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The Impact of the OCEAN Personality Model on the Perception of Crowds

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ABSTRACT

Most current crowd simulators animate homogeneous crowds, but include underlying parameters that can be tuned to create variations within the crowd. These parameters, however, are specific to the crowd models and may be difficult for an animator or naïve user to use. We propose mapping these parameters to personality traits. In this paper, we extend the HiDAC (High-Density Autonomous Crowds) system by providing each agent with a personality model. We use the OCEAN personality model as a basis for agent psychology. To each personality trait we associate nominal behaviors; thus, specifying personality for an agent leads to an automation of the low-level parameter tuning process. We describe a plausible mapping from personality traits to the existing behavior types and analyze the overall emergent crowd behaviors. Finally, we validate our mapping by user studies that assess the perception of the traits in the animations illustrating such behaviors.

Keywords

Crowd simulation, OCEAN personality model, autonomous agents.

1. INTRODUCTION

Simulating the behavior of animated virtual crowds has been a challenging task for the computer graphics community. The semantics underlying the motion of real crowds should be studied extensively in order to achieve realistic behavior in virtual ones. Psychology studies human nature so that salient behavior characteristics may be captured. There has been extensive research on incorporating psychological models into the simulation of autonomous agents. In the present study, however, we are not interested in the personality of an individual *per se* but the incorporation of a personality model into large groups of people. We thus examine, by changing the parameters, how subgroups of people with different personality traits interact with each other, and accordingly, how the global crowd behavior is influenced. It is up to the user to decide the percentage and the distribution of the specific personality traits in the crowd.

Personality is a pattern of behavioral, temperamental, emotional, and mental traits for an individual. There is still considerable controversy in personality research over how many personality traits there are, but the Five Factor or OCEAN model is popular and it is the one we have chosen for this study [1]. The five factors, which are orthogonal dimensions of the personality space, are *openness*, *conscientiousness*, *extroversion*, *agreeableness* and *neuroticism*. Openness describes a dimension of personality that portrays the imaginative and creative aspect of human character. Conscientiousness determines how much an individual is organized and careful. Extroversion is related to how outgoing and sociable a person is. Agreeableness is friendliness, generosity and the tendency to get along with other people. Finally, neuroticism refers to emotional instability and the tendency to experience negative emotions. Each factor is bipolar and composed of several traits, which are essentially the adjectives that are used to describe people [2]. We have mapped these trait terms to the set of behaviors in an existing crowd simulation system, HiDAC (High-Density Autonomous Crowds) [3]. In order to verify the plausibility of our mapping we have conducted tests that evaluate users' perception of the personality traits in the generated animations.

HiDAC models individual differences by assigning each individual different psychological traits, such as impatience, panic, and leadership behaviors, and physiological traits, such as energy level, speed, etc. The user normally sets these parameters to model the non-uniformity and diversity of the crowd. In this extended work, we free the user of the tedious task of low-level parameter tuning, and combine all these behaviors in distinct personality factors.

2. SYSTEM

We combine a *standard* personality model with a high-density crowd simulation to create plausible variations in the crowd and permit a novice user to dictate these variations [4].

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2.1 HiDAC

HiDAC is a high density crowd simulation system, which addresses the simulation of local behaviors and global way-finding of crowds in a dynamically changing environment. The behaviors of autonomous agents in HIDAC are governed by the combination of geometrical and psychological rules. Psychological attributes include impatience, panic, and leadership behaviors. Physiological attributes are determined by traits, such as locomotion, energy levels, maximum speed. Agents are provided with skills, such as navigation in complex environments, communication, learning, and certain kinds of decision-making. Furthermore, they have perception so that they can react to obstacles, other agents, and dynamic changes in the environment.

In order to achieve realistic behavior, collisions are handled both by avoidance and response forces. Over long distances, collision avoidance is applied so that agents can steer around obstacles. Collision response is utilized over shorter distances to prevent agents from overlapping with each other and with the environment.

In addition to the usual crowd behavior, agents might show pushing behavior or can wait for other agents to pass first depending on their politeness and patience. Pushing behavior arises from varying the personal space threshold of each individual. Impatient agents do not respect others' personal space and they appear to push their way through the crowd. Relaxed agents temporarily stop when another agent moves into their path, while impatient agents do not respond to this feedback and tend to 'push'.

2.2 Integrating the OCEAN Model into HiDAC

The crowd is composed of subgroups with different personalities. Variations in the characteristics of the subgroups influence the emergent crowd behavior. The user can add any number of groups with shared personality traits and can edit these characteristics during the course of the animation.

