Simulating Urban Pedestrian Crowds of Different Cultures

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Models of crowd dynamics are critically important for urban planning and management. They support analysis, facilitate qualitative and quantitative predictions, and synthesize behaviors for simulations. One promising approach to crowd modeling relies on micro-level agent-based simulations, where the interactions of simulated individual agents in the crowd result in macro-level crowd dynamics which are the object of study. This article reports on an agent-based model of urban pedestrian crowds, where *culture is explicitly modeled.* We extend an established agent-based social agent model, inspired by social psychology, to account for individual cultural attributes discussed in social science literature. We then embed the model in a simulation of pedestrians and explore the resulting macro-level crowd behaviors, such as pedestrian flow, lane changes rate, and so on. We validate the model by quantitatively comparing the simulation results to the pedestrian dynamics in movies of human crowds in five different countries: Iraq, Israel, England, Canada, and France. We conclude that the model can faithfully replicate urban pedestrians in different cultures. Encouraged by these results, we explore simulations of mixed-culture pedestrian crowds.

CCS Concepts: • **Computing methodologies → Modeling methodologies**;

Additional Key Words and Phrases: Social simulation, agent-based simulation, pedestrian, crowd modeling, culture modeling

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1 INTRODUCTION

Accurate models of crowd dynamics are critically important for urban planning and management. Such models can be used as part of safety and homeland security decision-support systems (e.g., responding to demonstrations (Fridman and Kaminka 2013)), urban planning, pedestrian traffic management (Fridman and Kaminka 2010; Pelechano et al. 2007; Helbing 2001; Daamen and Hoogendoorn 2003; Arikawa et al. 2007; Bandini et al. 2016; Batty et al. 2003), and emergency response (e.g., building evacuation (Tsai et al. 2011; Kretz 2007; Yamashita and Umemura 2003)). The models generate synthetic behaviors for simulation, support analysis, and facilitate qualitative and quantitative predictions.

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One promising approach to crowd modeling relies on micro-level agent-based simulations, where the interactions of simulated individual agents in the crowd result in macro-level crowd dynamics, which are the object of study. Much progress has been made pursuing this approach, for example, in modeling pedestrians (Fridman and Kaminka 2010; Pelechano et al. 2007; Helbing 2001; Daamen and Hoogendoorn 2003), emotional contagion in crowds (Tsai et al. 2011), and in studying evacuation dynamics (Tsai et al. 2011; Kretz 2007; Yamashita and Umemura 2003).

Unfortunately, most agent-based simulations of crowds do not account for *culture*. Some existing models can be parameterized for basic micro-level parameters that vary with culture (e.g., walking speed). But in general, important individual cultural factors are ignored. Moreover, while social science literature on effects of culture in physical crowds is extensive when it comes to individual interactions, it only rarely addresses macro-level phenomena. These open challenges are particularly true of *mixed-culture crowds*, in which the rise of crowd dynamics out of individual interactions is inherently difficult to predict and parameterize.

This article reports on agent-based simulations of urban crowds, where *culture is explicitly modeled*. Specifically, we examine the impact of individual—micro-level—cultural differences on macro-level crowd dynamics in pedestrians. To do this, we used an extended *social comparison* model of social agent decision-making (Fridman and Kaminka 2011), shown to produce high-quality simulations of pedestrians (Fridman and Kaminka 2010). We add hierarchical comparison capabilities and spatial preferences to the model, to account for individual cultural parameters found in social sciences literature: personal spaces, speed, avoidance side, and group formations.

We analyze videos of urban pedestrians in five countries (Iraq, Israel, England, Canada, and France), and we show the cultural differences in the individual attributes. By comparing the simulation results to the data extracted from the videos, we quantitatively show that the social agent model is able to faithfully simulate macro-level pedestrian phenomena, such as pedestrian flows and number of collisions requiring lane changes, which differ with culture. In other words, we are able to accurately simulate culture-homogeneous pedestrians. Encouraged by these results, we examine the impact of pedestrians from mixed cultures on observable pedestrian dynamics.

2 BACKGROUND

We begin by placing this work in the larger context of urban computing. We then describe closely related work in both social psychology as well as computer science.

Pedestrian Modeling and Urban Computing. Urban computing (Kindberg et al. 2007; Zheng et al. 2014; Salim and Haque 2015) is a modern research field marrying computer science with civil engineering, geography and demographics, urban planning, transportation, and other areas that are concerned with urban spaces. It is often described in the context of analyzing data from urban sources (including GIS databases, fixed passive sensors, pedestrians carrying passive or active sensing devices, social networks, cameras, and more). However, it also encompasses model-based analysis, in particular, to address planning and design in urban context.

For instance, work on pedestrian navigation (e.g., Arikawa et al. (2007)) uses *data* from GPS-enabled cell phones and cars, online weather and traffic reports, and indoor localization to track pedestrian movements, determine congestion points, traffic and public transportation conditions, and more. This data analysis is augmented with *models*: road and pedestrian walkway maps, public transportation time-tables, and historical data. The data and models together inform pedestrian navigation planning algorithms, which generate potential routes for reaching one point from another, predicting travel time, monetary costs, walking efforts, and so on.

Pedestrian mobility models and data analysis are a part of urban computing, specifically in the context of investigating human urban social behavior. Articles on pedestrian mobility or more general urban social behavior are often sought explicitly in the call for articles for urban computing research meetings (see, for instance, the submission calls for *Urban Computing (UrbComp)* (e.g., Wolfson and Zheng (2012) and Koonin et al. (2013)), *Urban Computing and Modern Cities (UCMC)*, *Smart Cities and Urban Computing*, and others. Both data and models of pedestrian mobility are used to assist online and offline urban planning and design, both in the context of normative pedestrian traffic (Bandini et al. 2016), as well as in anomalous conditions (such as in emergencies and special events (Batty et al. 2003)).

We are not the first to address culture in the larger context of urban computing. Williams and Dourish (2006) discuss the importance of explicitly distinguishing culture in the development of cities and urban spaces, and in urban computing processes applied to cities in different places in the world. Christopoulou et al. (2012) examine the connection between culture and computing in the opposite direction; they study how urban computing affects the urban culture in cities of two different countries. Both investigations examine culture from a broad, city-wide, sociological perspective. In contrast, while we are inspired by research in social and behavioral sciences (see the following), we examine the effect of culture on—relatively—fine details: such as the flow of pedestrian crowds. Also, in contrast to this previous work, we address *mixed-culture* crowds, as would be the case of tourist pedestrians in a city.

Pedestrians and Cultures in Social and Behavioral Sciences. Our work is informed and inspired by social and behavioral sciences views on cultural and other variations in human group interactions, in particular, in urban pedestrians.

Hall investigated *proxemics*, the distances that pedestrians keep from each other across different cultures (Hall 1963; Hall and Hall 1990). He defined four distances: *intimate*, *personal*, *social*, and *public*. Growing outward, the *personal distance* applies to interactions among good friends or family members. The *social distance* applies to interactions among acquaintances, and the *public distance* is used for other interactions.

Many researchers have investigated proxemics and other temporal and spatial characteristics of pedestrian motions. For example, Beaulieu (2004) showed that changes in the distances depend, among other things, on relationships to the closest person and also on cultural background. In general, our findings from analyzing movies of urban pedestrians in several countries are in agreement with earlier findings, even in single culture studies.

Costa (2010) investigated the effects of group size, gender composition, and homogeneity, on the spatial clustering and shape of the group as its members move together. The large-scale study focused on data from a single country (Italy) and is therefore limited to a single culture. Nevertheless, our findings in multiple cultures are in agreement (e.g., mixed-gender groups walk slower in all cultures).

Bandini et al. (2016) and Gorrini et al. (2016) report on the analysis of pedestrian movies from Italy and from Japan. They present several findings that are particularly related. For example, they find that the personal distance does not change with motion speed (which is also a characteristic of our agent decision-making model). They also find that *dyads* (two-person groups) walk slower than individuals, which agrees with our findings.

Seitz et al. (2016) and Tempelton et al. (2015) take a critical look at computer simulations of crowd and call on greater involvement of findings and theories from social psychology. In particular, they propose incorporating aspects of *self-categorization theory* (Turner 1985). We agree with the recommendation to incorporate more social psychology into crowd research, though we are inspired by a different social psychology theory, *social comparison theory* (Festinger 1954).

Levin and Norenzayan (1999) examined the cultural differences in the *pace of life* (which includes mean walking speed) in 31 countries. They showed people in England and France walk faster than people in Jordan or Syria. This finding is supported in our empirical analysis of data from different countries.

Berkowitz (1971) studied urban pedestrians in 20 locations, in six national groupings. This study shows that countries differ in the frequency of groups within urban pedestrian motion.

Chattaraj et al. (2009) examined whether there are cultural differences in emergent pedestrian lanes in corridors. For instance, they found that the speed of Indian individuals is less dependent on density than the speed of Germans, and that Germans maintain greater personal space.

