Received: 25 April 2019 | Accepted: 29 April 2019
DOI: 10.1002/cav.1899

SPECIAL ISSUE PAPER

WILEY

Investigating cultural aspects in the fundamental diagram using convolutional neural networks and virtual agent simulation

Rodolfo Migon Favaretto[1] | Roberto Rosa dos Santos[1] | Soraia Raupp Musse[1] | Felipe Vilanova[2] | Angelo Brandelli Costa[2]

[1]Virtual Humans Simulation Laboratory (VHLab)—Graduate Program in Computer Science, Pontifical Catholic University of Rio Grande do Sul (PUCRS), Porto Alegre, Brazil

[2]Graduate Program in Psychology, Pontifical Catholic University of Rio Grande do Sul (PUCRS), Porto Alegre, Brazil

Correspondence
Rodolfo Migon Favaretto, Virtual Humans Simulation Laboratory (VHLab), School of Technology/Pontifical Catholic University of Rio Grande do Sul, Ipiranga Avenue, 6681 Partenon, 90619-900 Porto Alegre-RS, Brazil.
Email: rodolfo.favaretto@edu.pucrs.br

Funding information
Coordenação de Aperfeiçoamento de Pessoal de Nível Superior, Grant/Award Number: 001; Office of Naval Research Global; Conselho Nacional de Desenvolvimento Científico e Tecnológico; Fundação de Amparo à Pesquisa do Estado do Rio Grande do Sul

Abstract

This paper presents a study, organized in two phases, regarding group behavior in a controlled experiment focused on differences in an important attribute that vary across cultures—personal spaces. First, we want to study and compare the spatial behavior different populations adopt with respect to their personal space. Second, we want to use simulation of virtual agents to artificially generate movements of people in similar situations and validate them using real video sequences. Our main goal is to be able to extract from video sequences and then simulate variations in populations in a coherent way with literature that studies cultural aspects. In addition to the cultural aspects, we also investigate the personality model in the studied videos using OCEAN (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism). Finally, we propose a way to simulate the fundamental diagram experiment from other countries using the OCEAN psychological trait model as input. Results indicate that the simulated countries have consistent characteristics with the expected literature.

KEYWORDS

convolutional neural networks, cultural aspects, group behaviors, virtual human simulation

1 | INTRODUCTION

Crowd analysis is a phenomenon of great interest in a large number of applications. Surveillance, entertainment, and social sciences are fields that can benefit from the development of this area of study. Literature dealt with different applications of crowd analysis, for example, counting people in crowds,[1,2] group and crowd movement and formation,[3,4] and detection of social groups in crowds.[5,6] Normally, these approaches are based on personal tracking or optical flow algorithms and handle as features speed, directions, and distances over time. One issue associated with this area is related to available data sets since, sometimes, we do not exactly have the filmed scenario we wanted to have. This is the main motivation of this work, that is, the possibility of generating artificially data sets to be analyzed using computer vision, in our case, considering virtual population. Therefore, since we are interested in cultural aspects, we want to simulate virtual people that corresponds to plausible and realistic populations in some way.

Recently, some studies have investigated cultural difference in videos from different countries using fundamental diagrams (FDs).[7–12] The FDs, originally proposed to be used in traffic planning guidelines,[13,14] are diagrams used to describe the relationship among three parameters: (i) density of people (number of people per square meter), (ii) speed (in meters per second), and (iii) flow (time evolution).[9] In the work of Zhang,[15] FDs were adapted to describe the relationship between pedestrian flow and density and are associated to various phenomena of self-organization in crowds, such as pedestrian lanes and jams, such that when the density of people becomes really high, the crowd stops moving. It is not the first time cultural aspects are connected with FDs. Chattaraj et al.[16] suggested that cultural and population differences can also change the speed, density, and flow of people in their behavior.

Favaretto et al. discussed cultural dimensions according to Hofstede analysis[17] and presented a methodology to map data from video sequences to the dimensions of Hofstede cultural dimensions theory[18] and a methodology to extract crowd-cultural aspects[19] based on the big-five personality model (or OCEAN [Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism]).[20] In their work, Favaretto et al. proposed a way to map geometrical features (such as speed, angular variation, and distances[21]) from pedestrians tracking to OCEAN dimensions.[22]

In this paper, we want to investigate the cultural aspects of people when analyzing the result of FDs among two different countries, namely, Brazil and Germany, and use this information in order to simulate crowds that can be affected by different cultures. The FD was chosen since the populations are performing the same task in a controlled environment with the same amount of individuals. We also propose a way to simulate other countries using OCEAN as input to generate the geometrical features (such as speed, angular variation, etc.) of each pedestrian. The next section discusses the related work, and in Section 3, we present details about the proposed approach with a statistical analysis (Section 4), followed by the discussion and final considerations in Section 5.

2 | RELATED WORK

Cultural influence can be considered in crowd attributes as personal spaces, speed, pedestrian avoidance side, and group formations.[23] Personal space refers to the preferred distance from others that an individual maintains within a given setting. This area surrounding a person's body into which intruders may not come is the personal space.[24] It serves mainly to two main functions: (i) communicating the formality of the relationship between the interactants and (ii) protecting against possible psychologically and physically uncomfortable social encounters.[25] People from various cultural backgrounds differ with regard to their personal space.[26] These differences reflect the cultural norms that shape the perception of space and guide the use of space within different societies.[27]

Recently, a study on personal space employing a projective technique was conducted in 42 countries.[28] Participants had to answer a graphic task marking which distance they would feel comfortable when interacting with: (a) a stranger, (b) an acquaintance, and (c) a close person. This way, the authors could evaluate the projected metric distance for (a) social distance, (b) personal distance, and (c) intimate distance. The number of countries assessed in the study of Sorokowska et al.[28] promotes conclusions from different cultures and indicated some new possible categorization of the cultures and to design objects or implement changes in the real world.