An agent's personality π is a five-dimensional vector, where each dimension is represented by a personality factor, Ψ_i. The distribution of the personality factors in a group of individuals is modeled by a Gaussian distribution function N with mean μ_i and standard deviation σ_i:

$$\pi = \langle\Psi_O, \Psi_C, \Psi_E, \Psi_A, \Psi_N\rangle,$$

$$\Psi_i = N(\mu_i, \sigma_i^2), \text{ for } i \in \{O, C, E, A, N\}$$

where $\mu \in [0, 1], \sigma \in [-0.1, 0.1]$

The overall behavior β for an individual is a combination of different behaviors. Each behavior is a function of personality as:

$$\beta = (\beta_1, \beta_2, ..., \beta_n)$$

$$\beta_j = f(\pi), \text{ for } j = 1, \ldots, n$$

Since each factor is bipolar, Ψ can take both positive and negative values. For instance, a value of 9 for extroversion means that the individual has extroverted character; whereas a value of -9 means that the individual is highly introverted.

2.3 Personality-to-Behavior Mapping

The agents' personality factors (adjectives) are mapped into low-level parameters and the built-in behaviors in the HiDAC model, as shown in Table 1. A positive factor takes values in the range [0.5, 1], whereas a negative factor takes values in the range [0, 0.5). A factor given without any sign indicates that both poles apply to that behavior. For instance E+ for a behavior means that only extroversion is related to that behavior; introversion is not applicable. As indicated in Table 1, a behavior can be defined by more than one personality dimension. The more adjectives of a certain factor defined for a behavior, the stronger is the impact of that factor on that behavior. Thus, we assign a weight to the factor's impact on a specific behavior. For instance, ω_{EL} is the weight of extroversion on leadership and it takes a value in the range [0, 1]. The sum of the weights for a specific type of behavior is 1. Now, we can see how the mapping from a personality dimension to a specific type of behavior is performed.

Table 1. Low-level parameters vs. trait-descriptive adjectives

Leadership	Assertive, social, unsocial, calm, fearful	E, N
Trained/not trained	Informed, ignorant	O
Communication	Social, unsocial	E
Panic	Oversensitive, fearful, calm, orderly, predictable	N, C+
Impatience	Rude, assertive, patient, stubborn, tolerant, orderly	E+, C, A
Pushing	Rude, kind, harsh, assertive, shy	A, E
Right preference	Cooperative, predictable, negative, contrary, changeable	A, C
Avoidance/personal space	Social, distant	E
Waiting radius	Tolerant, patient, negative	A
Waiting timer	Kind, patient, negative	A
Exploring environment	Curious, narrow	O
Walking speed	Energetic, lethargic, vigorless	E
Gesturing	Social, unsocial, shy, energetic, lethargic	E

We have defined the behavior parameters for an agent *i* as follows:

Leadership*:* Leaders tend to have more confidence in themselves and they help others find their way through a building. They remain calm under emergency situations. Each agent has a leadership percentage determined by its extroversion, and stability. The leadership behavior is computed by:

$$\beta_i^{Leadership} = \omega_{EL}\psi_i^E + \omega_{NL}(1-\psi_i^N)$$

where $\beta_i^{Leadership} \propto$ E, $\beta_i^{Leadership} \propto^{-1}$ N, and $\beta_i^{Leadership} \in [0, 1]$.

Trained: Trained agents have complete knowledge about the environment. Since being trained requires curiosity and trained people are informed, this parameter is associated with openness.

Being trained is a Boolean parameter, and therefore, it is represented by a probability function. As openness increases, the probability that the agent is trained increases as:

$$P_i(Trained) = \psi_i^O$$

$$\beta_i^{Trained} = \begin{cases} 1 & if \;\; P_i(Trained) \geq 0.5 \\ 0 & otherwise \end{cases}$$

where $P_i(Trained) \propto$ O and $\beta_i^{Trained} \in \{0, 1\}$.

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Communication: This parameter determines whether the agents communicate with each other to give information about the explored areas during a building evacuation. Similar to being trained, communication depends on the probability of agent behavior. As extroversion increases, the probability that the agent communicates increases as:

$$P_i(Communication) = \psi_i^E$$

$$\beta_i^{Communication} = \begin{cases} 1 & if \;\; P_i(Communication) \geq 0.5 \\ 0 & otherwise \end{cases}$$

where $P_i(Communication) \propto$ E and $\beta_i^{Communication} \in \{0, 1\}$.

