime. Table 4 shows the execution time for simulating agents in several different scenarios, the timings were computed on a 3.2 GHz Intel i7 processor. In all cases, the simulation ran at interactive rates.

Scenario	Agents	Obstacles	Time (msec)
Hallway	70	2	0.4
Narrowing Passage	200	2	1.9
Pass Through	404	0	1.4
Evacuation	215	125	4.5

Table 4: Performance timings per frame.

6.4. Validation Study

To validate our personality mappings, we performed a follow-up user study where we asked questions targeted at evaluating how well our model performed at producing simulations with the expected behavior. The study was taken by 19 participants (39% female, average age 37±16), 72% of whom had participated in the original study. This follow-up study consisted of three sections. This validation study used entirely new videos to reduce participant bias. In the first two sections, a personality trait was selected at random, and a pair of videos were generated: one showing a simulation of that trait using the values in Table 3, and one chosen to contrast the selected trait. Participants were asked to choose which of the two videos better showed the personality trait in question. The first section of the study evaluated the six personality adjectives (aggressive, assertive, shy, active, impulse, and tense). The second section evaluated the PEN traits after a brief explanation of each of their meanings to the participants. These sections were intended to measure how well a given personality attribute could be reproduced by our method.

In a third section, participants were shown a video where agents were chosen to display a high level of one adjective while maintaining no increase in another one (e.g. Active, but not Aggressive). Participants were then asked to choose which of the two adjectives better described the video. This task was intentionally chosen to be challenging, as it explores to what degree our mapping can model each adjective independent of the others. Some combinations (such as "Impulsive, but not Active") were not used in the study as the mapping suggested the adjectives were too strongly correlated to be independently varied within the domain of allowed velocities.

The results of the three sections are summarized in Table 5. For all three sections the model predicted the perceived personalities correctly at a statistically significant rate (p<.05). For all results, the statistical p-values were calculated using a a one-tailed test with an exact binomial calculation of probability. The low p-values provide strong evidence these results are due capturing a mapping of traits to parameters and not just statistical noise.

Sec.	Description	Accuracy	p-value
1	Chose video from adjective	87%	1e-7
2	Chose video from PEN trait	96%	1e-11
3	Chose adjective from video	72%	1e-7

Table 5: Performance on validation study

We can further break down the results of the study by analyzing the results for each adjective separately. In the first section, users perform with a 100% success rate at identifying which videos corresponded to Assertive, Shy, and Active. Aggressive and Impulsive were also identified at a high, statistically significant, rate of 80% and 85% respectively.

When combined with the more difficult task of separating two simultaneous personalities constraints (such as Shy, but not Impulsive) the overall success rate drops. However, participants were still able to correctly identify most adjectives at a statistically significant rate. Figure 9 shows a graph of the breakdown of the overall success rate for all questions involving each of the six adjectives. An asterisk next to the adjective indicates a statistically significant result (p<.05).

This data suggests the traits of "Aggressive" and "Impulsive" were hard to vary independently without affecting the perceived levels of other traits, such as Assertiveness and Shyness. This result is consistent with the high correlations seen between these adjectives in the initial user study.

Our method also performed well at generating the specific PEN personality traits. Figure 10 shows the success rate for questions involving the PEN values. The high success rate indicates participants were easily able to apply the high level concepts behind the PEN model to evaluating various behaviors in the simulations.

7. Limitations and Conclusions

7.1. Limitations

Our approach has some limitations. Our current implementation only explores variation allowed by the RVO2 library, we

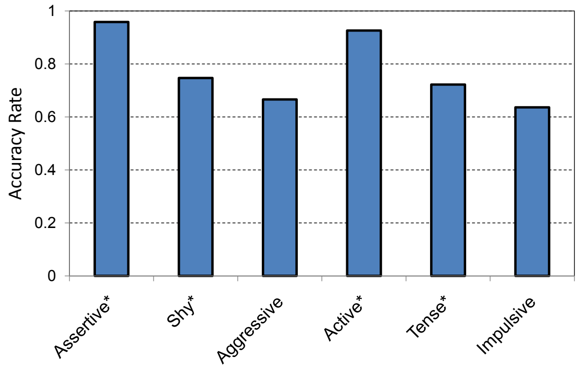


Figure 9: **Adjective Success Rate.** Rate at which user responses matched the indented adjective for all questions involving the six personality adjectives studied. *indicates statistically significant (p<.05).