The project of public transportations, for example, can be improved by the analysis of real personal space in different countries, since the invasion of personal space in trains elicits psychophysiological responses of stress.[29] Furthermore, the project of human-robots has also been improved through the analysis of personal space.[30] As it is important that robots do not invade the personal space of its users, the configuration of its distances might benefit from studies that employ analysis of daily preferred interpersonal distances across different countries.

Our idea here is to identify different aspects among populations from Brazil and Germany regarding distances in an individual's personal space. However, differently from the projective technique proposed by Sorokowska et al.,[28] we want to use video sequences, real populations, and computer vision techniques to proceed with personal space analyses. The next section presents the methodology adopted to detect and track the individuals in the experiment and how we perform the statistic information extraction.

3 | THE PROPOSED APPROACH

We propose a two-step methodology responsible for trajectory detection and statistical data extraction/analysis. The first part aims to obtain the individual trajectories of pedestrians in real videos using machine learning algorithms.

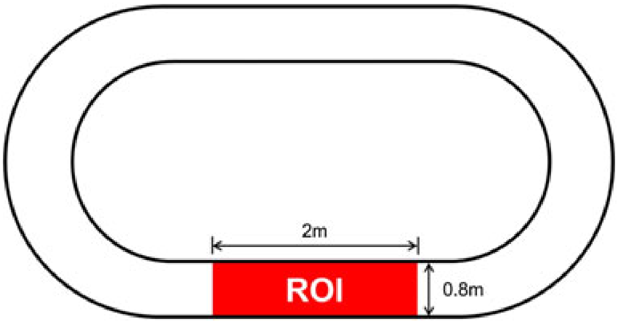


FIGURE 1 Sketch of the experimental setup. ROI, region of interest[16]

(a) (b)

FIGURE 2 Some pictures extracted from the experiment. (a) Brazil with $N = 34$. (b) Germany with $N = 34$

This experiment in Brazil was conducted as described in the work of Chattaraj et al.,[16] with the same populations ($N=1$, 15, 20, 25, 30, and 34) and physical environment setup as illustrated in Figure 1. In addition, we obtained from Germany* video with populations ($N=1$, 15, 25, and 34); hence, $N=20$ and 30 filmed in Brazil were not used in our analysis. The length of the corridor is $l_{\text{corr}} = 17.3$ m. The width of the passageway is $w_{\text{corr}} = 0.8$ m, which is sufficient for a single-person walk. In addition, we can observe a rectangle of 2 m $\times$ 0.8 m, which illustrates the region of interest (ROI) where the populations were captured to be analyzed, as proposed in the work of Chattaraj et al.[16]

For the experiment, the camera was positioned at the top, eliminating the video perspective. All the individuals were initially uniformly distributed in the corridor. After the starting instruction, every individual should walk around the corridor twice and then leave the environment while still walking a reasonable distance away, eliminating the tailback effect. Figure 2 shows the experiment performed in Brazil and Germany, with $N = 34$ (where N is the number of people).

In the first step of our method, people detection and tracking is performed using convolutional neural networks. In the second step, statistical information is obtained from trajectories and analyzed in order to find neighbor individuals and compute distances among them. These modules are presented in sequence.

3.1 | People detection and tracking

Since our goal was to accurately track the issues involved in the FD experiment, we decided to use the recent convolutional neural networks. We use the real-time detection framework Yolo with the reference model Darknet.[31] Initially, we used trained models with public data sets, namely, COCO[32] and PASCAL VOC.[33] However, due to the very different camera position in the video sequences, the tracking did not work well, as can be seen in Figure 3a.

*We have access to such videos due to the authors of the database of PED experiments, available at http://ped.fz-juelich.de/db/.

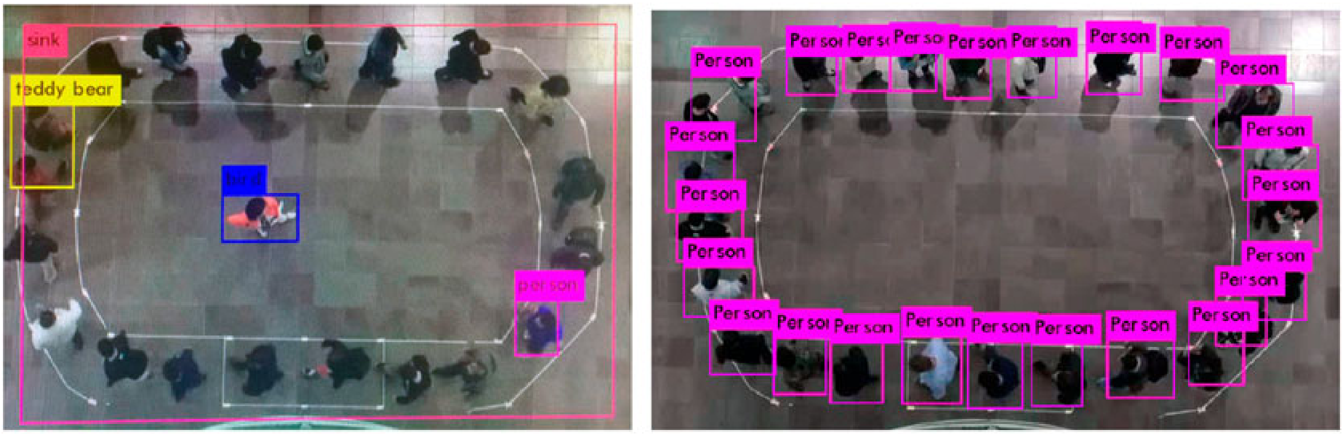


FIGURE 3 (a) Test using VOC and trained pattern configuring. (b) Training results in a video from Brazil