Panic: Under emergency situations, agents show panic behavior depending on their stability and conscientiousness traits. When they panic, their walking speed increases and they do not respect waiting rules.

$$\beta_i^{Panic} = \omega_{NP}\psi_i^N + \omega_{CP} f(\psi_i^C)$$

$$f(\psi_i^C) = \begin{cases} -2\psi_i^C + 2 & if \;\; \psi_i^C \geq 0 \\ 0 & otherwise \end{cases}$$

where $\beta_i^{Panic} \propto$ N, $\beta_i^{Panic} \propto^{-1}$ C+ and $\beta_i^{Panic} \in [0, 1]$.

Impatience: The impatience parameter is implemented by dynamically modifying the route selection based on environmental changes. It depends on the politeness and assertiveness of an agent.

$$\beta_i^{Impatience} = \omega_{EI} f(\psi_i^E) + \omega_{AI}(1-\psi_i^A) + \omega_{CI}(1-\psi_i^C)$$

$$f(\psi_i^E) = \begin{cases} 2\psi_i^E - 1 & if \;\; \psi_i^E \geq 0 \\ 0 & otherwise \end{cases}$$

where $\beta_i^{Impatience} \propto$ E+, $\beta_i^{Impatience} \propto^{-1}$ A, C , and $\beta_i^{Impatience} \in [0, 1]$.

Pushing: HiDAC can realistically simulate an individual's respect for others: an agent can try to force its way through a crowd by pushing others, exhibit more respectful behavior when desired, make decisions about letting others walk first, and queuing when necessary. Disagreeable agents tend to push others more as they are harsh and impolite. Similarly, extroverted agents show pushing behavior as they tend to be assertive.

$$P_i(Pushing) = \omega_{EP}\psi_i^E + \omega_{AP}(1-\psi_i^A)$$

$$\beta_i^{Pushing} = \begin{cases} 1 & if \;\; P_i(Pushing) \geq 0.5 \\ 0 & otherwise \end{cases}$$

where $P_i(Pushing) \propto$ E, $P_i(Pushing) \propto^{-1}$ A and $\beta_i^{Pushing} \in \{0, 1\}$.

Right preference: When the crowd is dispersed, individuals tend to look for avoidance from far away and they prefer to move towards the right hand side of the obstacle they are about to face. This behavior shows the individual's level of conformity to the rules. The right preference behavior is a probability function. If an agent is disagreeable or non-conscientious, then that agent can make right or left preference with equal probability. On the other hand, an agent prefers the right side by increasing probability proportional to its agreeableness and conscientiousness values if these are positive.

$$P(Right) = \begin{cases} 0.5 & if \;\; \psi_i^A < 0 \;\; or \;\; \psi_i^C < 0 \\ \omega_{AR}\psi_i^A + \omega_{CR}\psi_i^C & otherwise \end{cases}$$

$$\beta_i^{Right} = \begin{cases} 1 & if \;\; P_i(Right) \geq 0.5 \\ 0 & otherwise \end{cases}$$

where $P_i(Right) \propto$ A, C , and $\beta_i^{Right} \in \{0, 1\}$.

Personal space: Personal space determines the territory in which an individual feels comfortable. Agents try to preserve their personal space when they approach other agents and when other agents are approaching from behind. However, these two values are not the same. According to the research on Western cultures, the average personal space of an individual is found to be 0.7 meters in front and 0.4 meters behind [5]. The personal space of an agent *i* with respect to another agent *j* is thus:

$$\beta_{i,j}^{PersonalSpace} = \begin{cases} 0.8 * f(i,j) & if \;\; \psi_i^E \in [0 \;\; \frac{1}{3}) \\ 0.7 * f(i,j) & if \;\; \psi_i^E \in [\frac{1}{3} \;\; \frac{2}{3}] \\ 0.5 * f(i,j) & if \;\; \psi_i^E \in (\frac{2}{3} \;\; 1] \end{cases}$$

$$f(i,j) = \begin{cases} 1 & if \;\; i \; is \; behind \;\; j \\ 0.4/0.7 & otherwise \end{cases}$$

where $\beta_{i,j}^{PersonalSpace} \propto^{-1}$ E and $\beta_{i,j}^{PersonalSpace} \in \{0.5, 0.7, 0.8\}$.