Models of Pedestrians. There are two general approaches to modeling social phenomena via computational modeling: *macro-level modeling* (e.g., Gilbert and Troitzsch (2005) and Fridman and Kaminka (2013)) focuses on modeling the processes that shape social changes, typically at the level of entire populations or at least major subgroups. In contrast, *micro-level agent-based modeling* focuses on separate modeling of each agent, where the group behavior results from simulating interactions of multiple agents. We follow the latter approach in this article.

Henderson (1974) compared pedestrian movement to gas-kinetic fluids and showed that they can be modeled using Maxwell-Boltzmann theory. Based on Boltzmann-like equations, Helbing (2001) developed a general behavior model for simulation of crowd dynamics. The proposed model models *social forces* caused by interaction between individuals, and *external forces* due to the environment. Lämmel and Plaue (2012) take this approach further, adding and experimenting with explicit collision avoidance mechanisms to the social forces, in particular in controlled settings where two pedestrians crowds with different headings intersect. These investigations do not take culture into account as we do here. Barwolff et al. (2012) examine different models and methods for simulating such settings with a growing number of agents and increasing agent complexity.

Moussaïd et al. (2010) showed that social interactions among group members create different group walking formations (shapes) and examine the impact of these on the pedestrian flow. They show that in low density settings, group members tend to walk side by side. As the density increases the group members tend to move in a V-like pattern formation, which reduces the flow. Zanlungo et al. (2014, 2016) provide a mathematical model for such small groups (two- and three-pedestrian groups), and show how the velocity is affected by the group size, but also the gender and social relations of the members. While they consider social roles but focus on a single culture, we address multiple cultures. Thus, for instance, we address additional variables influencing behavior, such as collision avoidance side preferences.

Many pioneering investigations have focused on controlled settings when conducting quantitative comparison between simulated pedestrians and human crowd motion, captured in video. Daamen and Hoogendoorn (2003) performed controlled experiments in pedestrian flow in bi-directional motion. Participants in these experiments wore specially-colored caps to enable automated tracking. Johansson et al. (2007) recorded videos in natural settings. However, they investigate indoor settings, where the floor tiling was used to facilitate automated tracking. In contrast to these and similar investigations, we study videos of pedestrians in uncontrolled urban settings. Indeed, with the advent of computer vision methods and the ubiquity of urban sensors (e.g., webcams, such as those we use in this research), a growing number of investigations evaluate models against real-world data from unrestricted urban settings.

Many pedestrian crowd models can in principle account for basic cultural parameters such as proxemics and walking speed. In contrast to these, we go to greater depth in modeling cultural effects dependent on gender (e.g., on speed, grouping, and proxemics). We also model culture-heterogeneous crowds. However, some of these model individual traits that we do not.

Blue and Adler (2000) used cellular automata to simulate collective behaviors, in particular pedestrian movement. They showed that simple rules result in the formation of lanes in movement, similarly to those formed in human pedestrian movement (Wolff 1973). The High-Density Autonomous Crowds (HiDAC) system, models each individual agent as a combination of psychological and geometrical rules with a social and physical forces (Pelechano et al. 2007). Such agents can exhibit variety of crowd behaviors ranging from panic evacuation to leaving a cinema after a movie. Similarly, we add spatial preference rules to the decision-making loop of agents (in particular, in the culturally biased selection of collision avoidance side). However, the HiDAC system does not account for culture.

Some investigations explore heterogeneous crowds, which are reminiscent of the mixed-culture crowds we simulate in this article. Toyama et al. (2006) modeled varied pedestrian characteristics, such as speed, gender, repulsion level, and so on. Durupinar et al. (2008) explore heterogeneous crowd simulations in which individuals have varying personality traits, such as *extroversion* and *openness*.

More recent work considering heterogeneous crowds have focused on the presence of subgroups (e.g., families or friends) within the crowd, and their effect on crowd dynamics. Manenti et al. (2010, 2011) examine proxemics in the presence of groups, where agents seek to remain close to their group. More recently, Vizzari et al. (2015) expand this model further and validate it with real world data. These investigates are related to our own use of social comparison processes to drive agents towards others that are similar to them. The algorithms we present in this article specifically consider both social groups (e.g., members of a family will identify each other as belonging to the same group), as well as gender. This is done as to model cultural gender equality biases, which are not addressed in the previous work.

3 CULTURE IN URBAN PEDESTRIANS

We apply the following methodology in this investigation. We report on the collection (Section 3.1) and analysis (Section 3.2) of videos of pedestrians in unrestricted, uncontrolled, natural settings in five different countries. We show (Section 3.3) that indeed the pedestrian crowds in these videos differ in along selected individual cultural attributes reported in the literature.

3.1 Movies of Pedestrians: Data Collection

We recorded movies of pedestrians in five different cultures: Iraq, Israel, England, Canada, and France. The details are described in the following:

— The movies from Iraq were recorded from a web camera overlooking the yard in front of the Hussein mosque in Karbala.[1] In total, we recorded over 30 different 3h videos (over 90h) in this location. The videos were recorded during different times of the day. About a third of the videos were irrelevant due to static views, or because the web camera was off, and so on. Of the remaining videos, we randomly chose six of the movies and analyzed the first three minutes of each. Thus, in total, we utilized 18min of pedestrian dynamics in Iraq.
— The movies from Israel were similarly recorded from a web camera overlooking the Western Wall in Jerusalem.[2] We recorded over 30 videos during different times of the day, again each 3h long. A third of these videos were found to be irrelevant for the same reasons associated with Iraq and among the remaining ones we randomly selected four movies and analyzed the first 3min of each. Thus, in total, we utilized 12min of films depicting pedestrian dynamics in Israel.

[1] https://alkafeel.net/live/.
[2] https://english.thekotel.org/kotel/kotel_cameras/.

— The movies from England were manually recorded in London in two different locations: Two movies from the London Eye (1:23 and 0:31min long), and one from the Millennium Bridge (31s long).
— The movies from Canada were manually recorded from a high-rise building, overlooking one of the streets in downtown Vancouver in the morning and also in the afternoon. In total, we analyzed four movies that are 0:15, 0:24, 1:18, and 3:36min long.
— The movies from France were manually recorded in Paris from the top of the Eiffel tower. The movies were taken in the afternoon and portray two streets that lead to the Eiffel tower. In total, we analyzed two movies of two different locations that are 1:40 and 2:47min long.

In all cases, videos were recorded by stationary *uncalibrated* cameras overlooking urban scenes. The Iraq and Israel videos were recorded in religious sites, where pedestrians move about within a general area, rather than a walkway; they therefore have more freedom in selecting their heading. The France and England movies were recorded in tourist locations, focusing on pedestrian traffic on walkways and sidewalks, less than 10m wide. The Canada movies were recorded in the urban downtown.

3.2 Pedestrian Video Analysis

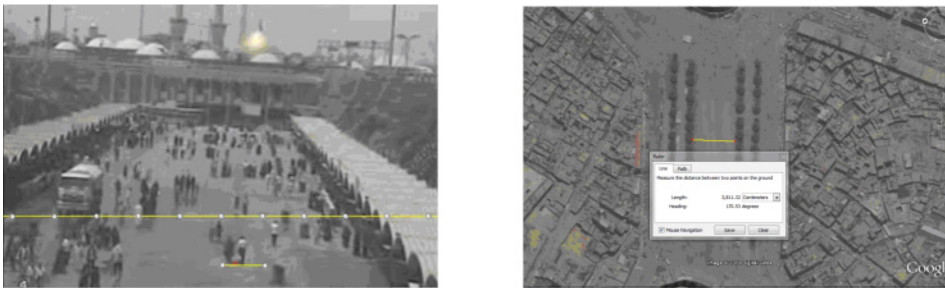
Based on social science literature (see Section 2), we focus on the following individual (micro-level) cultural parameters: personal space (Hall and Hall 1990; Hall 1963; Beaulieu 2004), base walking speed (Levine and Norenzayan 1999), avoidance side (Moussaïd et al. 2009), and group formations (in particular, gender-heterogeneity, size, and shape, e.g., whether side-by-side, or one gender in front (Moussaïd et al. 2010)).

For the purpose of analysis, we used a total of 45min of videos. Overall, four subjects were asked to independently analyze the movies, two different subjects for each movie. Each subject measured the *group formations*, *walking speed*, and *avoidance side* as described in the following; the mean measurements were used.

To extract the group formations, the subjects counted the number of individuals and the number of groups. For each individual the subjects were asked to specify whether the pedestrian was a man or a woman. For each group the subjects were asked to specify the size of the group; couples, three people or more and also the gender composition of each group; two women, two men, a man and a woman, woman with child, and so on. To extract the avoidance side the subjects were asked to count the number of individuals or groups that passed other pedestrians either from the left or right avoidance side.