TABLE 1 Configuration of the data set

Goal	Images	Annotations	Country
Train	128	3,833	Brazil
Valid	96	1,536	Brazil
Test—15 people	1,596	23,530	Brazil
Test—25 people	3,124	73,250	Brazil
Test—34 people	5,580	178,448	Brazil
Test—15 people	2,372	71,846	Germany
Test—25 people	3,322	74,005	Germany
Test—34 people	3,504	110,500	Germany

TABLE 2 Accuracy (%) obtained

Country	15 people	25 people	34 people
Brazil	98.2%	98.4%	97.8%
Germany	93.0%	92.3%	91.0%

Hence, we proceed with data set generation to be used for network training. We used the videos with 20 and 30 people performed in Brazil. We choose these two experiments (with 20 and 30 pedestrians) for the training process because we do not have the corresponding amount of people from the Germany data set. We included in the training data set one image from 50 frames, resulting in 45 images for a movie with 20 people and 83 images for a video with 30 people. Table 1 shows the number of images used in the training, validation, and testing phases. The obtained accuracy in our method for videos from Brazil was 98.2% with 15 people, 98.4% with 25 people, and 97.8% with 34 people. Table 2 demonstrates the accuracy of both countries in the respective videos.

3.2 | Statistical data extraction and analysis

As a result of the tracking process, described in the last section, we obtained the two-dimensional position $\vec{X}_i$ of person i (in meters), at each time step in the video. Positions are used to compute the FD. We adopted the already used hypothesis[34] to approximate the personal space using a Voronoi diagram (VD). Indeed, we use the output of the VD to compute the neighbor of each individual in order to calculate the pairwise distances. As our pedestrian tracking could not be applied to find out the order of pedestrians in the video (we do not know the order in which the pedestrians were tracked, e.g., i and $i+1$), we use the output of the VD to compute the neighbor of each individual (pedestrians in front and behind) to calculate distances between each pedestrian and his/her predecessor. Thus, the distance between individual i and the one in front of him/her $i+1$ is considered the personal space of i, in this work. Hence, we compute such distances in the ROI, at the first moment the second individual enters the ROI, as illustrated in Figure 1.

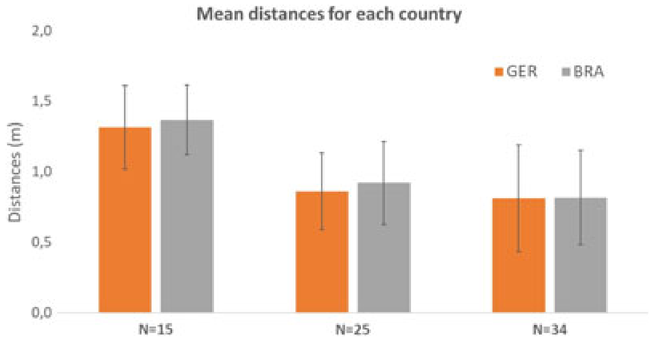


FIGURE 4 Mean personal distances observed in each population

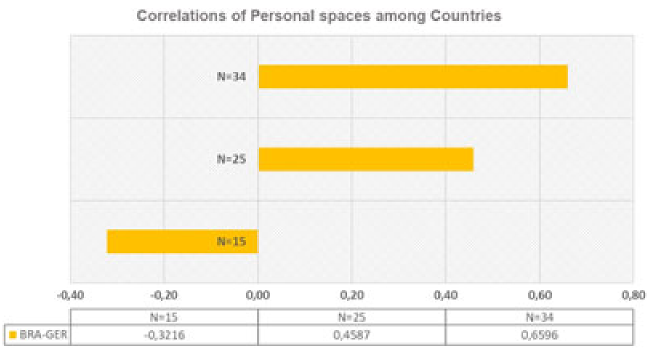


FIGURE 5 Correlations of personal space among the countries

Once we have computed all personal spaces for all individuals from the two populations, we conducted the following analysis. First, we show in Figure 4 the mean distances observed in each population. As expected, the personal space reduces as the density increases. The correlations of distances among the two populations are shown in Figure 5.

As can be observed in Figure 5, Pearson's correlations among the populations increase as the densities increase. Based on this affirmation, our hypothesis is that in high densities, people act more as a mass and less as individuals,[35] which ultimately affects behaviors according to their own culture. This assumption is coherent with one of the main literature on mass behavior.[36]

Once we studied the FDs in real video sequences, we decided to propose a way to simulate those populations in the same scenario. In order to do that, we propose to use the work of Favaretto et al.,[19] where the authors described a way to extract OCEAN from video sequences, that is, generating geometrical data from the OCEAN model. The next section describes how we do it in our work.

3.3 | Simulating FD

In this section, we describe our proposal to simulate the FD. Our idea is to simulate FD experiments with varied populations. Once, in last section, we analyzed the FD in two countries, our main goal here is to investigate if we can simulate the FD for other countries in a coherent way, if compared with the literature. That is why we have chosen the OCEAN psychological traits model, proposed by Goldberg,[37] to serve as input in our method. Our hypothesis is that there is a correlation between the OCEAN model and how people react in scenarios as the FD. In addition, it has been already used in the context of simulation. For instance, Durupınar et al.[38] developed a simulation model based on psychological traits aiming to represent emotions and emotion contagion between agents in an effective way.