Waiting radius: In an organized situation, individuals tend to wait for space available before moving. This waiting space is called the waiting radius and it depends on the kindness and consideration of an individual, i.e., the agreeableness dimension.

$$\beta_i^{WaitingRadius} = \begin{cases} 0.25 & if \;\; \psi_i^A \in [0 \;\; \frac{1}{3}) \\ 0.45 & if \;\; \psi_i^A \in [\frac{1}{3} \;\; \frac{2}{3}] \\ 0.65 & if \;\; \psi_i^A \in (\frac{2}{3} \;\; 1] \end{cases}$$

where $\beta_i^{WaitingRadius} \propto$ A and $\beta_i^{WaitingRadius} \in \{0.25, 0.45, 0.65\}$.

Waiting timer: If two individuals are heading to the same direction, they wait for the other to move first. The time they wait, i.e., the duration that they show patience towards the other, depends on their agreeableness.

$$\beta_i^{WaitingTimer} = \begin{cases} 1 & if \;\; \psi_i^A \in [0 \;\; \frac{1}{3}) \\ 5 & if \;\; \psi_i^A \in [\frac{1}{3} \;\; \frac{2}{3}] \\ 50 & if \;\; \psi_i^A \in (\frac{2}{3} \;\; 1] \end{cases}$$

where $\beta_i^{WaitingTimer} \propto$ A and $\beta_i^{WaitingTimer} \in \{1, 5, 50\}$.

Exploring the environment: Individuals are assigned specific behaviors to perform. The number of actions they complete depends on their curiosity. Open people are more likely to explore different experiences, and hence, perform more actions. The openness factor determines the time an individual spends on exploring the environment. Thus, the number of actions that an individual completes increases by the degree of openness.

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$$\beta_i^{Exploring} = 10\psi_i^O$$

where $\beta_i^{Exploring} \propto$ O and $\beta_i^{Exploring} \in [0, 10]$.

Walking speed: The maximum walking speed is determined by an individual's energy level. As extroverts tend to be more energetic while introverts are more lethargic, this parameter is controlled by the extroversion trait.

$$\beta_i^{WalkingSpeed} = \psi_i^E + 1$$

where $\beta_i^{WalkingSpe\ ed} \propto$ E and $\beta_i^{WalkingSpe\ ed} \in [1, 2]$.

Gesturing: The amount of gestures used during a conversation is a sign of how sociable a person is. Outgoing people use more gestures than shy people, which is an indication of extroversion.

$$\beta_i^{Gesturing} = 10\psi_i^E$$

where $\beta_i^{Gesturing} \propto$ E and $\beta_i^{Gesturing} \in [0, 10]$.

3. EVALUATION

In order to evaluate if the suggested mappings are correctly perceived, we conducted user studies. We created several animations to see how global crowd behavior is affected by modifying the personality parameters of subgroups.

3.1 Design of the Experiment

We created 15 videos presenting the emergent behaviors of people in various scenarios where the crowds' behavior is driven by the settings assigned through the OCEAN model. The scenarios range from evacuation drills to cocktail parties or museum galleries.

The mapping from HiDAC parameters to OCEAN factors is done through trait-descriptive adjectives. We find the correspondence between our mapping and the users' perception of these trait terms in the videos in order to validate our system. 70 subjects (21 female, 49 male, ages 18-30) participated in the experiment. We showed the videos to the participants through a projected display and asked them to fill out a questionnaire consisting of 123 questions-- about 8 questions per video. The videos were shown one by one; after each video, participants were given some time to answer the questions related to the video. The participants did not have any prior knowledge about the experiment. Questions assess how much a person agrees with statements such as "I think the people in this video are kind." or "I think the people with green suits are calm." We have used questions containing the adjectives that describe each of the OCEAN factors instead of asking directly about the OCEAN factors, since we consider that the general public, not being familiar with the OCEAN model could have difficulties answering questions such as "Do the people exhibit openness?" Although the participants are proficient in English, in order to prevent any misconceptions, definitions of the adjectives were attached to the questionnaires. Definitions were taken from the Merriam-Webster dictionary. The answers were selected from a scale between 0 and 10, increasing by 1, where 0 = *totally disagree*, 5 = *neither agree nor disagree*, 10 = *totally agree*. We omitted the antonyms from the list of adjectives for the sake of conciseness. Thus, the remaining adjectives were: *assertive, calm, changeable, contrary, cooperative, curious, distant, energetic, harsh, ignorant, kind, orderly, patient, predictable, rude, shy, social, stubborn, and tolerant*.