To estimate walking speed, the subjects sampled 10 pedestrians in each movie, counting their steps within 15s. The samples took into account the relative frequency of formations. For example, if a particular movie contained 40% individual men, 10% individual women, 30% groups of three men, and 20% pairs of men and woman, then we sampled the velocities of four randomly chosen men, one woman, three groups of three men, and two pairs of men and women. For groups, they were asked to count the number of footsteps only for an arbitrarily chosen representative.

Estimating the proxemics (in particular, the personal and social distances between people) proved particularly challenging, as we use uncalibrated cameras, over which we have no control, and whose position, angle, and height is unknown. This makes it difficult to use computer vision techniques. We therefore used two techniques: Using *Google Earth* to determine the objects' sizes, or comparison with the known sizes of familiar objects (such as cars or sports-field dimensions). If only one technique was feasible, then we used only one measurement; otherwise, we took the mean value between the two measurements.



(a) Estimation based on known objects.

(b) Estimation using Google Earth imagery.

Fig. 1. Personal space estimation.

We present an example in which we used both techniques to estimate the distance. In one of the movies from Iraq, a truck passed by the pedestrians (Figure 1(a)). The standard width of a truck is 8ft (2.4384m). We measured the truck's width on the screen (marked in yellow) and found that it was 0.98cm. We then drew a line between the two people in the movie (marked in red) and found that it was 0.15cm on the screen. We thus deduced that the distance in reality is: $(0.98/0.15) \times 2.4384\text{m} = 37\text{cm}$.

To verify these estimations, we used *Google Earth*. We found that the width of the area is 38m (including the white shades; see Figure 1(b)). Each segment in the yellow line (Figure 1(a)) is therefore 2.375m. Again, simple math shows the personal distance marked is approximately 36cm.

3.3 Results: Cultural Differences in Pedestrian Videos

The results show that indeed the five countries vary in their cultural parameters. We present the analysis of the results of each parameter, that is, gender group formations (size, makeup, etc.), walking speed, collision avoidance side, and personal spaces.

Group Tendency, Composition, and Spatial Formations. We begin by examining the groups and their makeup. Table 1 presents the results of gender group formations. The first column corresponds to the examined formations. Then, we present the distribution of each of these formations by culture: Iraq, Canada, Israel, and France. Each value is the mean of two measurements, by two subjects.

In Tables 2–5, we present additional statistics from analysis of groups in the movies. First, we examined the portion of pedestrians that move as individuals versus groups. Table 2 presents the results. The first column corresponds to the formation (individuals or groups). Then, we present the distribution of the pedestrians in each culture examined. The results show that in Vancouver, Canada, people move more as individuals than as groups. In every other country there is a higher tendency of pedestrians to move as groups.

We also checked whether pedestrians who move in groups tend to do so in homogeneous or heterogeneous gender groups. The results are presented in Table 3. The findings show that in Iraq, Canada, Israel, and England, pedestrians move more in homogeneous gender groups. Indeed, in France, we observed many couples, that is, a man and a woman, who move together.

We also examined the pedestrian cultural tendency concerning the sizes of the groups. For all the pedestrians that move in groups, we provide the statistics on their distribution into groups of several sizes, such as groups of 2, 3, 4, and more. Table 4 presents these results, which show that in Iraq there is a higher tendency to move in larger groups than in the other countries examined.

Table 1. Distribution of Gender Group Formation

Formation	Iraq	Canada	Israel	England	France
1 man	20.9%	42.4%	33.3%	12.4%	9.21%
1 woman	6.88%	17.3%	14.6%	5.53%	4.61%
2 men	15.4%	14%	15.7%	24.9%	14.5%
2 women	12.3%	9.05%	11.8%	10.1%	11.8%
1 man next to 1 woman	5.22%	4.94%	9.27%	24.9%	35.5%
1 man in front of 1 woman	2.61%	0	0.36%	3.69%	5.26%
1 man & 1 child	0.71%	0	1.78%	3.69%	1.32%
1 woman & 1 child	2.14%	0	1.43%	3.69%	0
3 men	8.9%	7.41%	6.42%	5.53%	0
3 women	7.47%	4.94%	4.28%	0	1.97%
1 man next to 2 women	4.27%	0	0.53%	2.76%	1.97%
1 man in front of 2 women	1.78%	0	0	1.38%	0
2 men & 1 child	0.71%	0	0	0	0
2 women & 1 child	1.42%	0	0	0	0
1 man, 1 woman & 1 child	1.42%	0	0.18%	1.38%	5.92%
2 men & 1 woman	0.71%	0	0	0	7.89%
2 men, 1 woman & 1 child	0.47%	0	0	0	0
2 women & 2 children	0.95%	0	0	0	0
3 men & 1 child	1.42%	0	0	0	0
1 man & 3 women	0	0	0	0	0
4 women	4.27%	0	0	0	0

Table 2. Frequency of Individuals Versus Groups in Movies

Formation	Iraq	Canada	Israel	England	France
Individuals	28%	60%	48%	18%	14%
Groups	72%	40%	52%	82%	86%

Table 3. Gender Heterogeneity of Groups

Groups	Iraq	Canada	Israel	England	France
Heterogeneous	23%	12%	21%	42%	66%
Homogeneous	77%	88%	79%	58%	34%

Table 4. Size of Group Formations

Group size	Iraq	Canada	Israel	England	France
Groups of 2	64%	77%	84%	91%	85%
Groups of 3	30%	23%	16%	9%	15%
Groups of 4 and more	6%	0	0	0	0

According to experts, men in Arabic countries demonstrate a greater tendency to walk in front of women than in other countries, where they usually walk side by side. We checked whether this finding was supported in the videos from Iraq and compared it to the videos from the other countries. The results presented in Table 5 show that in Iraq this tendency was observed in 33% of the couples, higher than in the other countries.

Table 5. Man and Woman Spatial Formation

Formation	Iraq	Canada	Israel	England	France
Man next to woman	67%	100%	96%	87%	87%
Man in front of woman	33%	0	4%	13%	13%

Table 6. Pedestrian Speed (Mean Number of Steps in 15s)

Formation	Iraq	Canada	Israel	England	France
1 man	25.3	27.8	26.7	28.7	27.3
1 woman	22.1	27.6	24.9	23.5	26
2 men	23.2	27.8	24.5	26.2	26.3
2 women	20.6	31.2	22.6	24.1	26.3
1 man next to 1 woman	23	28	22.5	25	24.8
1 man in front of 1 woman					23
1 man & 1 child			31.5		
1 woman & 1 child					
3 men	23	30.5	25	28.7	
3 women	20	26.2	30		
1 man next to 2 women	23			20	
1 man in front of 2 women	22				
2 men & 1 child					
2 women & 1 child					
1 men, 1 woman & 1 child					23.8
2 men & 1 woman					24
2 men, 1 woman & 1 child					
2 women & 2 children					
3 men & 1 child					
4 women	25.9				

Table 7. Walking Speed, by Gender and Country

Formation	Iraq	Canada	Israel	England	France
men	25.3	27.8	26.7	28.7	27.3
women	22.1	27.6	24.9	23.5	26

Pedestrian Speed. We then examined individual speed, and its variance based on gender and grouping in the different cultures. Table 6 presents the results of pedestrians' speed (measured in steps per 15s; the conversion to distances introduces noise that is not relevant at this stage. We will discuss the noise in Section 5). Again, the first column corresponds to the examined formations. Then, we present the mean speed of two samples of each examined formation for each culture: Iraq, Canada, Israel, and France.

Table 7 shows that men walk faster than women in all the cultures that were observed. As for the difference in the cultures, we find that Iraqi pedestrians walk the slowest (this agrees with (Levine and Norenzayan 1999)).

Next, we examined the effects of grouping on speed. In this case, we examined the mean speed of pedestrians who move as individuals versus the mean speed of pedestrians who move in groups. The results presented in Table 8 show that in all cultures people as individuals move faster than people in groups.

Table 8. Speed of Individuals Versus Groups

Formation	Iraq	Canada	Israel	England	France
Individuals	25.1	28.6	25.7	26.5	26.6
Groups	23	27.3	24.6	25	24.9

Table 9. Speed of Homogeneous Versus Heterogeneous Gender Groups

Formation	Iraq	Canada	Israel	England	France
Mixed groups	23.4	25.8	22.8	24.5	24
Men homogeneous groups	24.1	28.8	26.3	26	26.8
Women homogeneous groups	21.5	26.5	24.5	23.8	25.6

Table 10. Avoidance Side

Avoidance side	Iraq	Canada	Israel	England	France
Right	62%	63%	41%	77%	45%
Left	38%	37%	59%	23%	55%

Table 11. Personal Space Maintained by Men and Women Within Groups (in Centimeters)

Group Type	Iraq	Canada	Israel	England	France
Mixed gender	26.5		46	50.3	35
Men only	43.8	65.8	66.5	49.5	57.5
Women only	18.3	70	50.3	52	40.5
Mean space	32.7	67.9	57.9	50.3	41.7

We also examined whether there is a difference in mean speed between homogeneous and heterogeneous gender groups of all the pedestrians that move in groups. Moreover, we examined whether there is a difference in speed among groups of men versus groups of women. The results summarized in Table 9 show that in Iraq and England the group of women are the slowest of the the groups. However, in all the cultures the groups of men are the fastest of the groups.