Therefore, there is a specific literature presenting the OCEAN of different countries[39] that can inform input values in our method. As mentioned before, Favaretto et al.[19] comprehend equations to map pedestrian behavior, from a video sequence, to OCEAN individual values. Hence, we extended this model to propose a way to, having the OCEAN as input, find out geometrical information regarding how people evolve in simulations. We decided to use three parameters to simulate the FD, which are achieved based on equations proposed by Favaretto et al.[19]: *collectivity*, *angular variation*, and *linear speed*.

TABLE 3 Relationship between the agent features and input OCEAN (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) dimensions

Agent features	Related input
Collectivity (ϕ_i)	E, A, N
Angular variation (α_i)	O, E, ϕ_i
Speed (s_i)	C, E, α_i

Collectivity is related to group cohesion, that is, the higher the cohesion, the more collective behaviors the population has.[40] According to Dyaram and Kamalanabhan,[41] members of a strongly cohesive group tend to stay together, not leaving the group, and to be an active part of it. Angular variation is computed as a function of the vector that represents the goal direction of agent i, and the third parameter represents the linear speed of i. These three parameters were proposed in the work of Favaretto et al.[19] and are inversely mapped, in this work, to be computed, having OCEAN values as input, as described in the following equations. Equation (1) describes collectivity ϕ_i of agent i as a function of E_i, A_i, and N_i, which state that, for some of input OCEAN parameters for i,

$$\phi_i = \frac{2\frac{A_i}{100} + \frac{50}{8N_i - 100} + 2\frac{E_i}{100} + 2\left(1 - \frac{N_i}{100}\right)}{7}. \tag{1}$$

Equation (2) describes the angular variation of i as a function of O_i, A_i, and ϕ_i parameters, that is,

$$\alpha_i = \frac{1 - \frac{O_i}{100} + 1.208 - \frac{1}{16\phi_i} - \frac{E_1}{100}}{2}. \tag{2}$$

Equation (3) refers to the linear speed of agent i, and it is impacted by E_i, C_i, and α_i parameters, that is,

$$s_i = \frac{\frac{0.04C_i - (4\alpha_i)^{-1}}{4} + \frac{\frac{E}{100} - \alpha_i + 1}{2}}{2}. \tag{3}$$

Table 3 shows a summarization of the relations among OCEAN and geometric parameters. Collectivity is related to the Extraversion, Agreeableness, and Neuroticism traits; angular variation is related to agent Openness, Extraversion, and cohesion; and, finally, speed is dependent on Consciousness, Extraversion, and angular variation.

It is important to notice that the Extraversion trait is related to all features. As mentioned in the work of Favaretto et al.,[19] the Extraversion trait comprehends the majority of items related to crowd behavior, thus being necessary for all equations as proposed in the present work.

We use ϕ_i, α_i, and s_i of agent i to impact its motion in the FD. Virtual humans are modeled to move in a predefined order in an FD scenario having α and s as angular and linear speed, respectively. Agent collectivity is used to define the cohesion of the group of which the agent is a member. A group's cohesion is calculated as the mean value of its participants' collectivity factor ϕ.

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.[18]

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 and break the group structure. This cohesion distance is calculated as follows:

$$\mu_g = H_s - \left(\zeta_g \left(\frac{H_s - H_p}{\zeta_{\max}}\right)\right), \tag{4}$$

where H_p is Hall's personal space and H_s is Hall's social space. These distance spaces are described by Hall,[27] who defines regions that a person feels comfortable to maintain at each specific personal or social level. The $\zeta_{\max}$ 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 $\mu_g = 3.6$ m, that is, this group can have its members more spread in the environment. On the other hand, if $\zeta_g = 3$, then $\mu_g = 1.2$ m, which means that members, in a more cohesive group, stay close to

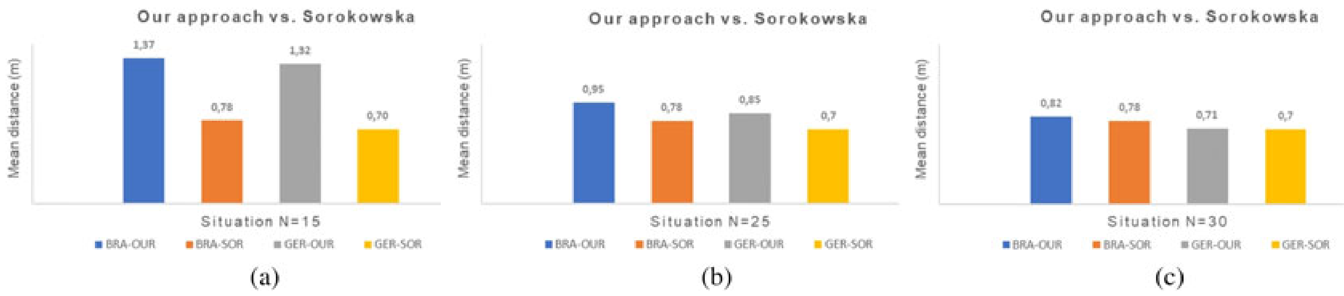


FIGURE 6 Our approach versus that by Sorokowska et al.[28] with different numbers of people in the experiment. (a) When $N = 15$. (b) When $N = 25$. (c) When $N = 34$

each other in order to be a group, since they have a strong connection and are more attracted to each other. Using these definitions, we simulated some populations as presented in the next section.