3.2 Sample Scenarios

The simulated scenarios help us observe how the suggested parameters affect the global behavior of a crowd. In the implemented settings, novel, emergent formations are realized and behavior timings are also affected. We explain a selection of scenarios that have been shown to the participants in our experiments.

A sample scenario testing the impact of openness takes place in a museum setting as one of the key factors determining openness is the belief in the importance of art. A screenshot from the sample animation can be seen in Figure 1. *Curiosity* and *ignorance* are the tested adjectives for this setting. There are three groups of people, with openness values 0, 0.5 and 1. Here, the number of tasks that each agent must perform is mapped to openness, where a task means looking at a painting. The least open agents (with blue hair) leave the museum first, followed by the agents with openness values of 0.5 (with black hair). The most open agents (with red hair) stay the longest. Participants are asked how they perceive each of these groups.

Another one of our videos assesses how extroverts and introverts are perceived according to their distribution around a point of attraction. Figure 2 shows a screenshot from our test video where the agents in blue suits are extroverted with $\mu = 0.9$ and $\sigma = 0.1$ and the agents in grey suits are introverted with $\mu = 0.1$ and $\sigma = 0.1$. The ratio of introverts to extroverts in a society is found to be 25 %, according to which we assigned the initial number of agents [6]. At the end of the animation, introverts are left out of the ring structure around the object of attraction. As extroverts are faster, they approach the attraction point in a shorter time. In addition, when there are other agents blocking their way, they tend to push them to reach their goal. The figure also shows the difference between the personal spaces of individuals with introverted and extroverted personality. Thus, being *social*, *distant*, *assertive*, *energetic,* and *shy* is questioned for this animation.

In order to test whether the personalities of people creating congestion are distinguished, we showed the participants two videos of same duration and asked them to compare the characteristics of the agents in each video. Each video consists of two groups of people moving through each other. The first video shows people with high agreeableness and conscientiousness values ($\mu = 0.9$ and $\sigma = 0.1$ for both traits), whereas the second video displays people with low agreeableness and conscientiousness values ($\mu = 0.1$ and $\sigma = 0.1$ for both traits). In the first video, groups manage to cross each other while in the second video congestion occurs after a fixed period of time. Such behaviors emerge as agreeable and conscientious individuals are more *patient*; they don't push each other and are always *predictable* as they prefer the right side to move on. Figure 3 shows how congestion occurs due to low conscientiousness and agreeableness values. People are stuck at the center, and they refuse to let other people move, thus they are also *stubborn*, *negative,* and not *cooperative*.

Figure 4 shows a screenshot from the animation demonstrating the effect of neuroticism, non-conscientiousness and disagreeableness on panic behavior. A total of 13 agents are simulated. Five of the agents have neuroticism values of $\mu = 0.9$ and $\sigma = 0.1$, conscientiousness values of $\mu = 0.1$ and $\sigma = 0.1$ and agreeableness values of $\mu = 0.1$ and $\sigma = 0.1$. The remaining agents, which are stable, have neuroticism values of $\mu = 0.1$ and $\sigma = 0.1$, conscientiousness values of $\mu = 0.9$ and

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σ = 0.1 and agreeableness values of μ = 0.9 and σ = 0.1. The agents in green suits are neurotic, less conscientious, and disagreeable. It can be seen in the figure that these agents tend to panic more, push other agents, force their way through the crowd, and rush to the door. These agents are not *predictable*, *cooperative*, *patient,* or *calm* but they are *rude*, *changeable*, *negative*, and *stubborn*.

Figure 1. Openness tested in a museum. The most open people (red-heads) stay the longest, whereas the least open people (blue-heads) leave the earliest.

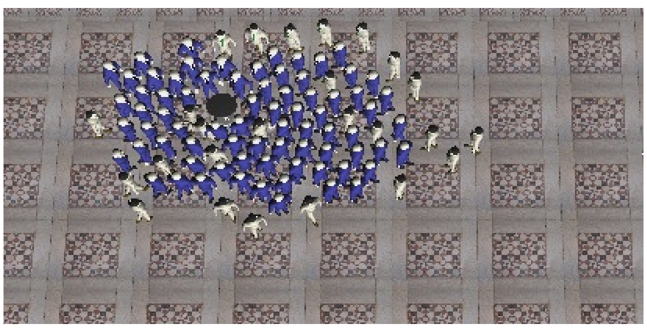

Figure 2. Ring formation where extroverts (blue suits) are inside and introverts are outside.

