Simulating Crowds with OCEAN Personality Traits

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ABSTRACT

Most of the techniques available nowadays for crowd simulation are focused on a specific situation, like people evacuation. Even if one consider heterogeneous crowds, very few of existing methodologies consider the psychological traits of individuals in order to determine the behavior of agents. Therefore, this work aims to add psychological factor as input for agents simulation, which is going to determine their group behavior and, therefore, how individuals move and evolve in virtual environments. The proposed input is the individuals OCEAN attributes which are used to parametrize BioCrowds, a crowd simulation method. We implemented two different parameterizations to map from OCEAN to crowd parameters and compare results. Obtained results with both methods indicate a positive correlation, once they presented a similar behavior in both tested scenarios. In addition, we show how heterogeneous behaviors we can generate in comparison to original BioCrowds.

CCS CONCEPTS

• **Computing methodologies → Simulation types and techniques**; **Interactive simulation**;

KEYWORDS

Crowd Simulation, OCEAN, Psychological models

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1 INTRODUCTION

The area of crowd simulation has been the studying focus for several researchers through many years because of its numerous and varied applications in diverse fields. It can be used to simulate large crowds of people [17], crowd's navigation [2, 15, 16], among others. Although the existence of a large number of techniques in literature for control and parametrizations of crowds [2, 12, 15], most of them are focused on a specific situation, where agents have skills to perceive the world, seek goals, avoid collisions, among others. One existing challenge is to simulate realistic individuals in crowds considering the diversity of behaviors caused by personality aspects. Very few of the existing methods for crowd simulation take into account such aspects [1, 3, 4]. These traits can be very useful in providing specific information about a crowd, which can be translated into different behaviors such as desired speed, group cohesion, eye gazing, among others.

The goal of this work is to extend the Biocrowds [2] model, allowing it to consider psychological traits for agents. Specifically, we are interested about implement and compare two different psychological theories in order to define the crowd behavior. The first one is proposed by Durupinar et al. [4] and aims to define individual behaviors based on OCEAN attributes in a empiric way based on psychological theories present in literature. Succinctly, OCEAN is a psychological traits model proposed by Goldberg [9], which tries to define the personality of an individual. More details about it will be presented on Section 3.2. The second one is based on Favareto et al. [7] and it is also empirical, but input data comes from real crowds in video sequences. Our main contribution is to propose a framework where different personality parametrization can be tested using a crowd simulator. It is important to emphasize that, although we chose BioCrowds [2] as our crowd simulation method, any other crowd simulator could be used.

2 RELATED WORK

Several ways to simulate crowds were developed in last years. The origin of crowd simulation goes back to Reynolds [15] and Helbing [12] works, which evolved in time thanks to many contributions. One of the state-of-art methods was developed by Van den Berg et al. [16], named Optimal Reciprocal Collision Avoidance (ORCA). It is a velocity-based method for collision avoidance between multiple agents and was developed originally for the robot industry. Using the ORCA method, He et al. [11] present an algorithm to simulate group behavior, similar with the observed behavior in real life. Such groups are dynamic, meaning each one can have any format and number of agents inside it.

Durupinar et al. [3] developed a simulation model based on psychological traits which aims to represent emotions and emotion contagion between agents in an effective way. To this end, the OCEAN (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism) psychological traits model, proposed by Goldberg [9] is used. In short, the agent's personality with its impression of other agents, as well the environment itself, will change this agent emotion, which can lead to a behavior change. In general, this change of behaviors is visually perceived by animation as gestures and poses.

3 PROPOSED MODEL

We propose to extend Biocrowds model [2] in order to include psychological aspects of people into the crowd. Figure 1 presents

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the overview of our model. As previously mentioned, we work with two methods presented in literature, as proposed by Durupinar et al. [4] and Favaretto et al. [7]. The input are the agents OCEAN (on the left of the figure). More specifically, the user defines the agents' OCEANs and also specifies the groups structure. In next sections, we firstly describe the groups parameters we intend to deal in our work (see Section 3.1). Then, Section 3.2 details the proposed method to simulate the individuals psychological traits.