4 | EXPERIMENTAL RESULTS

In this section, we present results about the FD investigation, first based on video sequences and then based on simulations.

4.1 | FD in video sequences compared with the literature

We performed a comparison among the preferred distances people keep from others, evaluated in a study performed by Sorokowska et al.[28] and the results obtained from the experiment performed in our approach. In the work of Sorokowska et al., the answers were given on a distance (0–220 cm) scale anchored by two human-like figures, labeled A and B. Participants were asked to imagine that he or she is Person A. Then, the participant was asked to rate how close Person B could approach, so that he or she would feel comfortable in a conversation with Person B. Figure 6 shows the comparison of three different FD scenarios, containing 15, 25, and 34 people. In our approach, we measure the distances Person A keeps from Person B right in front of him or her. As said before, we used the VD to determine which person is the neighbor of the other. For the comparison, in the approach by Sorokowska et al., we select the evaluation from acquaintance people, where the people are not close but not strangers, similar to people in our experiment.

As we can see in Figure 6, in spite of the fact that distances from our approach are higher than the ones from the work of Sorokowska et al., the proportion is similar in all the scenarios. People from Brazil keep higher distances from others than people from Germany. (According to our approach, in the $N = 15$ configuration, people from Brazil are about 0.5 m more distant from each other than in Germany, whereas in the approach by Sorokowska et al., people from Brazil are 0.8 m more distant.) It is interesting to notice that as the number of people increases, the more similar the values get to the values obtained by Sorokowska et al. (when $N = 34$, the values are quite similar). Although they are different experiments, our method proves in a real scenario that people actually behave according to the preferences answered in the research by Sorokowska et al.

4.2 | FD in simulations compared with the literature

In this work, we simulated an FD scenario using BioCrowds[42] for the same populations tested using the similar environmental setup, as described in the work of Chattaraj et al.,[16] adding goals (represented as red flags) at every corner of the scenario, as shown in Figure 7. As output, BioCrowds generates the position of each agent at each frame, similar to the tracking process performed with the FD videos.

The agents are programmed to seek the next goal anticlockwise; this way, they keep looping. Knowing the agent in front of it, we are able to calculate the Euclidean distance between them; this distance is the personal distance of this agent. With this method, we are able to determine the personal distance of every agent during the simulation.

Based on the work of Favaretto et al.,[19] we executed simulations using the OCEAN presented by McCrae[39] for German and Hispanic American groups (it was input to compute collectivity, angular variation, and linear speed, as described in

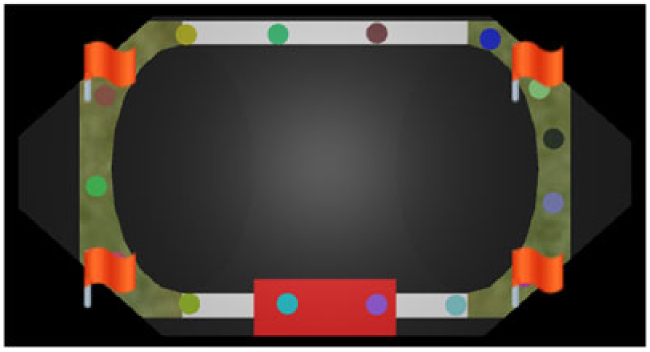


FIGURE 7 Example of the fundamental diagram experiment in BioCrowds with goals and 15 agents

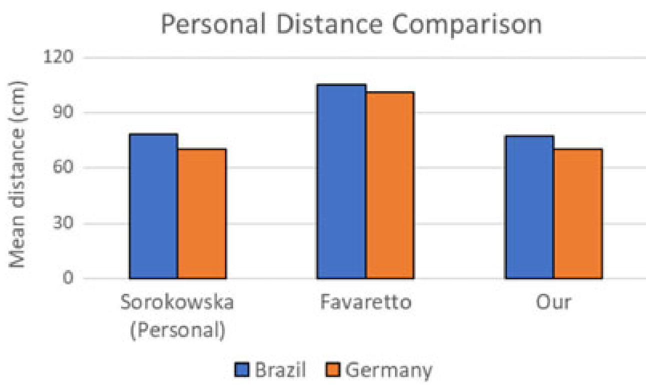


FIGURE 8 Comparison between the personal distances found with the Favaretto et al. videos,[19] Sorokowska et al. study,[28] and our method for Brazilian and German cultures