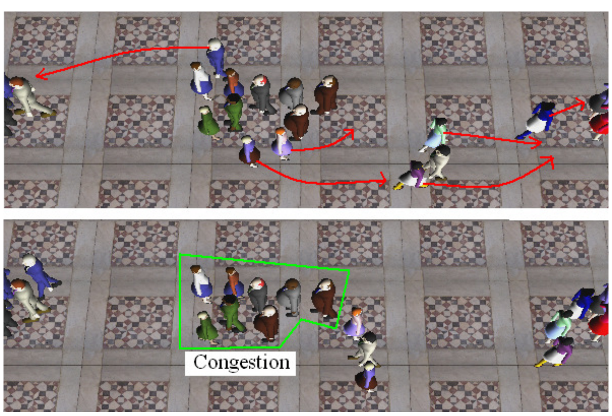

Figure 3. People with low conscientiousness and agreeableness value cause congestion.

Figure 4. Neurotic, non-conscientious and disagreeable agents (in green suits) show panic behavior.

3.3 Analysis

After collecting the participants' answers for all the videos, we first organized the data for the adjectives. Each adjective is classified by its question number, the actual simulation parameter and the participants' answers for the corresponding question. We calculated the Pearson correlation(*r*) between the simulation parameters and the average of the subjects' answers for each question. For instance the adjective *assertive* is asked 8 times, which indicates a sample size of 8. Thus, the correlation coefficient between the actual parameters and the means of the participants' answers is calculated between these 16 values, 8 for each group.

Furthermore, we grouped the relevant adjectives for each OCEAN factor in order to assess the perception of personality traits, which is the actual purpose of our experiment. The evaluation process is similar to the evaluation of adjectives; this time considering the questions for all the adjectives corresponding to an OCEAN factor. For instance, as openness is related to curiosity and ignorance, the answers for both of these adjectives is taken into account. Again, we averaged the subjects' answers for each question; then, we computed the correlation with the actual parameters and the mean throughout all the questions asking for *curious* and *ignorant*.

In order to estimate the probability of having obtained the correlation coefficients by chance, we computed the significance of the correlation coefficients. Significance is taken as 1-*p*, where *p* is the two-tailed probability that is calculated considering the sample size and the correlation value. Higher correlation and significance values suggest more accurate user perception.

3.4 Results and Discussion

The correlation coefficients and significance values for the adjectives are depicted in Figure 5 along with the data table showing the exact results. Correlation values are sorted in ascending order. The pink data points indicate the significance of the correlation coefficients. As can be seen from the data table, significance is low (<0.95) for the adjectives *changeable*, *orderly*, *ignorant*, *predictable*, *social* and *cooperative*. Low significance is caused by low correlation values for *changeable* and *orderly*. However, although the correlation coefficients are found to be high for *predictable, ignorant*, *social* and *cooperative,* low significance can be explained due to small sample size.

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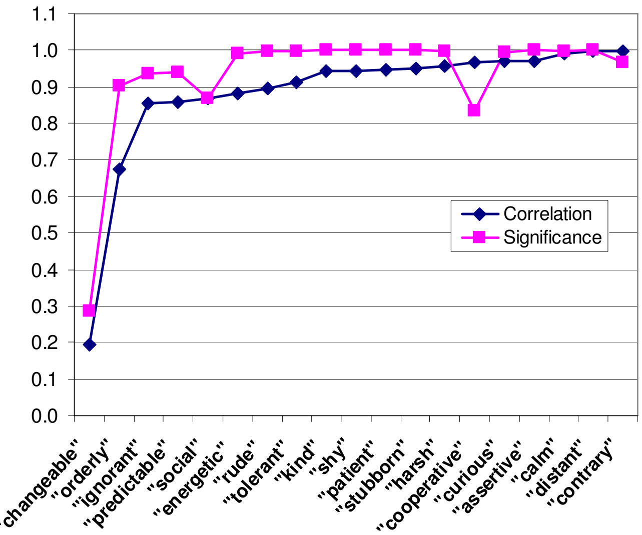
From the participants' comments, we figured out that the term *changeable* is especially confusing. In order to understand the reason, we can consider the aforementioned setting where two groups of agents cross each other. Non-conscientious agents are identified as *rude*, however; they are perceived as persistent in their rudeness, causing the participants to mark lower values for the question asking changeability. The same problem holds for *predictable* as well. One of the participants' comments suggest that if a person is in a rush, you can predict that person to push others. However, *predictable* has higher correlation despite these comments and although it implies an opposite meaning to *changeable*. This could be due to the relatively low significance for *predictable*. Non-conscientious agents that cause congestion are perceived as less *predictable*, which indicates that changing right preference and rude behavior decreases the perceived predictability.