Avoidance Side. Table 10 presents the distribution of pedestrians preferring collision avoidance on the left or on the right in the different countries. The results show that in Iraq, Canada, and England the pedestrians prefer the right side, while in Israel and France they prefer the left side.

Proxemics. Finally, the video analysis shows that there are cultural differences in personal spaces. Table 11 shows the personal spaces within groups, as well as the mean personal space. We examined whether there is a difference in the personal spaces kept by men and women in the same group. We distinguished between heterogeneous gender groups, homogeneous male groups and homogeneous female groups. The results show that in Iraq, Israel, and France women maintain a smaller personal space than men. The biggest gap between the group of men and the group of women was observed in Iraq. The results of the mean space shows that in Iraq pedestrians who walk in groups maintain the smallest personal space than in the other cultures observed.

4 A CULTURED SOCIAL-AGENT MODEL PEDESTRIAN

We have been investigating a social comparison model of crowd behavior, inspired by Festinger's (1954) *social comparison theory* (SCT), which is still developed in social psychology today (Suls and

Wheeler 2000). The key idea in Festinger's theory is that when people lack objective means for appraisal of their opinions and capabilities, they compare their opinions and capabilities to those of others that are similar to them. They then attempt to correct any differences found.

In previous work, we reported on a concrete distributed algorithm (inspired by SCT) that controls the decision-making of each individual agent separately. It can generate simulated group contagion phenomenon (Fridman and Kaminka 2011) and realistic pedestrian behavior, in comparison to videos of urban pedestrians (Fridman and Kaminka 2010). However, it does not account for cultural differences between individuals.

We describe this baseline algorithm briefly (the reader is referred to Fridman and Kaminka (2010, 2011) for details). We then present its extension to account for the cultural differences in the spatial behavior preferences of pedestrians.

4.1 Baseline Social Comparison Decision-Making

The baseline algorithm is run in a distributed fashion by all simulated pedestrians. Each agent (denoted $\mathcal{A}$) considers those around it, up to its range of visual perception, subject to occlusions. Each *observed* agent A_i is taken to be a tuple of k state features $\langle f_1^{A_i}, \dots, f_k^{A_i} \rangle$. Essentially, each agent A_i is a point in a k-dimensional space, where the various dimensions correspond to agent state features, such as location in x, y coordinates, heading, group (e.g., family), and so on.

The observing agent $\mathcal{A}$ considers the state similarity between itself and each other agent A_i. It does this by calculating a similarity value $Sim(\mathcal{A}, A_i)$ (Equation (1)). We measure similarity independently along each feature dimension. The similarities in different dimensions are functions $s_{f_j}(f_j^{\mathcal{A}}, f_j^{A_i}) : f_j \times f_j \mapsto [0, 1]$, where $1 \leq j \leq k$. The function s_{f_j} defines the similarity in feature f_j between the two agents $\mathcal{A}$ and A_i. A value of 0 indicates complete dissimilarity. A value of 1 indicates complete similarity (identity).

We use normalized Euclidean distance (inverted) to measure similarity in position: A value of 0 means that the agents are as far apart as possible (at the end of the visual range). A value of 1 means that they are positioned in the same location. Headings are compared by measuring angle differences up to $\pm 180°$: 0 when the angle difference is $\pm 180°$ (heading in opposite directions), 1 when the angle difference is 0. Groups (which are denoted by unique ID, e.g., color or string) are compared via the equality function: 1 if equal, 0 otherwise.

To determine the overall similarity between two agents, we use a weighted sum over the functions s_{f_j}. With each feature f_j, we associate a weight $w_j \geq 0$. The similarity between two agents is then given by Equation (1):

$$Sim(\mathcal{A}, A_i) \triangleq \sum_{j=1}^{k} s_{f_j}(f_j^{\mathcal{A}}, f_j^{A_i}) \cdot w_j. \tag{1}$$

Given the similarity $Sim(\mathcal{A}, A_i)$ for all agents A_i in its vicinity, the observing agent $\mathcal{A}$ removes from consideration agents whose similarity is above a given threshold S_{max} or below a threshold S_{min}.[3] Finally, of those remaining, the agent with the highest similarity value is selected (denoted A_{max}, Equation (2)):

$$A_{max} \triangleq \operatorname*{argmax}_{A_i} Sim(\mathcal{A}, A_i), \quad \text{s.t.} S_{min} \leq Sim(\mathcal{A}, A_i) \leq S_{max}. \tag{2}$$

[3]Festinger writes (1954): "When a discrepancy exists with respect to opinions or abilities there will be tendencies to cease comparing oneself with those in the group who are very different from oneself."

Once the agent A_{max} is determined, the observing agent $\mathcal{A}$ takes actions to reduce the discrepancies between itself and A_{max}. Where applicable, the agent applies its action with a *gain*, a numeric value that grows with the difference.[4]

Applied to generation of pedestrian motion, the process described previously was used to make lane change, moving velocity (walking speed), and heading decisions. For instance, one feature used in determining similarity was the position (with the normalized distance used for similarity as noted previously). Agents may decide to get closer to other agents (minimizing difference in position), and using *a gain multiplier* to control their velocity (faster when more distant, up to the top allowed velocity). See Fridman and Kaminka (2010) for details.

4.2 An Extended Social Comparison Process

Some basic parameters that affect behavior depending on cultures could be easily modeled using the previous algorithm. For instance, by varying the base walking speed and the velocity gain for different agents, one could simulate rudimentary *pace of life* (Levine and Norenzayan 1999) effects. Just as easily, preference for a side to avoiding a collision is easily modeled as a bias in the selection of a corrective action.

Possibly, though with less fidelity, by modifying the thresholds S_{min}, S_{max}, one could trigger responses at closers or farther distances, thus approximating the proxemics of the *personal* space. Anything below S_{min} would be considered within the *intimate* space, and anything above S_{max} would be considered in the *social* space.

However, such tweaks do not adequately model cultural behavior in pedestrians. First, we note that walking speed and proxemics changes with gender (see the results in Section 3). Second, gender determines groupings and motion patterns. In some cultures, for instance, married mixed-gender couples would not walk side by side, but one gender before the other.

We therefore extend each agent with features that are affected by culture or affect the behavior in different cultures. These include:

- Avoidance side preference (left or right; similarity 1 if equal, 0 otherwise).
- Gender g (male or female; similarity 1 if equal, 0 otherwise), for example, for modeling of gender-equality biases. And conditioned on the gender:
  - A comparison tendency p_g (the probability of choosing comparison target with the same gender as the agent);
  - Base walking speed for the culture (in the experiments, we use three speeds—see Section 5.1);
  - Preference for *three* proxemics: *personal*, *social*, and *public* (Hall 1963; Hall and Hall 1990) (see Section 5.1 for experiment details).

An important aspect of utilizing the last three parameters is that their affect changes depending on the gender. The results from observing pedestrians (Section 3) demonstrate that walking speed, personal spaces, and even group walking formations vary, depending on the gender and the mixing of genders within a group. In particular, they vary with gender equality (as it pertains to pedestrian motion).

We expand the process described previously to account for gender equality biases. The key is that instead of selecting a single target for comparison (Equation (2)), two possible targets are selected—one from each gender. One of these is selected as the comparison target, based on individual gender equality bias (represented in the probability p_g discussed previously). To the extent that there exists a preference to select one's own gender for comparison, the agent selects a

[4]Festinger writes (1954): "The stronger the attraction to the group the stronger will be the pressure toward uniformity."

comparison target of the same gender. Otherwise, if the agent is gender-neutral (maintains gender equality), it selects between the two candidates arbitrarily. The end result is that in cultures with less gender equality, "male" agents tend to compare themselves with males, and "female" agents, with females (gender similarity is 1 if equal gender, 0 otherwise)). In cultures with more gender equality, both types of agents choose arbitrarily without consider the gender of the target (i.e., the gender comparison is ignored; the weight of the gender similarity factor within overall agent similarity calculations is set to 0).

Concretely, the process is as follows.[5] For each gender g_G, including its own, $\mathcal{A}$ maintains comparison thresholds S^g_{min}, S^g_{max}. For each gender, it carries out the process described in Section 4.1, filtering out comparison target candidates, and finally choosing a single representative agent *for each gender g*. Essentially, this means that $\mathcal{A}$ partitions the agents around it based on their gender, and generates a single candidate comparison target for each partition.