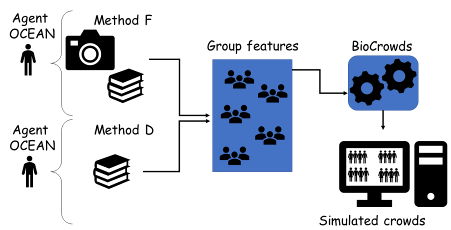

Figure 1: Overview of our method. The input is the agents OCEAN and two methods from literature have been considered in our work: Methods F and D that generate group features for the crowd to be simulated. Then BioCrowds simulates the agents motion based on the features.

3.1 Group Features Generation

Groups in real life are not the same: they can have different goals to achieve, velocities, cohesions, etc. According to Dyaram et al. [5], members of a strongly cohesive group tend to stay together, being an active part of it. In our method, a cohesion value ζ_g is set to define how much a group g tends to stay together, in the interval [0,3], where 0 is the lowest cohesion value and 3 is the highest. This interval was defined according to the work proposed by Favaretto et al. [6]. Furthermore, a cohesion distance value μ_g is defined to represent the maximum distance an agent can be away from the rest of the group g, without leaving it (i.e. breaking the groups structure). This cohesion distance is calculated as follows: $\mu_g = Hs - (\zeta_g(\frac{Hs-Hp}{\zeta_{max}}))$, where $Hp = 1.2m$ is the Hall's personal space and $Hs = 3.6m$ is the Hall's social space. These distance spaces are described by Hall [10], which defines regions, called by the author "proxemics", that a person tends to maintain to feel comfortable. ζ_{max} value stands for Maximum Cohesion ($\zeta_{max} = 3$) and represents the higher cohesion value a group can achieve. For instance, if $\zeta_g = 0$ for a certain low cohesive group g, then $\mu_g = 3.6$ meters, i.e. this group can have its members more spread in the environment.

In addition we compute the separation distance ($\delta_g = Hs + Hp - \mu_g$). If an agent gets farther from the rest of the group than δ_g, it is removed from such group and creates a new group for itself. Such distance is defined as follows: $D_{i,g} = d(p_i, p_g)$, where d is the Euclidean function that computes the distance between the agent i position and the center of its group g. In a similar way, if a non-grouped agent j has its distance to the center of the closest group g smaller or equal than μ_g, and the same immediate goal, it can enter into this group. Also, groups of agents have a desired speed to be assigned among the members. We propose to connect this concept with group cohesion as well. We defined the mean desired speed of group g as $\bar{\psi}_g = 1.2$ m/s, as found in literature [8, 14]. We empirically defined a variation on such desired speed, varying from $var^{\psi_g}_{min} = 0$ to $var^{\psi_g}_{max} = 0.2$. So, the individual speed of an agent i is determined as a function of group speed ψ_g and a group standard variation σ_g which is computed as follows: $\sigma_g = var^{\psi_g}_{max} - ((var^{\psi_g}_{max} - var^{\psi_g}_{min})\frac{\zeta_g}{\zeta_{max}})$. So, agent i speed is $s_i = \bar{\psi}_g + \sigma_g$. Just as group desired speed, the desired default value for angular variation of groups members is set as $\alpha_g = 0$ with $var^{\alpha_g}_{min} = 0$ and $var^{\alpha_g}_{max} = 1$. With all defined, one vector V_g of group features is created for each group to be simulated, depending on the cohesion value (ζ_g): $V_g = \{\mu_g, \delta_g, \psi_g, \sigma^{\psi_g}_{min}, \sigma^{\psi_g}_{max}, \alpha_g, \sigma^{\alpha_g}_{min}, \sigma^{\alpha_g}_{max}\}$, which respectively states for cohesion distance, separation distance, mean desired speed, minimum variation of speed, maximum variation of speed, desired angular variation, minimum angular variation and maximum angular variation of group g.