Orderly is another weakly correlated adjective. Analyzing the results for each video separately, we found out that agents in evacuation drill scenarios are found to be *orderly*, although they show panic behavior. In these videos, even if the agents push each other and move fast, still some kind of order can be observed. This is due to the smooth flow of the crowd during building evacuation. The crowd shows collective synchrony, where individuality is lost. Although individuals are *impatient* and *rude*, the overall crowd behavior appears orderly. We assigned the same goal to the entire crowd in evacuation simulations, because our aim was to observe disorganization locally. For instance, *disorderly* agents look in a rush; they push other agents and they do not have solid preferences for direction choosing when crossing an agent in an evacuation scenario. Nevertheless, they still move to the same goal, which is the exit of the building. The crowd would appear more *disorderly* if everyone were running in different directions and changing directions for no apparent reason. Participants' answers suggest that they do not recognize orderliness where the goal is the same for the whole crowd. On the other hand, in another scenario, which shows the queuing behavior of a crowd in front of a water dispenser, participants can easily distinguish *orderly* versus *disorderly* individuals. *Orderly* agents wait at the end of the queue, whereas disorderly agents rush to the front. In this setting, although the main goal is the same for all the agents (drinking water), there are two distinguishable groups who act differently.

Figure 6 shows the correlation coefficients and their significance for the OCEAN parameters. These values are computed by taking into account all the relevant adjectives for each OCEAN factor. The correlations are sorted in ascending order. As can be seen from the figure, the significance of all the coefficients is high, with a probability of less than 0.5% of being by chance ($p < 0.005$). Significance is high because all the adjectives describing a personality factor are taken into account, achieving sufficiently large sample size.

Correlation coefficient for conscientiousness is comparatively low among all personality factors, showing that only about 44% of the traits are perceived correctly ($r^2 \approx 0.44$). In order to understand the underlying reason, we should consider the relevant adjectives, which are *orderly*, *predictable*, *rude* and *changeable*. Low correlation values for orderly and changeable reduce the overall correlation. If we consider only *rude* and *predictable* for conscientiousness, correlation increases by 18.6%. Thus, the results suggest that, people can observe the politeness aspect of personality in short-term crowd behavior settings more easily than the organizational aspects. This also explains why the perception of agreeableness is highly correlated with the actual parameters.

Figure 6 also shows that neuroticism is perceived the best. In this study, we have only considered the calmness aspect of neuroticism, which is tested in emergency settings and building evacuation scenarios.



(a)

Adjective	Correlation	Significance
"changeable"	0.199	0.288
"orderly"	0.674	0.903
"ignorant"	0.853	0.936
"predictable"	0.870	0.938
"social"	0.872	0.869
"energetic"	0.882	0.992
"rude"	0.897	0.997
"tolerant"	0.912	0.998
"kind"	0.943	1.000
"shy"	0.945	1.000
"patient"	0.948	1.000
"stubborn"	0.950	1.000
"harsh"	0.956	0.997
"cooperative"	0.967	0.834
"curious"	0.971	0.994
"assertive"	0.971	1.000
"calm"	0.988	0.999
"distant"	0.998	1.000
"contrary"	0.999	0.969

(b)

Figure 5. a) The graph depicts the correlation coefficients between actual parameters and subjects' answers for the descriptive adjectives (blue); significance values for the corresponding correlation coefficients (pink). b) Data table showing the correlation coefficients and significance values for descriptive adjectives.

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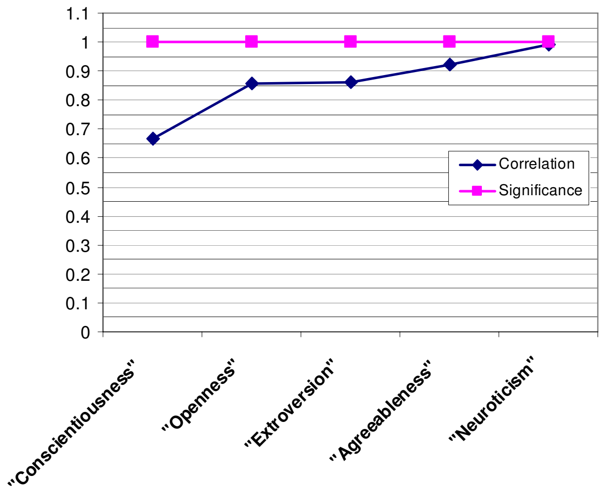