Then, one of these representative agents is chosen as the comparison target. This is done by a biased coin flip (with the bias being the probability p_g associated with $\mathcal{A}$, the agent carrying out the comparison). Once the comparison target is known, the process continues as described in Section 4.1: actions are selected (with a possible gain) to minimize the logical and physical distance to this agent, and so on.

5 EXPERIMENTS

The previous sections discussed individual traits that demonstrably vary with culture (Section 3), and an individual decision-making algorithm intended to generate behavior in accordance with these traits (Section 4). This section reports on experiments with the algorithm in a simulation of pedestrians (the simulation setup is described in Section 5.1).

First, in Section 5.2, we show that the algorithm, when seeded with *individual* cultural parameters such as walking speed, gender bias, and proxemics, can generate *global* crowd phenomena, which agree with those in the videos. Then, having established the fidelity level of the simulation, we use it in Sections 5.3–5.5 to examine hypothetical questions about such global phenomena: the impact of specific traits, global differences between cultures, and the effects of mixing pedestrians of different cultures.

5.1 Simulation Experiment Setup

The experiments used the OpenSteer simulation platform (Reynolds 2004). We simulated an infinite sidewalk where agents move in both directions. Each agent had a limited visual range to perceive others (up to the limits of the *public distance*, see the following); in case of possible collision the agents attempted to avoid each other, that is, change lanes.

We use a systematic procedure to translate real-world measures into simulation equivalents. The following serve as the controlled (independent) variables:

- **Proxemics.** We model the *personal*, *social*, and *public*. Hall (Hall and Hall 1990; Hall 1963) reported two settings of distances for these three spaces: *close* and *far*. The *close* settings defined the personal distance at 46cm, social distance at 120cm, and a public distance of 370cm. The *far* setting defined the personal distance at 76cm, social distance at 210cm, and a public distance at 760cm. We use Hall's values of close and far as the basis for the simulation, calibrated to the personal distance of the different cultures (measured as the mean distance between observed couples). In the translation for the simulation, we normalized based on

[5]This is a short description, used in the experiments described in this article. A more general algorithm—for *hierarchical* social comparison—is presented in detail in Fridman (2012).

the shortest (46cm). Thus, the three values for *close* ⟨46cm, 120cm, 370cm⟩, were translated into simulation distances of ⟨1, 2.6, 8⟩ and for *far* ⟨76cm, 210cm, 760cm⟩ were translated into ⟨1.65, 4.56, 16.5⟩.

— **Walking Speed** We defined three speeds of walking: *slow*, *average* and *fast*. We analyzed the data extracted from the different cultures, and divided the speed samples into the three groups of speed in our simulation, based on the 33rd and 67th percentiles. This is very low-resolution discretization of the walking speeds; a higher-resolution discretization may be better (Schultz et al. 2010). This resulted in three ranges of speed (still in units of steps per 15s): [20–24), [24–27), [27–31.5). We take the midpoint of each range as representative speed.

  To translate into standard units, we must determine step length in centimeters. However, approximately 50 years of studies of step length ((Murray et al. 1969) is an early example) show it varies quite significantly. Indeed, both mean step length and variance carry significant clinical (Hausdorff et al. 2001; Hollman et al. 2011; Bayle et al. 2016) and non-clinical (Tripathy 2004; Owings and Grabiner 2004) information and are the subject of intense study. For example, see the published back-and-forth debate between Danion et al. (2003, 2004) and Hausdorff (2004) on the importance of step length, frequency, and variability and the different factors that affect them, as well as recent attempts at modeling some of these factors in simulating pedestrians (Seitz et al. 2014; von Sivers and Köster 2015).

  As our focus is on cultural features rather than stepping behaviors, we decided to fix the velocities using a single scalar estimate of the step length. Various resources (e.g., Answers.com (2011)) suggest 75cm as a reasonable estimation for a human's average step length. Using this value, we converted the representative speeds to 1.1m/s, 1.27m/s, and 1.46m/s, respectively. By normalizing to human body width, we set OpenSteer speeds to 2.27, 2.62, and 3.01, respectively.

Note that these settings of the independent variables are a very crude calibration of individual settings, as we essentially discretized the walking speeds, the proxemics, and so on, and use ordinal discrete scales. An additional independent variable often needed in the simulation is the *density*: the number of pedestrians in a given area.

Data from the video analysis is only used for this initial calibration of *individual* parameters. The simulation is run, and validation is carried out on quantitative *global* crowd measures (dependent variables)):

— Pedestrian flow: number of agents that cross a line, divided by the width of the line and the time the process takes
— Mean speed: over all agents (this is different from the set individual speed, which each agent may or may not be able to achieve)
— Mean number of collisions: between two agents, averaged over all agents
— Mean number of lane changes: the number of direction changes of the agent that are above a predetermined threshold, averaged over all agents

5.2 Experiment 1: Comparison to Human Data

The most important underlying question is whether the fidelity of the simulation is sufficient to support conclusions concerning urban pedestrian motion. Thus, first, we want to examine whether the cultured social agent model, embedded in the OpenSteer simulation, can faithfully simulate the urban pedestrian behavior.

Table 12. Density in Urban Pedestrian Movies

Movie	Length	Width	Area	Number of pedestrians (mean)	Density
France1	25m	5m	125m^2	8.238	0.0658
France2	16.5m	5.5m	90.75m^2	5.5	0.0606
Canada	9m	3.9m	35.1m^2	4.428	0.1262
London	12m	12m	144m^2	7.4	0.0514

To do this, we ran over a 100h of simulation using the previous values. All results in the following are averaged over 30 runs. We quantitatively compared the macro level measures (flow and mean speed) generated by the simulation to those of the crowds in the videos. We did not compare the number of collisions for this part, since humans rarely collide (not even once in the video recordings).

To carry out this comparison, we recreated the *initial* settings from four of the videos in the simulation. Specifically, we set the density of the pedestrian crowd (how many pedestrians per unit area); we set the individual discrete parameters of agents and groups per the individual parameters in the videos; and we ran the simulation for the same time as the videos.

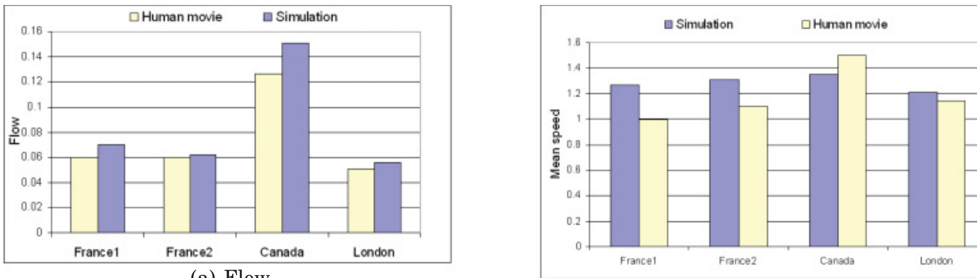
5.2.1 Flow Comparison. It has been shown that density has a large impact on the flow (Steffen and Seyfried 2010). Thus, to quantitatively compare the simulation flow to the human pedestrian flow, we had to account for the density. To extract the density from the examined human pedestrian movies, we sampled the number of pedestrians in a defined area every 5s, and used the average number over all the samples. We analyzed the flow from 4 different movies, two from France (1:40min and 2:47min each), one from Canada (3:36min) and one from London (31s). The analysis was done only on the portions of the videos in which the sidewalk was visible, and thus allowed estimating the width despite the uncalibrated camera view.

Table 12 presents the densities found in the movies. The first column presents the examined video, then we present the length and the width of the sidewalk, the resulting squared area, the average number of pedestrians in the area, and finally the density. The density was measured according to the following equation: $\frac{\#pedestrians}{area}$.

The flow values were manually extracted from the four videos of the human pedestrians, which were analyzed, in the following manner: For each video, we counted the number of pedestrians who passed a certain line (determined as the "finish line," that is, one of the height borders of the sidewalk). The time variable was assigned with the number of seconds measured and the width of the sidewalk as defined in Table 12. The flow was calculated as follows: the number of agents that crossed a certain line divided by the width of the line and the time the process took.

To quantitatively compare the flow extracted from the human pedestrian movies to the simulation flow, we created an accurate approximation of the human pedestrians' analyzed scene. First, we converted the values from the human pedestrian analysis into simulation values. We used the ratio between the width of the person in the human pedestrian scene (which was approximately 0.5m), and the width of the agent in the simulation (which was 1). For example, in the movie from Canada, the size of the measured sidewalk was 9×3.9m, thus in our simulation it was converted to 18×7.8 based on the conversion rate.

Figure 2(a) depicts these conversions. The x-axis corresponds to the examined movie and the y-axis corresponds to the flow measurement. For each movie, we present two bars, a blue bar corresponding to the flow extracted from the human movie and a white bar corresponding to the flow received from our simulations. The results indicate a 15% error in France1, a 4% error in France2, and a 10% error in London. The maximal error was 16% (in the movie from Canada). The mean



(a) Flow (b) Mean Speed

Fig. 2. Comparison of simulation and real-world crowd flow and mean speed.

error was 11%. Note that overall a perfect match is impossible due to the fact that the simulation uses a low-resolution, discrete results (e.g., only three values for speed) and representative values. This may also explain the potential discrepancy in that simulated flow in Canada is lower than observed, while speed is higher.