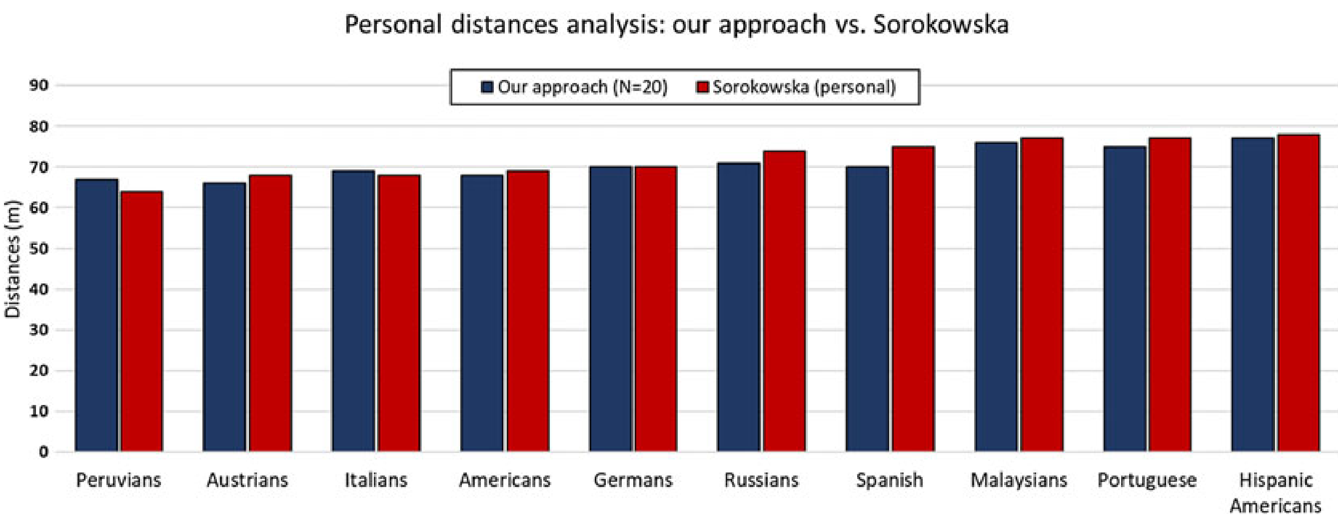


FIGURE 9 Comparison between personal distances obtained with our method and that in the work of Sorokowska et al.[28] Such data were obtained by simulating 20 agents in the virtual fundamental diagram and compared with the results in the work of Sorokowska et al.[28] in 10 countries

Section 3.3). For Germany, the used inputs are as follows: $O = 56.7$, $C = 46.7$, $E = 47.3$, $A = 49.1$, and $N = 52.8$. For Brazil, we assumed the following values for the Hispanic American group: $O = 51.2$, $C = 51.6$, $E = 47.5$, $A = 47.1$, and $N = 49.5$. With this setup, we collected the personal distances of all agents (we considered $N = 20$) during the simulation and calculated the mean personal distance value of all agents. Figure 8 shows a comparison chart between the results obtained by each study for both cultures.

Although the obtained values are different for every approach, we observe a similar behavior in all of them, for example, Brazilian personal distances are slightly greater than Germans' in all approaches. In addition, our simulation model obtained results very similar to those described by Sorokowska et al.[28]

Along with the comparison between real crowds and the literature for countries Brazil and Germany, we executed simulations for other cultural groups (countries) represented both in the Sorokowska et al.[28] and McCrae[39] studies. By comparing the simulated personal distances, obtained using the McCrae[39] cultural OCEAN as input, with Sorokowska et al.[28] results, we formatted the obtained results in Figure 9.

It is easy to see that in some country populations, for example, Italians, Americans, Germans, Malaysians, and Hispanic Americans (in *X*-axes), the values of personal spaces are very similar. It indicates that the input according to the McCrae[39] OCEAN values is correlated with the physical space occupied by agents in our simulation, when compared to real pedestrians.

5 | DISCUSSIONS AND FINAL CONSIDERATIONS

In this paper, we have presented some comparatives in the cultural aspects of groups of people in video sequences from two countries: Brazil and Germany. Since one important aspect to be considered in behavior analysis is the context and environment where people are acting, we worked with the FD experiment proposed by Chattaraj et al.[16]; in this way, people from both countries performed exactly the same task. Our hypothesis is that by fixing the environment setup and the task people should apply, we could evaluate the cultural variation of individual behavior.

In the analysis, we found out that as the density of people increases, people are more homogeneous. It indicates that people assume a group-level behavior instead of an individual-level behavior according to his/her culture or personality. It is an interesting and concrete proof of several theories about mass behavior, as discussed in the works of Vilanova et al.[35] and Le Bon.[36]

We show some differences among Brazil and Germany in the personal space of individuals in terms of distances between individuals. These differences are evidences of cultural behavior of people from each country, mainly in low-density or small groups, when the individuals are not acting as a crowd. We performed a comparison among the personal spaces pedestrians keep from others in the videos of the FD with the study proposed by Sorokowska et al.[28] It was interesting to see that the personal spaces observed in the videos from Brazil and Germany in the FD experiment are in accordance with those presented through subject answers given in the work of Sorokowska et al.

As an application of investigation regarding FDs, we proposed a way to simulate the FD experiment from other countries since we have only videos from Germany and Brazil. For this, we use the OCEAN of each country as input to discover the collectivity, angular variation, and linear speed of each agent in the simulation. We also used Sorokowska distances to compare the distances between agents obtained in the simulations of each country. The results are also in accordance with those in the work of Sorokowska et al.[28]

For future work, we intend to keep investigating the cultural aspects in video sequences, focused on medium and low densities, since it seems to be more different in terms of culture at these densities of pedestrians. We also intend to increase our set of video data, addressing other countries and improving our simulations.

ACKNOWLEDGEMENTS

This study was supported in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES)—Finance Code 001. The authors would also like to thank the Office of Naval Research Global (USA) and the following Brazilian agencies: Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPQ) and Fundação de Amparo à Pesquisa do Estado do Rio Grande do Sul (FAPERGS).

CONFLICT OF INTEREST

The authors declare no potential conflict of interest.