3.2 Psychological Traits

We chose to work with the OCEAN (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism) psychological traits model, proposed by Goldberg [9], since it is the most accepted model to define an individual's personality. We selected two different works which relates individual OCEAN traits and agents behaviors. First one is presented by Durupinar et al. [4] and proposes a simulation model based on OCEAN traits to change the visual behavior of agents. The second model is proposed by Favaretto et al. [7], which describes a way to map data captured in real video sequence to individual-level traits based on individual and group features. There is a natural challenge in evaluating the result of crowd simulation with personalities: it is hard to find data about such traits that can be used in this context. So, we propose to implement two psychological definitions to evaluate their coherence, as discussed in Section 4.

It is important to understand each OCEAN factor individually. To do so, we should take into account the definition of each factor, in short: *i)* Openness (O) = [0;1]: reflects the degree of curiosity, creativity and a preference for novelty and variety; *ii)* Conscientiousness (C) = [0;1]: reflects the tendency to be organized and dependable;*iii)* Extraversion (E) = [0;1]: reflects the sociability and talkativeness; *iv)* Agreeableness (A) = [0;1]: reflects the tendency to be cooperative and compassionate with others; and *v)* Neuroticism (N) = [0;1]: reflects the degree of emotional stability. Following such definition, we proceed to map OCEAN attributes based on Durupinar and Favaretto into our group features (called henceforth as Methods D and F).

3.2.1 Method D. As previously mentioned, Durupinar et al. [4] proposed a simulation model based on OCEAN traits to represent the visual behavior of agents. Table 1 shows the relationship (third column) between OCEAN traits (second column) and some proposed Durupinar's behaviors (first column) used in our mapping, as shown in Durupinar et al. [4] work. In order to define the agent desired speed, the Durupinar's Walking speed ψ_i was chosen. Therefore, the desired speed value s_i of agent i is $s_i = 1.2(\psi^D_i - 1)$, where $\psi_g = \frac{\sum^n_{i=1} s_i}{n}$ states for the group speed and replaces the default value defined in Section 3.1. Moreover, the speed deviation σ_g is

Table 1: Relationship between OCEAN traits and Durupinar's behaviors used for our mapping. Imp_{gD} **stands for Durupinar's Impatience Such mapping is proposed by Durupinar et al. [4].**

Behavior	OCEAN traits	Equation
Walking Speed	E	$\psi_i^D = E_i + 1$
Exploring Environment	O	$Ex_i^D = O_i.10$
Impatience	C,E,A	Imp_{gD}

defined following the definition in Section 3.1. To define the angular variation, the Exploring Environment behavior was chosen, because it seems logical to think that the more an agent wants to explore a given environment, the more it is going to deviate from its original path. Plus, this behavior is a direct mapping from the Openness trait from OCEAN, which evaluate, among other things, the curiosity of an individual. Therefore, the agent angular variation value α_i is defined as $\alpha_i = 1 - \frac{Ex_i^D}{10}$, where Ex_i^D represents the Durupinar's exploring environment and α_i actually represents a percentage of a maximum angle (i.e. 90^o). In addition, $\alpha_g = \frac{\sum_{i=1}^n \alpha_i}{n}$ states for the group angular variation and also replaces the default value from Section 3.1. For cohesion, the Durupinar Impatience behavior was chosen, since it incorporates tolerant and orderly behaviors, necessary to maintain a group. Imp_i^D is calculated as follows for agent i: $Imp_i^D = (w_{E,I}F_{E_i}) + (w_{A,I}(1-A_i)) + (w_{C,I}(1-C_i))$, where $w_{E,I}, w_{A,I}$ and $w_{C,I}$ are weights for each OCEAN's E, A and C traits and should sum 1. We empirically defined them as $w_E = 0.1, w_A = w_C = 0.45$. F_{E_i} can assume two values depending on E_i attribute: if the OCEAN E trait is positive (i.e. $E_i \geq 0.5$), it assumes the value $F_{E_i} = (2E_i) - 1$. Otherwise, $F_{E_i} = 0$, as described in Durupinar work [4]. Then, the group impatience is defined as $Imp_g = \frac{\sum_{i=1}^n Imp_i^D}{n}$ and the group cohesion ζ_g is $\zeta_g = 3(1 - Imp_g)$. The value is multiplied by 3 in order to keep this parameter between 0 and 3.