5.2.2 Speed Comparison. In this experiment, we quantitatively compared the mean speed of human pedestrians in the examined movies to the our agents' mean speed. The human pedestrians' mean speed is the mean speed values calculated from the video analysis. The simulation mean speed is the mean speed value calculated from the simulations.

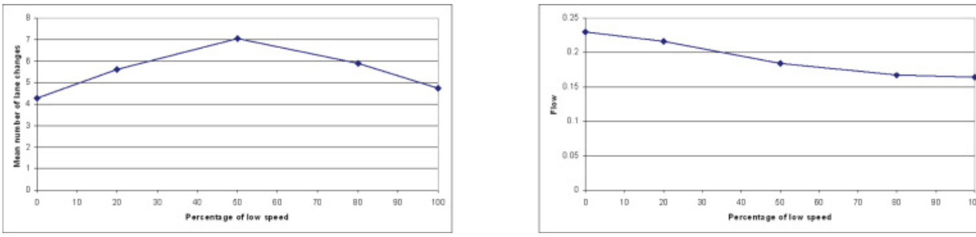
Figure 2(b) presents the results. The x-axis corresponds to the examined movies and the y-axis corresponds to the mean measurement. For each movie, we present two bars, a blue bar corresponding to the mean speed that was extracted from the human movie and a white bar corresponding to the mean speed from our simulations. The results show 21% error in France1, which was the maximal error, a 16% error in France2, a 10% error in Canada, and a 6% error in London. The mean error was 13%.

5.3 Experiment 2: Impact of Each of the Cultural Parameters on Pedestrian Dynamics

Having established the fidelity of the simulation using the extended agent model, we now turn to examining the impact of the cultural parameters on the overall pedestrian dynamics. In all the experiments in this section, we set the sidewalk size to 110×20 and the number of agents too 100. To account for group formations, we divided our agents into two categories, 30% individuals and 70% in groups as observed in some of the movies, and also in Moussaïd et al. (2010). Furthermore, we divided the agents into different group sizes and gender formations, namely couples of women, groups of three men, mixed-gender couples, and so on, as follows:

- Individuals: 30%
- Groups: 70%. Divided as follows:
  - 5/7 in formations of groups of 2 (couples): all men, all women, and mixed couples (equal parts)
  - 1/7 in formations of groups of 3: all men, all women (equal parts)
  - 1/7 in formation of groups of 4, which we defined as husband, wife and 2 children.

Speed. First, we examined the influence of the mixed speed population on the pedestrian behavior produced. We initialized the passing side of all the agents as the right side, the personal space of all the agents as *close*, and the group formations as described previously. We varied the percentage of agents who walked at a low (1.0) speed (versus a fast speed of 1.33): 0% at a low



(a) Lane Changes (b) Flow

Fig. 3. The effect of mixed speed.

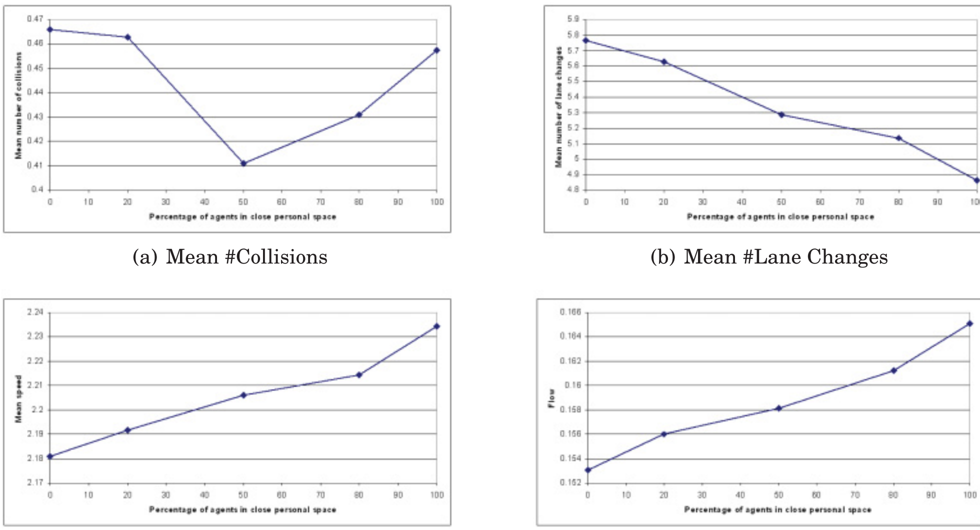
speed, 20%, 50%, 80%, or 100%, and we examined the impact of the mixed speed population on the flow of the pedestrians, and the mean number of lane changes.

We examined whether the agents' mixed speeds have an effect on the number of lane changes. The findings presented in Figure 3(a) show that homogeneous speed (low or high) result in less lane changes. According to a two-tailed t-test, there is no significant difference between the high speed population and the low speed population in the number of lane changes ($p = 0.2$). Moreover, the mixed speed populations demonstrated the highest number of lane changes. The number of lane changes in the population where 50% of the agents walked at a high speed and 50% at a low speed, was found to be significantly different than the population of agents that all walked at a low speed and the population of agents that all walked at a high speed(two-tailed t-test, $p < 0.01$ in both cases).

Figure 3(b) shows the influence of the mixed speed population on the flow of pedestrians. The results are not surprising, the more agents that move at a higher speed the higher the flow. As we can see in the results, the highest flow was found in the population of agents that all walked at the highest speed and the lowest flow was of the population with lowest speed. However, an interesting finding was the ratio between the changes in the population that caused changes in the flow. For example, if we increased our population from 0% low speed to 20% low speed the flow decreased by 6%. Moreover, there was only 1% difference in the flow between the population of agents that all walked at the lowest speed and the population of the agents in which 80% walked at the lowest speed.

Personal Space. In this experiment, we examined whether the difference in personal spaces among the agents had an impact on the pedestrian behavior produced. We initialized the avoidance side of all the agents to the right, the speed of all the agents to 1 (which is a slow pace) and the group formation was defined as detailed previously. We varied the percentage of agents with close personal space (versus far personal space) 0%, 20%, 50%, 80%, or 100%, and we examined its impact on the flow of pedestrians, the mean speed, the number of collisions and the number of lane changes.

First, we examined whether personal space had an impact on the number of collisions between the agents. The results shown in Figure 4(a) demonstrate that a significant difference was revealed in the number of collisions between the agents with close personal space and those with far personal space (two-tailed t-test, $p < 0.01$). The mean number of collisions of agents was 0.47 for those with close personal space and 0.49 for those with far personal space. Though it seems that the difference between these values is not large it was found to be statistically significant. Surprisingly, the lowest number of collisions was found to be among the mixed group where 50% of agents maintain a close personal space while walking and 50% maintain a far space. Moreover, a significant difference was found between the homogeneous far personal space group (all agents



(a) Mean #Collisions (b) Mean #Lane Changes

(c) Mean Speed (d) Flow

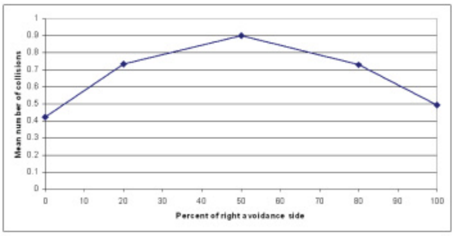
Fig. 4. The effect of personal space.

maintained a far personal space) and the heterogeneous group (50% of the agents maintained a close space and 50% maintained a far space) according to the two-tailed t-test ($p < 0.01$). However, no significant difference was found between the homogeneous close personal space group (all agents maintained a close personal space) and the heterogeneous group (50% of the agents maintained a close personal space and 50% maintained a far personal space) according to the two-tailed t-test ($p = 0.09$).

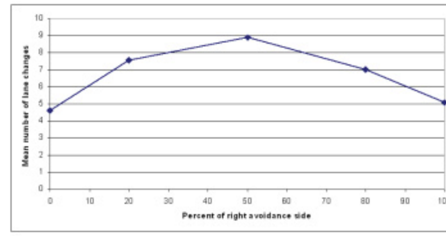
We then examined whether personal space has an impact on the number of lane changes. The results are presented in graph form in Figure 4(b). While it seems there is almost no difference in the results, the difference in the number of lane changes between agents maintaining close personal space and those maintaining far personal space was found to be statistically significant according to the two-tailed t-test ($p < 0.01$). The agents that maintained close personal space made less lane changes. The results also show that there is a significant difference between the homogeneous groups (all agents with close personal space or all agents with far personal space) and the heterogeneous group (50% of the agents with close personal space and 50% with far) according to the two-tailed t-test ($p = 0.01$ and $p = 0.03$, respectively).