ORCID

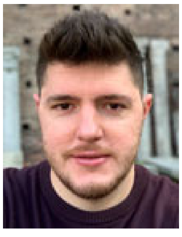
Rodolfo Migon Favaretto https://orcid.org/0000-0002-8940-7813

REFERENCES

1. Chan AB, Vasconcelos N. Bayesian Poisson regression for crowd counting. Proceedings of the IEEE 12th International Conference on Computer Vision (ICCV); 2009 Sep 29–Oct 2; Kyoto, Japan. Piscataway, NJ: IEEE; 2009. p. 545–551.
2. Cai Z, Yu ZL, Liu H, Zhang K. Counting people in crowded scenes by video analyzing. Proceedings of the 9th IEEE Conference on Industrial Electronics and Applications (ICIEA); 2014 Jun 9–11; Hangzhou, China. Piscataway, NJ: IEEE; 2014. p. 1841–1845.
3. Zhou B, Tang X, Zhang H, Wang X. Measuring crowd collectiveness. IEEE Trans Pattern Anal Mach Intell. 2014;36(8):1586–1599.
4. Jo H, Chug K, Sethi RJ. A review of physics-based methods for group and crowd analysis in computer vision. J Postdr Res. 2013;1(1):4–7.
5. Shao J, Loy CC, Wang X. Scene-independent group profiling in crowd. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2014 Jun 24–27; Columbus, OH. Piscataway, NJ: IEEE; 2014. p. 2227–2234.
6. Feng L, Bhanu B. Understanding dynamic social grouping behaviors of pedestrians. J Sel Top Signal Process. 2015;9(2):317–329.
7. Jelić A, Appert-Rolland C, Lemercier S, Pettré J. Properties of pedestrians walking in line: fundamental diagrams. Phys Rev E. 2012;85:036111. http://link.aps.org/doi/10.1103/PhysRevE.85.036111
8. Seyfried A, Steffen B, Klingsch W, Boltes M. The fundamental diagram of pedestrian movement revisited. J Stat Mech Theory Exp. 2005;2005(10): P10002. http://stacks.iop.org/1742-5468/2005/i=10/a=P10002
9. Wu N. A new approach for modeling of fundamental diagrams. Transp Res A Policy Pract. 2002;36(10):867–884. http://www.sciencedirect.com/science/article/pii/S096585640100043X
10. Flötteröd G, Lämmel G. Bidirectional pedestrian fundamental diagram. Transp Res B Methodol. 2015;71:194–212. http://www.sciencedirect.com/science/article/pii/S0191261514001908
11. Cao S, Seyfried A, Zhang J, Holl S, Song W. Fundamental diagrams for multidirectional pedestrian flows. J Stat Mech Theory Exp. 2017;2017(3):033404. http://stacks.iop.org/1742-5468/2017/i=3/a=033404
12. Cao S, Lian L, Chen M, Yao M, Song W, Fang Z. Investigation of difference of fundamental diagrams in pedestrian flow. Phys A Stat Mech Appl. 2018;506:661–670. http://www.sciencedirect.com/science/article/pii/S0378437118305120
13. Weidmann U. Transporttechnik der fussgänger. Zürich, Switzerland: Institut für Verkehrsplanung, ETH Zürich; 1993.
14. Predtechenskii VM, Milinskii AI. Planning for foot traffic flow in buildings. New Delhi, India: Amerind; 1978.
15. Zhang J. Pedestrian fundamental diagrams: Comparative analysis of experiments in different geometries. Jülich, Germany: Forschungszentrum Jülich; 2012. Schriften des Forschungszentrums Jülich: IAS Series. Vol. 14.
16. Chattaraj U, Seyfried A, Chakroborty P. Comparison of pedestrian fundamental diagram across cultures. Adv Complex Syst. 2009; 12(3):393–405.
17. Hofstede G. Dimensionalizing cultures: the Hofstede model in context. Online Read Psychol Cult. 2011;2(1):8.
18. Favaretto RM, Dihl L, Barreto R, Musse SR. Using group behaviors to detect Hofstede cultural dimensions. Proceedings of the IEEE International Conference on Image Processing (ICIP); 2016 Sep 25–28; Phoenix, AZ. Piscataway, NJ: IEEE; 2016. p. 2936–2940.
19. Favaretto RM, Dihl L, Musse SR, Vilanova F, Costa AB. Using big five personality model to detect cultural aspects in crowds. Proceedings of the Conference on Graphics, Patterns and Images (SIBGRAPI); 2017 Oct 17–20; Niteroi, Brazil. Piscataway, NJ: IEEE; 2017. p. 223–229.
20. Jr PTC, McCrae RR. NEO PI-R: Inventário de personalidade neo revisado. São Paulo, Brazil: Vetor Editora; 2007.
21. Favaretto RM, Dihl L, Musse SR. Detecting crowd features in video sequences. Proceedings of the Conference on Graphics, Patterns and Images (SIBGRAPI); 2016 Oct 4–7; São Paulo, Brazil. Piscataway, NJ: IEEE; 2016. p. 201–208.
22. Favaretto RM, Knob P, Musse SR, Vilanova F, Costa AB. Detecting personality and emotion traits in crowds from video sequences. Mach Vis Appl. 2018:1–14.
23. Fridman N, Kaminka GA, Zilka A. The impact of culture on crowd dynamics: an empirical approach. Proceedings of the 2013 International Conference on Autonomous Agents and Multi-Agent Systems (AAMAS); 2013 May 6–10; St. Paul, MN. Richland, SC: International Foundation for Autonomous Agents and Multiagent Systems; 2013. p. 143–150. http://dl.acm.org/citation.cfm?id=2484920.2484946
24. Sommer R. Personal space: The behavioral basis of design. Upper Saddle River, NJ: Prentice-Hall; 1969. https://books.google.com.br/books?id=j2xLjwEACAAJ
25. Aiello JR, Thompson DE. Personal space, crowding, and spatial behavior in a cultural context. Boston, MA: Springer; 1980.
26. Baxter JC. Interpersonal spacing in natural settings. Sociometry. 1970;33(4):444–456. http://www.jstor.org/stable/2786318
27. Hall ET. The hidden dimension. New York, NY: Doubleday; 1966.
28. Sorokowska A, Sorokowski P, Hilpert P, et al. Preferred interpersonal distances: a global comparison. J Cross Cult Psychol. 2017;48(4):577–592.
29. Evans GW, Wener RE. Crowding and personal space invasion on the train: please don't make me sit in the middle. J Environ Psychol. 2007;27(1):90–94. http://www.sciencedirect.com/science/article/pii/S0272494406000636
30. Walters ML, Dautenhahn K, Te Boekhorst T, Koay KL, Syrdal DS, Nehaniv CL. An empirical framework for human-robot proxemics. Procs of new frontiers in human-robot interaction. 2009.
31. Redmon J, Farhadi A. Yolo9000: better, faster, stronger. arXiv 2016. arXiv preprint arXiv:1612.08242.
32. Lin T, Maire M, Belongie SJ, et al. Microsoft COCO: common objects in context. CoRR. 2014. https://doi.org/abs/1405.0312.
33. Everingham M, Eslami SMA, Gool LV, Williams CKI, Winn J, Zisserman A. The pascal visual object classes challenge: a retrospective. Int J Comput Vis. 2015;111(1):98–136.
34. Jacques JCS, Braun A, Soldera J, Musse SR, Jung CR. Understanding people motion in video sequences using Voronoi diagrams. Pattern Anal Appl. 2007;10(4):321–332. https://doi.org/10.1007/s10044-007-0070-1