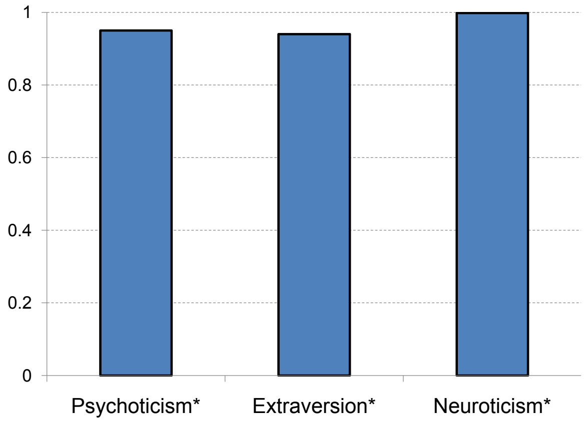


Figure 10: **PEN Success Rate.** Rate at which user responses matched the intended personality trait for questions involving the PEN traits. *indicates statistical significant (p<.05).

would like to use this approach with other collision avoidance and simulation methods to see if more drastic variation in behavior is possible. Moreover, we focused mainly on local behaviors and interactions between agents. However, the longer-term decision-making process includes global navigation and path-planning which are not modeled adequately by the simulation parameters used in this work. Given the large difference in approach between local and global planning, it is possible other personality models such as the Myers-Briggs Type Indicator [MMQH99] might be more appropriate to capture such behaviors.

Additionally, we compute a generic mapping between simulation parameters and personality traits which is intended to hold across a wide variety of scenarios. By focusing on more specific scenarios, we may be able to find more precise mappings for those particular scenarios. Finally, it may be useful to take into account other aspects of cognitive modeling to derive mappings such as mapping the effect of internal weightings in decision networks.

7.2. Conclusion

We have presented a perceptually driven formulation to model the personality of different agents in a crowd simulations. Our approach can successfully generate crowd simulations in which agents appear to depict specific, user-specified personalities, such as assertive, shy, and impulsive. Furthermore, we have shown that our approach can successfully generate simulations where agents appear to have various levels of the established PEN personality traits. Finally, we proposed two novel factors (PC1 and PC2) which are highly orthogonal, and are able to capture more than 95% of the linear correlation captured in our experimental data. To the best of our knowledge, this is the first factor-model specifically targeted at analyzing various perceived personalities in crowd simulations.

In the future, we would like to evaluate our approach with other crowd simulation and collision avoidance techniques, including cellular automata and social-force models. We would further like to adopt the same data-driven techniques to build mappings from simulation parameters to other personality trait theories, such as the OCEAN model. We would also like to investigate the extent that our proposed two-factor model is appropriate for human behaviors in real-world crowds (perhaps based on video footage). Additionally, we have focused only on computing the trajectory of the agents. Other aspects of virtual agents such as posture, facial expression, and walking style can provide clues to an agent's personality and we would like to take them into account in our future evaluations.

Acknowledgments This work was supported in part by ARO Contract W911NF-10-1-0506, NSF awards 0917040, 0904990 and 1000579, and Intel.

References

[CE72] CATTELL R., EBER H.: The 16 personality factor questionnaire. *Institute for Personality and Ability Testing* (1972).

[CM92] COSTA P., MCCRAE R.: *Revised NEO Personality Inventory (NEO PI-R) and Neo Five-Factor Inventory (NEO-FFI)*. Psychological Assessment Resources, 1992.

[DAPB08] DURUPINAR F., ALLBECK J., PELECHANO N., BADLER N.: Creating crowd variation with the OCEAN personality model. In *Autonomous agents and multiagent systems* (2008).

[DK95] DRAYCOTT S. G., KLINE P.: The big three or the big five-the epq-r vs the neo-pi: a research note, replication and elaboration. *Personality and Individual Differences* (1995).