3.2.2 Method F. Favaretto et al. [7] described a way to map equations to compute individual-level traits from video sequences, based on individual and group features. Based on proposed equations we generated inverse functions, in accordance to Favaretto model. The cohesion of a group ζ_g is the mean value of the agents cohesion ζ_i within the group, as described: $\zeta_g = 3\frac{\sum_{i=1}^n \phi_i}{n}$, where i is an agent of group g and n is the total number of agents inside this group. The result is limited between 0 and 1, so it is is multiplied by 3 in order to keep this parameter between 0 and 3, as defined by Favaretto. The collectivity value ϕ_i of a certain agent i is calculated as defined in Equation 1, where i is the agent, ϕ_i^Q is the result of the partial collectivity based on an equation Q_n from Favaretto's mapping in the NEO PI-R questionnaire [7] and ϕ_i is the agent final collectivity calculated as the mean value of the partial results. Also, $\phi_i > 0$ to avoid division problems in Equation 2. For clarity, we replicate some part of the table from [7] with some NEO-PI questions (Table 2). For instance, in Equation 1, when we mention $\phi_i^{Q_{9-10}}$ we are referencing questions 9 and 10, as shown in Table 2.

$$\phi_i^{Q_{9-10}} = A_i, \qquad \phi_i^{Q_{13}} = \frac{50}{800N_i - 100},$$
$$\phi_i^{Q_{22-23}} = E_i, \qquad \phi_i^{Q_{24-25}} = 1 - N_i,$$
$$\phi_i = \frac{2\phi_i^{Q_{9-10}} + \phi_i^{Q_{13}} + 2\phi_i^{Q_{22-23}} + 2\phi_i^{Q_{24-25}}}{7}, \tag{1}$$

Table 2: Equations from each NEO PI-R item selected. [7]

NEO PI-R Item	Equation
1 - Have clear goals, work to them in orderly way	$Q_1 = s_i + \frac{1}{\alpha_i}$
2. Follow same route when go somewhere	$Q_2 = \alpha_i$
9. Rather cooperate with others than compete 10. Try to be courteous to everyone I meet	$Q_{9-10} = \phi_i$
12. Usually seem in hurry	$Q_{12} = s_i + \alpha_i$
13. Often disgusted with people I have to deal with	$Q_{13} = \varphi_i + \frac{1}{\phi_i}$
15. Would rather go my own way than be a leader	$Q_{15} = \frac{1}{Q_{14}}$
22. Feel need for other people if by myself for long 23. Find it easy to smile, be outgoing with strangers 24. Rarely feel lonely or blue 25. Seldom feel self-conscious around people	$Q_{22-25} = \vartheta_i + \phi_i$

In addition to group cohesion, we also compute the group angular variation value α defined as: $\alpha_g = \frac{\sum_{i=1}^n \alpha_i}{n}$, where i is an agent of group g, n is the total number of agents inside this group and α_i is the angular variation of i, which is computed according to Equation 2. For this attribute, we compute the percentage of a maximum possible angle (i.e. 120^o). An agent individual angular variation factor α_i, similar to the agent collectivity ϕ_i, is the mean value of partial equations $\alpha_i^{Q_n}$ involving the questions Q_n from the NEO PI-R questionnaire set (illustrated in Table 2), where angular variation α is used, as shown in Equation 2:

$$\alpha_i^{Q_2} = 1 - O_i, \qquad \alpha_i^{Q_{15}} = 1.3125 - E_i - \frac{1}{16\phi_i},$$
$$\alpha_i = \frac{\alpha_i^{Q_2} + \alpha_i^{Q_{15}}}{2}, \tag{2}$$

where ϕ_i is the previous result of the agent collectivity. The mean speed value of a group ψ_g is calculated as follows: $\psi_g = 1.2\frac{\sum_{i=1}^n s_i}{n}$, where i is an agent of the group, n is the total number of agents inside this group and s_i is the speed factor of an agent, which is multiplied by the human desired speed (i.e. 1.2 m/s). Similar to angular variation α_i and collectivity ϕ_i, the speed s_i is also the mean value of partial equations $s_i^{Q_n}$ represented in the Equation 3.

$$s_i^{Q_1} = \frac{\varrho C_i - (4\alpha_i)^{-1}}{4}, \qquad s_i^{Q_{12}} = \frac{2E_i - \alpha_i + 1}{3},$$
$$s_i = \frac{s_i^{Q_1} + s_i^{Q_{12}}}{2}, \tag{3}$$

where α_i is the agent angular variation result and ϱ is a normalization factor for the Consciousness C input, defined as $\varrho = 5.25$

in accordance to Table 2. Finally, the speed deviation σ_g is defined following the definition in Section 3.1. At the end of method F, we have for each group: : $F_g = \{\zeta_g, \phi_g, \alpha_g, \psi_g\}$, which respectively states for cohesion, collectivity, angular and speed variations of group g.

3.3 BioCrowds Simulation

In this section we describe the last phase of our model, where, based on group parameters found in last sections, we simulate the motion of groups and agents. The Cohesion value ζ_g is responsible to keep the group cohesive, it means, keep the agents of the group together and more or less close to each other. The Desired Speed value ψ_g defines the optimal speed for agents inside this group and, therefore, is the speed that agents want to reach. This value is directed affected by the group Speed Deviation σ_g. When agents are instantiated, their speed value is randomly set between the interval $[\psi_g - \sigma_g, \psi_g + \sigma_g]$. As it was explained in Section 3.1, the Speed Deviation value σ_g is calculated in function of the group Cohesion ζ_g, so, the higher the Cohesion value, the less the Speed Deviation for the group. Finally, the Angular Variation value α_g is responsible to define how straight agents of a given group g are going to move towards their goal. So, a low value for this parameter should generate a more straight movement.

4 EXPERIMENTAL RESULTS

During the simulations, some information is recorded regarding the agents: their positions and the time each of them arrives at its final goal. In next sections we present some achieved results obtained with our method in two different scenarios.

4.1 Goal Seeking Scenario

First scenario aims to evaluate a very important crowd behavior: goal seeking. We modeled a 30x30 meters scenario with four goals. Ten agents, part of same group, start near to the upper right corner and have the same pre-defined schedule, i.e. to reach all four goals in a certain order: G2, G1, G4 and G3. It was ran eight test simulations for each method (i.e. Methods D and F). For each of them, we configured OCEAN values in order to achieve the attributes with values as defined in Table 3. Such values, used in each method, are presented in Table 4. The idea is to check if the cohesion value really impacts on the willingness of agents to stay inside a group. Plus, it is expected some difference concerning groups formation when changing its desired speed and angular variation. High cohesion value is defined in the interval $[2.5; 3]$ and low cohesion value in $[0; 1]$. As well, high desired speed value is defined between $[1; 1.2]$ and low desired speed in $[0.2; 0.4]$ and high angular variation value is defined between $[60; 90]$ degrees and low angular variation in $[0; 15]$. In order to evaluate the obtained results, some metrics were defined, as follows: Time (total simulation time (in seconds), Maximum quantity of groups (formed during the simulation), Average speed (in m/s), Average angular variation (in degrees) and Average distance (the average distance, in meters, which agents kept from its group's center). These metrics are used in next sections where we simulate agents in BioCrowds using the setup defined in this section. Table 4 shows the input parameters for both Method D and Method F, where an underline d means the parameter is for Method D and an underline f means it is for Method F.