Figure 4(c) shows the results of the effect of personal spaces of the agents on their speed. The results show that agents that maintain close personal space have a higher mean speed than agents that maintain a far personal space, even though both groups were initialized with the same speed. Moreover, a significant difference was found between agents with close personal space and far personal space (two-tailed t-test, $p < 0.01$). Differences in the mean speed were also revealed between the homogeneous groups (all agents maintained close personal space or all maintained far personal space) and the heterogeneous group (50% of agents kept a close personal space and 50% kept a far space) according to the two-tailed t-test ($p < 0.01$ in both cases).

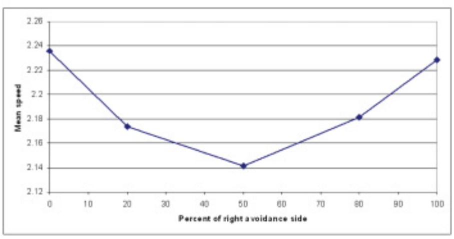
In addition, we examined the impact of the personal spaces of the agents on the flow. As depicted in Figure 4(d), the results show that agents with close personal space demonstrate a higher flow than agents with far personal space. As we have shown in our results presented earlier, the agents that move while maintaining a far personal space have a higher number of collisions and a higher



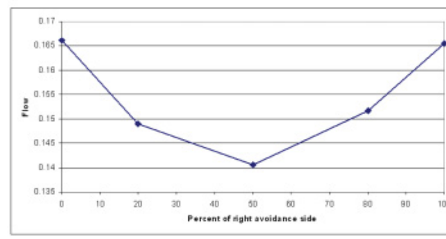
(a) Mean #Collisions



(b) Mean #Lane Changes



(c) Mean Speed



(d) Flow

Fig. 5. The effect of avoidance side.

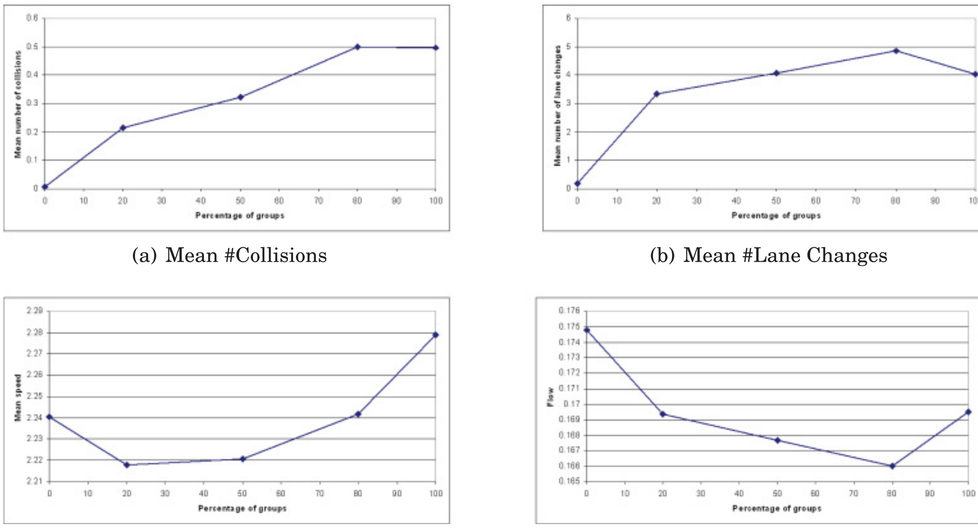
number of lane changes than agents that maintain close personal space, which affect their mean speed and eventually their flow.

Avoidance Side. Furthermore, we examined whether the pedestrian's avoidance side has an impact on the pedestrian dynamics. In this experiment, we initialized the speed of all the agents at a slow pace, the group formation was set as detailed previously and the personal space of all the agents was defined as close. We varied the percentage of agents with right avoidance side (versus left avoidance side) between 0%, 20%, 50%, 80%, and 100%, and we examined the impact of these mixed populations on the pedestrian's flow, mean speed, number of collisions and number of lane changes.

First, we examined whether the agent's avoidance side had any impact on the number of collisions between the agents. The results presented in Figure 5(a) show that the lowest number of collisions was found in homogeneous groups where all agents used the right avoidance side or all agents used the left avoidance side. The highest number of collisions was found in the heterogeneous group where 50% of agents used the right avoidance side and 50% used the left avoidance side. Moreover, the difference between the homogeneous groups and the heterogeneous group was found to be statistically significant according to the two-tailed t-test ($p < 0.01$ in both cases).

Figure 5(b) represents the results of the effect of agents' avoidance side on the number of lane changes. Similar to the previous results, the lowest number of lane changes was found in the homogeneous groups where all agents either used the right or the left avoidance side and the highest number of lane changes was found in heterogeneous group where 50% of the agents used the right avoidance side and 50% used the left avoidance side. Again a significant difference was found between the homogeneous and heterogeneous groups, according to a two-tailed t-test ($p < 0.01$ in both cases).

We also examined the impact of the avoidance side on the agents' mean speed. The results, as depicted in Figure 5(c), reveal that the homogeneous group of agents had a higher mean speed than the heterogeneous group of agents. Moreover, a significant difference was revealed between these groups (two-tailed t-test, $p < 0.01$ in both cases).



(a) Mean #Collisions (b) Mean #Lane Changes

(c) Mean Speed (d) Flow

Fig. 6. The effect of groups with same speed.

We then examined the impact of the agents' avoidance side on their flow. Figure 5(d) clearly shows a higher flow among the homogeneous groups of agents than the heterogeneous group of agents.

Group Formations with a Fixed Speed. In this experiment, we examined whether the pedestrians movement in different groups has an impact on the pedestrian behavior produced. We initialized the avoidance side of all the agents to the right, the speed of all the agents at a slow pace and the personal space of all the agents as close. We varied the percentage of agents that move in groups (versus individuals) between 0%, 20%, 50%, 80%, or 100%, and we examined their impact on the pedestrians' flow, mean speed and the number of collisions. The distribution into the different sizes and gender formations of all the agents that walked in groups was the same as described previously.

Figure 6(a) displays the effect of the groups on the number of collisions. The results clearly show that the higher the number of groups in the population the higher the number of collisions. Moreover, a significant difference was found in the number of collisions between populations where all agents moved in groups and populations where all the agents moved as individuals, according to the two-tailed t-test ($p < 0.01$).

Moreover, we examined the influence of groups on the number of lane changes. The results are illustrated in Figure 6(b). The findings clearly show that the population in which all agents walk individually have the lowest number of lane changes. There is a significant difference in number of lane changes between the population in which all the agents walk in groups and the population in which all the agents walk individually, according to the two-tailed t-test ($p < 0.01$). However, no significant difference was found between the homogeneous population where all agents walk in groups and the heterogeneous population where 50% of agents walk in groups and 50% walk as individuals, according to the two-tailed t-test ($p = 0.1$).

Then, we examined whether groups affect the pedestrian speed. The results in Figure 6(c) show that the population in which all the agents walk in groups walk at a higher speed. This finding

Table 13. Mean Speed of Different Formations in the Human Video Analysis

Formation	Mean speed (#footsteps per 15s)
Individual men	27.3
Individual women	25.3
Mixed group	23.9
Men homogeneous group	25.9
Women homogeneous group	23.7

was a bit unexpected. However, the main reason for this phenomenon is that the agents in groups occasionally accelerate to a higher speed to maintain the formations.

Finally, we examined the influence of group formations on the pedestrian flow. The results presented in Figure 6(d) show that agents that walk individually (0% groups) display the highest flow.

Group Formations with Varied Speeds. Similar to the previous experiment, we examined the impact of groups on pedestrian dynamics. However, as we have shown in Section 3.3, gender and different group formations walk at different speeds. In this experiment, we initialized the speed of each formation (individual men, individual women, groups of men, groups of women and mixed groups) based on the analysis of the data taken from the human movies (Section 3.3) and on the mean value of all the five cultures we sampled.

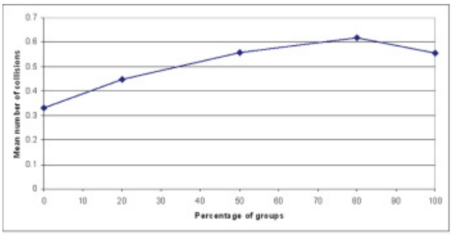
Table 13 presents the mean values of the different formations. The first column corresponds to the different formations and the second column corresponds to the mean speed across all five cultures in the specific formation. The results show that individual men walk at the highest speed while the group of women walk at the lowest speed.

Again, in this simulation, we initialized the avoidance side of all the agents to the right and the personal space of all the agents to close. However, the speed was set according to the formation to which the agent belonged. We varied the percentage of agents that walked in groups (versus individually): 0%, 20%, 50%, 80%, or 100% in groups, and we examined their impact on the pedestrians' flow, mean speed, and number of collisions.