[DPA*11] DURUPINAR F., PELECHANO N., ALLBECK J., GUDUKBAY U., BADLER N.: How the ocean personality model affects the perception of crowds. *IEEE Computer Graphics and Applications 31*, 3 (2011), 22–31.

[EE77] EYSENCK S., EYSENCK H.: The place of impulsiveness in a dimensional system of personality description. *The British journal of social and clinical psychology 16*, 1 (1977), 57.

[EE85] EYSENCK H., EYSENCK M.: *Personality and individual differences: A natural science approach*. Plenum Press New York, 1985.

[FTT99] FUNGE J., TU X., TERZOPOULOS D.: Cognitive modeling: knowledge, reasoning and planning for intelligent characters. In *SIGGRAPH* (1999), ACM Press, pp. 29–38.

[GCC*10] GUY S. J., CHHUGANI J., CURTIS S., LIN M. C., DUBEY P., MANOCHA D.: Pledestrians: A least-effort approach to crowd simulation. In *Symposium on Computer Animation* (2010), ACM.

[HFV00] HELBING D., FARKAS I., VICSEK T.: Simulating dynamical features of escape panic. *Nature 407* (2000).

[HMS95] HARVEY R. J., MURRY W. D., STAMOULIS D. T.: Unresolved issues in the dimensionality of the myers-briggs type indicator. *Educational and Psych. Measurement* (1995).

[JCP*10] JU E., CHOI M. G., PARK M., LEE J., LEE K. H., TAKAHASHI S.: Morphable crowds. *ACM Trans. Graph. 29*, 6 (2010), 140.

[LB97] LE BON G.: *The crowd: A study of the popular mind*. Macmillian, 1897.

[LCHL07] LEE K. H., CHOI M. G., HONG Q., LEE J.: Group behavior from video: a data-driven approach to crowd simulation. In *Symposium on Computer Animation* (2007), pp. 109–118.

[MLH*09] MCDONNELL R., LARKIN M., HERNÁNDEZ B., RUDOMIN I., O'SULLIVAN C.: Eye-catching crowds: saliency based selective variation. *ACM Transactions on Graphics (TOG)* (2009).

[MMON10] MCHUGH J., MCDONNELL R., O'SULLIVAN C., NEWELL F.: Perceiving emotion in crowds: the role of dynamic body postures on the perception of emotion in crowded scenes. *Experimental brain research* (2010).

[MMQH99] MYERS I., MCCAULLEY M., QUENK N., HAMMER A.: *MBTI manual*. Consulting Psychologists Press, 1999.

[PAB07] PELECHANO N., ALLBECK J., BADLER N.: Controlling individual agents in high-density crowd simulation. In *Symposium on Computer Animation* (2007).

[Per03] PERVIN L.: *The Science of Personality*. Oxford University Press, Oxford, 2003.

[Rey87] REYNOLDS C.: Flocks, herds and schools: A distributed behavioral model. In *SIGGRAPH* (1987).

[Rey99] REYNOLDS C. W.: Steering behaviors for autonomous characters. *Game Developers Conference* (1999).

[RWC00] REISE S. P., WALLER N. G., COMREY A. L.: Factor analysis and scale revision. *Pshycological Assesment* (2000).

[SS11] SALVIT J., SKLAR E.: Toward a Myers-Briggs Type Indicator Model of Agent Behavior in Multiagent Teams. *Multi-Agent-Based Simulation XI* (2011), 28–43.

[ST05] SHAO W., TERZOPOULOS D.: Autonomous pedestrians. In *Symposium on Computer animation* (2005), ACM, pp. 19–28.

[Sti00] STILL G.: Crowd dynamics, phd thesis. *Coventry, UK: Warwick University* (2000).

[TK87] TURNER R. H., KILLIAN L. M.: *Collective Behavior*. Prentice Hall, 1987.

[vdBGLM09] VAN DEN BERG J., GUY S. J., LIN M., MANOCHA D.: Reciprocal n-body collision avoidance. In *Inter. Symp. on Robotics Research* (2009).

[YT07] YU Q., TERZOPOULOS D.: A decision network framework for the behavioral animation of virtual humans. In *Symposium on Computer animation* (2007), pp. 119–128.