Table 3: Simulations parameters for Goal Seeking case.

Sim	Cohesion	Desired Speed	Angular Variation
1	High	High	Low
2	High	Low	Low
3	Low	High	Low
4	Low	Low	Low
5	High	High	High
6	High	Low	High
7	Low	High	High
8	Low	Low	High

Table 4: OCEAN Input for both Method D and Method F.

Sim	O_d	C_d	E_d	A_d	N_d	O_f	C_f	E_f	A_f	N_f
1	0.9	0.9	0.9	0.9	0.1	0.9	0.9	0.9	0.9	0.2
2	0.9	0.9	0.2	0.9	0.1	0.9	0.1	0.6	0.9	0.2
3	0.9	0.2	0.9	0.2	0.1	0.7	0.9	0.8	0.1	0.9
4	0.9	0.2	0.2	0.2	0.1	0.7	0.1	0.7	0.1	0.8
5	0.3	0.9	0.9	0.9	0.1	0.1	0.9	0.5	0.9	0.2
6	0.3	0.9	0.2	0.9	0.1	0.2	0.2	0.2	0.9	0.2
7	0.3	0.2	0.9	0.2	0.1	0.2	0.9	0.4	0.2	0.9
8	0.3	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.8

4.1.1 Results for Method D. For the simulations using Method D, the eight simulations presented in Table 3 and results are shown in Table 5. It is possible to notice that the expected result was achieved, i.e. groups with higher cohesion values had closest agents and vice-versa. For example, Sims 1 and 2 have have higher cohesion values (Table 3) and presented a lower value for Average Distance between agents (Table 5), while Sims 3 and 4 have low cohesion values (Table 3) and presented a higher value for Average Distance between agents (Table 5). In addition, the desired speed and angular variation seem to influence on group behavior, mainly in the group formation. For example, Sims 5 and 6 have a high cohesion values and a high angular variation value (Table 3). Even with the high cohesion value, the initial group split, forming two groups (Table 5). Sims 1 and 2 have the same initial parameters, except for the angular variation, which is lower (Table 3). In these cases, the initial group kept the same structure (Table 5). Simulations with higher cohesion presented lowest average distances, so agents stayed close to each other. Besides, when looking at the results for simulations with

Table 5: Results for Method D.

Sim	Time	Groups	Avg Spd	Avg Ang	Avg Dist
1	128	1	0.6	16.89	1.26
2	579	1	0.13	16.95	1.21
3	87	1	0.84	11.73	2.23
4	648	4	0.16	11.11	1.97
5	170	2	0.56	34.41	1.32
6	789	2	0.13	38.5	1.22
7	124	1	0.65	26.5	2.31
8	608	2	0.14	31.16	2.22

low angular variation, the only simulation which groups has been separated is the number 4, which had low cohesion.

It is interesting to notice that in simulations with high values of angular variation, even with high cohesion values (Table 3), agents were able to split into other groups (simulations numbers 5 and 6, in Table 5). A possible explanation for this behavior can be that agents may vary more their angles in related to the group's center direction, consequently moving away from their group and, therefore, splitting eventually. Yet, Table 5 also shows that the last two simulations (i.e. 7 and 8), with low cohesion values, had less or equal groups than the previous two (i.e. 5 and 6), with high cohesion values. It is possible that the angular variation may cause a great impact on the group formation.