(a)

OCEAN	Correlation	Significance
"Conscientiousness"	0.665	1.000
"Openness"	0.859	0.999
"Extroversion"	0.860	1.000
"Agreeableness"	0.922	1.000
"Neuroticism"	0.990	0.999

(b)

Figure 6. a) The graph depicts the correlation coefficients between actual parameters and subjects' answers for the OCEAN factors (blue); two-tailed probability values for the corresponding correlation coefficients (pink). b) Data table showing the correlation coefficients and the significance values for the OCEAN factors.

4. CONCLUSION

In this study, we first explain how we have integrated the OCEAN personality model into an existing crowd simulation system, HiDAC. In doing so, we have collected adjectives identifying each personality factor and defined a direct mapping between the parameters in HiDAC and the personality traits. Our system enables the simulation of heterogeneous crowds, where each subgroup is composed of individuals with similar personality traits. The user can specify the distribution and the values of the five personality factors within the crowd and can examine how subgroups of people with common characteristics act under particular circumstances. Next, we have evaluated how people perceive the differences of personality through user studies. The results are promising as they indicate high correlation between our parameters and the participants' perception of these parameters. Low correlation for some of the adjectives is due to the ambiguity of the terms.

In contrast to the low-level parameter tuning process in previous work, we now let the user choose from higher-level concepts related to human psychology. Thus, the user is freed from understanding the underlying methodologies used in HiDAC. Our mapping also decreases the number of parameters that need to be set from 13 to 5. Using a personality model enabled us to move a user's focus to the character of the agents instead of behavioral parameters while providing us with a somewhat widely accepted structure for describing character. Certainly an interface could be created that allows a user to create subgroups based on a set of adjectives instead of personality traits, but this would increase the number of parameters that could be set. Also, psychology and autonomous agents research has linked personality models to other psychological, sociological, and cognitive models. Integrating a personality model into a crowd simulator will enable us to expand our simulator and explore the effects of these other models on crowd simulations.

There are certainly other psychological models that could have been used. Emotion models, for one, have been referenced in autonomous agent research. Future research may include adding emotion to the agents, but while personality is a pattern of behavior (extended through time), emotions change according to the agent state and the situation. Hence emotions should evolve through the simulation, not be set by the animator. Certainly, personality impacts emotional tendency, and hence, is a foundation to build on. Furthermore, because personality is a pattern of behavior, it may aid in observers of the characters developing a sense of knowing the character. They may become individuals instead of just another collection of anonymous computer characters.

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RELATED WORK ON CROWD SIMULATION (SIDE BAR)

Crowd simulation research has evolved from the creation of reactive techniques to the implementation of crowds consisting of more complex agents. Reactive methods are limited in the sense that they do not present any knowledge representation, learning ability, reasoning or individual differences in the agents. For instance, flocking systems are rule-based and they specify an animation as a distributed global motion with a local tendency [1]. On the other hand, systems with cognitive control involve reasoning and planning to accomplish long-term tasks, and they concentrate on achieving full autonomy. A notable work towards creating more intelligent agents is the artificial life simulation by Tu and Terzopoulos, where artificial fishes are equipped with synthetic vision and perception of the environment, as well as behavior and learning centers [2]. Musse and Thalmann propose a crowd behavior model that implements group inter-relationship and introduces a multiresolution collision method specific to crowd modeling [3]. A complex pedestrian animation system, which incorporates perceptual, behavioral and cognitive control components, is introduced as a combination of rule-based and cognitive models [4].

Several studies integrate emotion and personality models and roles into the simulation of autonomous agents, thus representing the individual differences through psychological states. Egges et al. study the simulation of the personality, emotions and mood for conversational virtual humans [5]. Li et al. propose a framework that also uses the OCEAN model of personality to define and formulate a pedagogical agent in a social learning environment [6]. However, these studies focus on single agents as opposed to crowds.

Not until recently have researchers started to study the perception of crowd variety. Peters et al. conduct a study evaluating the perception of pedestrians [7]. The work aims at determining the effect of the orientation and context rules for characters in static scenes on perceived plausibility. McDonnell et al. analyze the perceptual impact of the cloning of virtual characters for simulating large crowds [8].

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