35. Vilanova F, Beria FM, Costa AB, Koller SH. Deindividuation: from Le Bon to the social identity model of deindividuation effects. Cogent Psychology. 2017;4(1).
36. Le Bon G. The crowd: A study of the popular mind. New York, NY: Cosimo Classics; 2006. Cosimo classics personal development.
37. Goldberg LR. An alternative "description of personality": the big-five factor structure. J Pers Soc Psychol. 1990;59(6):1216–1229.
38. Durupınar F, Güdükbay U, Aman A, Badler NI. Psychological parameters for crowd simulation: from audiences to mobs. IEEE Trans Vis Comput Graph. 2016;22(9):2145–2159.
39. McCrae RR. NEO-PI-R data from 36 cultures: Further intercultural comparisons. In: The five-factor model of personality across cultures. New York, NY: Springer Science & Business Media; 2002.
40. Lang NC, Sulman J. Collectivity in social group work: Concept and practice. London, UK: Psychology Press; 1987.
41. Dyaram L, Kamalanabhan TJ. Unearthed: the other side of group cohesiveness. J Soc Sci. 2005;10(3):185–190.
42. de Lima Bicho A, Rodrigues RA, Musse SR, Jung CR, Paravisi M, Magalhães M. Simulating crowds based on a space colonization algorithm. Comput Graph. 2012;36(2):70–79.

AUTHOR BIOGRAPHIES



Rodolfo Migon Favaretto has been a Professor with the Information and Communication Department at the Federal Institute of Rio Grande do Sul (IFSul) since 2015. He received his Ph.D. degree in computer science from the School of Technology, Pontifical Catholic University of Rio Grande do Sul (PUCRS). He received his master's degree in computer science from the Federal University of Pelotas (UFPel). He graduated with a degree in computer science from the Universidade Regional Integrada do Alto Uruguai e das Missões (URI).

Roberto Rosa dos Santos has been the Coordinator of the Information Technology Center of the Federal University of Health Sciences of Porto Alegre (UFCSPA) since 2010. He is a student taking up his master's degree in computer science at the School of Technology, Pontifical Catholic University of Rio Grande do Sul (PUCRS). He graduated with a degree in information systems from the Lutheran University of Brazil (ULBRA).

Soraia Raupp Musse received her Ph.D. degree in computer science from the École Polytechnique Fédérale de Lausanne, Lausanne, Switzerland, in 2000, under the supervision of Prof. D. Thalmann. She is currently an Associate Professor with the Department of Computer Science, Pontifical Catholic University of Rio Grande do Sul, Porto Alegre, Brazil, where she created (and still coordinates) the Virtual Human Laboratory, where projects supported by private companies and the Brazilian government are developed. Her current research interests include crowd simulation and analysis, facial animation and integration between computer graphics, pattern recognition, and computer vision.

Felipe Vilanova is a Graduate Student at the Pontifical Catholic University of Rio Grande do Sul (PUCRS) and a Member of the Center for Psychological Studies on At-risk Populations (CEP-Rua) at the Federal University of Rio Grande do Sul and of the research laboratory Prejudice, Vulnerability, and Psychosocial Processes (PVPP) at PUCRS.

Angelo Brandelli Costa is a Professor in the Psychology and Social Sciences Graduate Programs of the Pontifical Catholic University of Rio Grande do Sul (PUCRS). He is also a Specialist in Social Psychology and Health Psychology. He is a graduate of psychology from the Federal University of Rio Grande do Sul (UFRGS) and has a master's degree in social and institutional psychology as well as a Ph.D. degree in psychology also from UFRGS.

How to cite this article: Migon Favaretto R, Rosa dos Santos R, Raupp Musse S, Vilanova F, Brandelli Costa A. Investigating cultural aspects in the fundamental diagram using convolutional neural networks and virtual agent simulation. *Comput Anim Virtual Worlds*. 2019;30:e1899. https://doi.org/10.1002/cav.1899