4.1.2 Results for Method F. For the simulations with Method F mapping, the same eight simulations presented in Section 4.1 were executed. Table 4 shows the Method F input used for each simulation, as explained in Section 4.1. The same metrics defined in section 4.1 are computed and shown in Table 6. It is possible to notice that the result expected at the beginning was also achieved, meaning groups with higher cohesion values had closest agents and vice-versa. Yet, the desired speed and angular variation seems to have influence on group behavior, mainly in the group formation. As observed with Method D mapping, simulations with higher cohesion presented lowest average distances, so agents stayed close to each other. In fact, all simulations mapped with Method F obtained very similar results with the simulations with Method D. Figure 2 shows a comparison between the metrics found for both mappings and the original BioCrowds method, without psychological parameters, illustrated as a constant line. It indicates that both methods, when mapped to BioCrowds, present a similar correspondence. Also, the influence of OCEAN input on the original behavior of BioCrowds algorithm is clearly observed among all metrics and shown the main goal of this work.

Table 6: Results for Method F.

Sim	Time	Groups	Avg Spd	Avg Ang	Avg Dist
1	134	1	0.59	18.33	1.35
2	500	1	0.17	23.37	1.33
3	99	1	0.73	12.91	2.34
4	815	5	0.16	9.15	2.16
5	212	2	0.48	39.34	1.41
6	947	1	0.12	48.40	1.40
7	150	1	0.55	26.90	2.33
8	741	4	0.18	33.25	2.48

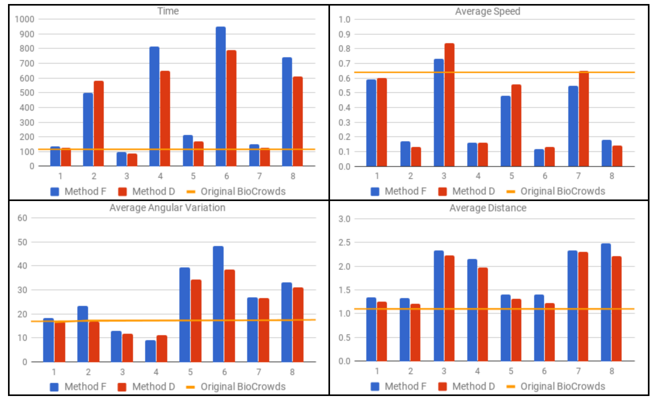

Figure 2: Comparisons between Method F and Method D. X axis is the simulation identifier (i.e. 1-8) and Y axis is the value for metrics. On the top/left: time, top/right: the average speed, on the bottom/left: average angular variation and bottom/right: average distance.

4.2 Evacuation Scenario

In this case-study, we want to create an evacuation scenario where agents spawn at the center of it and desire to reach one of the available exits. Our goal is to evaluate the psychological model in this type of event. We model a 30x30 meters scenario with four exit goals namely G1, G2, G3 and G4. A varying number of agents (i.e. 50, 100 and 200) start at the center of the environment and the number of groups is equal to the number of agents, i.e. there is no group in this simulation. Each agent has the goal to leave the environment using the closest exit.It was executed nine test simulations for each method (i.e. method D and method F), varying number of agents and OCEAN input. The idea is to verify how agents would behave with three different OCEAN inputs: a Neutral personality, a Blue personality (for example, a a pessimist/negative individual) and a Pink personality (for example, a optimistic/positive individual). In addition, we also evaluate the impact of quantity of agents on resulting metrics. Such personalities were chosen following the concept of emotion discussion in personalities, as observed in literature [13]: O+ (person is aware of his/her feelings), C+ (person is optimistic), C- (person is pessimist), E+ (person has a strong relationship with positive emotions), E- (person presents relationship with negative emotions), A+ (person has a strong relationship with positive reactions), A- (person presents relationship with negative reactions), N- (known by the emotional stability) and N+ (person feels negative emotions). It is expected that Pink agents move in higher speeds towards their goals, giving little or no importance to the group formation and having low angular variation. On the other hand, it is expected that Blue agents move in a slower pace, trying to stay together with other agents and having a higher angular variation than Pink agents. The quantity of agents used is 50, 100 and 200 and the OCEAN values used as input for both Method D and Method F is: *Neutral personality:* (O=0.5, C=0.5, E=0.5, A=0.5, N=0.5), *Blue personality:* (O=0.2, C=0.2, E=0.2, A=0.2, N=0.8) and *Pink personality:* (O=0.8, C=0.8, E=0.8, A=0.8, N=0.2).

4.2.1 Results for Method D in Evacuation Environment. For the simulations of the evacuation environment with Method D, the nine simulations with Blue and Pink personalities were executed. The same metrics defined in Section 4.1 are computed and shown in Table 7. It is interesting to notice that Pink agents move faster than the remaining ones. As a consequence, they achieve the goals in less time, if compared with the others. Blue agents presented higher angular variation and low speeds, so they take more time to achieve the goals.

Table 7: Results for Method D in Evacuation Environment

Sim	Qnt Agts	Type	Time	Avg Spd	Avg Ang
1	50	Neutral	50	0.36	24.53
2	100	Neutral	51	0.35	26.81
3	200	Neutral	62	0.31	31.88
4	50	Blue	200	0.14	39.37
5	100	Blue	241	0.13	40.37
6	200	Blue	246	0.12	43.35
7	50	Pink	23	0.76	16.27
8	100	Pink	26	0.70	19.64
9	200	Pink	30	0.62	22.35

4.2.2 Results for Method F in Evacuation Environment. Similar to Section 4.2.1 we executed the nine simulations and Table 8 shows the obtained results.Prior analysis show a similar behavior related to the defined personalities. Blue personality generated the slowest average speeds and speed deviations in both methods (i.e. Method D and Method F). Higher angular variations were also generated by Blue personalities in both methods. In the same way, Pink personalities generated similar behaviors in both methods. The fastest average speeds, highest average speed deviations and lowest angular variation, in both methods, resulted from the simulations with Pink personalities. By calculating the Pearson correlation between the results from Sections 4.2.1 and 4.2.2, we achieved values higher than 0.98 to both average speed and average angular variation in the evacuation scenarios. It indicates that proposed methods were able to reproduce similar behaviors with the two methods for psychological input. Therefore, with both methods presenting similar behaviors, we can not define that one method is better, or more fitted, than the other.

Table 8: Results for Method F in Evacuation Environment

Sim	Qnt Agts	Type	Time	Avg Spd	Avg Ang
1	50	Neutral	48	0.40	24.49
2	100	Neutral	54	0.39	27.79
3	200	Neutral	64	0.35	30.50
4	50	Blue	224	0.12	34.67
5	100	Blue	261	0.10	36.23
6	200	Blue	302	0.09	38.26
7	50	Pink	25	0.71	17.95
8	100	Pink	28	0.68	20.77
9	200	Pink	31	0.60	23.40

5 CONCLUSION AND FUTURE WORK

This work proposes an extension to BioCrowds model [2] in order to parametrize it to simulate psychological traits of crowds based on different methods. The obtained results show that our framework was able to generate heterogeneous group of agents, having different behaviors according to their psychological input. We are able to compare the results achieved with both methods (i.e. Method D and Method F), showing that they havea higher correlation. Also, the results achieved with Method F were pretty similar with the results achieved with Method D, in both scenarios, indicating that our framework is robust enough to receive two different psychological inputs and indeed generate similar behaviors. Our work has some limitations. So far, only two methods were mapped (i.e. Method D and Method F). A possible future work is to explore other psychological methods. Moreover, an interactive interface would be interesting, where the user could create its own psychological theory (with inputs and formulation to generate groups parameters, following what was explained in Section 3), test it and compare with others already implemented. It could be a helping tool for researches to define and test psychological hypotheses. Another future work is the investigation of Countries culture using our method. This prototype was developed at Unity, but we are still using simple visualizations and focusing on numerical results. In next work we intend to produce more attractive visual results in terms of environment and virtual human animations.

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