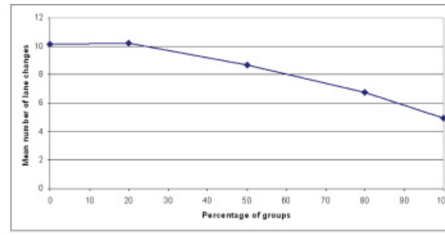
First, we examined the impact of group formations on the pedestrians' number of collisions. Figure 7(a) shows that individual agents had the lowest number of collisions. The highest number of collisions was observed in the mixed population, where 80% of agents walked in groups and 20% individually (mean value of collisions 0.63), that is, even higher than in the homogeneous population in which all the agents walked in groups (mean value of collisions 0.57). Moreover, this finding was found to be significantly higher according to the one-tailed t-test ($p < 0.01$).

In this experiment, we also examined the impact of groups on lane formation. In Figure 7(b), we can see that the higher the number of groups the higher the number of lane changes. A significant difference was revealed in the number of lane changes between the population in which all the agents walk in groups and the population in which all the agents walk individually, based on the two-tailed t-test ($p < 0.01$). Moreover, a significant difference was found between the homogeneous population in which all the agents walk in groups or all walk individually and the heterogeneous population in which 50% of the agents walk in groups and 50% walk individually, according to two-tailed t-test ($p < 0.01$ in both cases).

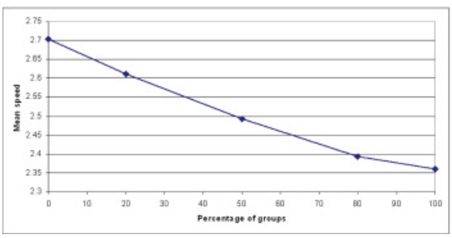
We also examined the impact of groups on the crowd mean speed. Figure 7(c) shows that the greater the number of groups, the lower the mean speed of the agents. As before, a significant difference was revealed in the agents' mean speed, between the population in which all the agents walked in groups and the population in which all the agents walked individually based on the two-tailed t-test ($p < 0.01$). Moreover, a significant difference was also revealed between the



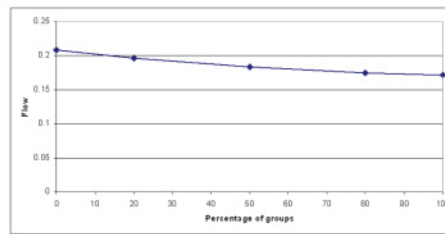
(a) Mean #Collisions



(b) Mean #Lane Changes



(c) Mean Speed



(d) Flow

Fig. 7. The effect of groups with varied speed.

homogeneous population in which all the agents walk in groups or all the agents walk individually and the heterogeneous population in which 50% of the agents walk in groups and 50% walk individually based on the two-tailed t-test ($p < 0.01$ in both cases).

Finally, we examined the influence of groups on the pedestrian flow. The results in Figure 7(d) show that the agents that walk individually (0% groups) have the highest flow. Moreover, we found that the greater the number of groups, the slower the flow.

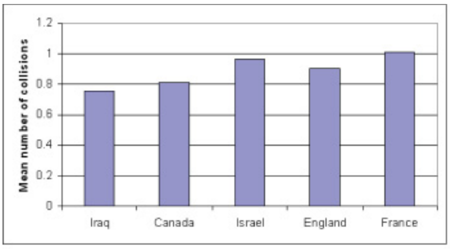
5.4 Experiment 3: Differences between Cultures

In this section, we present our findings concerning the different cultures, that is, Iraq, Israel, England, Canada, and France. We examined whether they have a different impact on pedestrian dynamics. For each culture, we set each of the cultural parameters (frequencies of formations, speed, personal space, and avoidance side) according to the values extracted from the real videos of the said culture as detailed in Section 3.

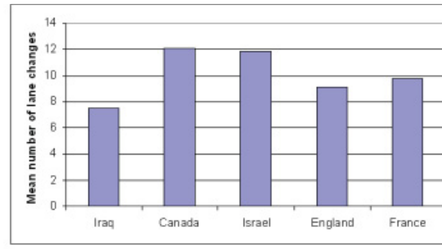
First, we examined whether there is a difference between cultures in the number of pedestrian collisions. The results presented in graph form in Figure 8(a) show that France had the highest number of collisions among the pedestrians. We believe that the main cause for this is the fact that the avoidance side was more heterogeneous in France than in the other countries (45% preferred the right avoidance side and 55% preferred the left avoidance side). The lowest number of collisions was in Iraq.

We then examined whether there is a difference between cultures in terms of the number of lane changes. The results in graph form in Figure 8(b) demonstrate that the lowest number of lane changes was found among the pedestrians in Iraq while the highest was in Canada. Furthermore, the pedestrians in Canada kept the greatest personal space between one another, which we believe is the main reason behind this result.

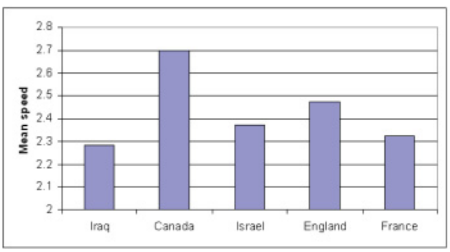
In addition, we examined whether there is a difference between cultures in pedestrians' speed. In Figure 8(c), we can see that the pedestrians in Canada have the highest mean speed. The lowest mean speed was found among the pedestrians in Iraq. These results were not surprising, since they



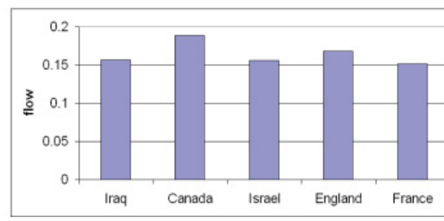
(a) Mean #Collisions



(b) Mean #Lane Changes



(c) Mean Speed



(d) Flow

Fig. 8. Differences between cultures.

were supported by the outcome of the human video analysis as detailed in Section 3. Namely, more pedestrians in Canada walk individually at a higher speed than in other cultures, while pedestrians in Iraq walk more in groups at a much slower speed than in other cultures.

Finally, we examined whether there is a difference between cultures in reference to the pedestrians' flow. The results presented in graph form in Figure 8(d) indicate that the highest flow was found in Canada, while the pedestrians in Iraq, Israel, and France provided the lowest flow.

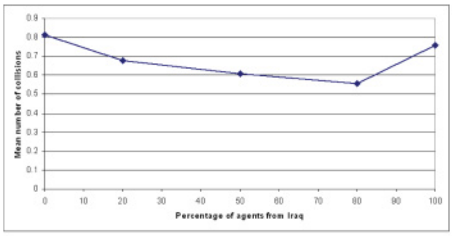
5.5 Experiment 4: Mixed Cultures

Lastly, we examined the effect of pedestrians of mixed cultures walking on the same sidewalk on pedestrian dynamics. For example, we checked the influence of a mixed population such as part of the pedestrians from Iraq and part from Canada on the pedestrian dynamics.

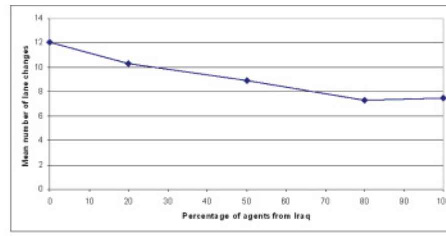
As it is infeasible to experiment with all the variations of cultures, we provide the examples of mixing between two cultures: Iraq and Canada. In this section, we assert that $x\%$ of the population are from Iraq, and $(100-x)\%$ are from Canada, and we vary the values of x: 20, 50, and 80. As in the previous section, we set each of the cultural parameters (frequencies of formations, speed, personal space, and passing side) based on the values taken from real videos of the culture as presented in Section 3.

First, we examined the impact of the mixed populations on the number of collisions. The results presented in graph form in Figure 9(a) show that the higher the percentage of Canadians in the population the higher the number of collisions. The lowest number of collisions were found in the population comprising 20% Canadians and 80% Iraqis. Moreover, a significant difference was found between populations comprising 20% Canadians and 80% Iraqis, and populations comprising 80% Canadians and only 20% Iraqis, according to the two-tailed t-test ($p < 0.01$).

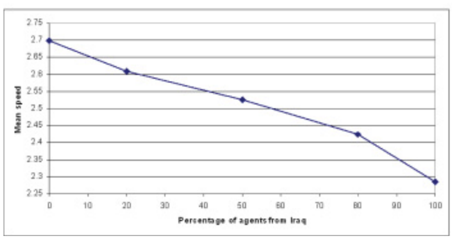
In the next experiment, we examined the impact of mixed populations (Canada and Iraq) on the number of lane changes. The results presented in graph form in Figure 9(b), as in the previous experiment demonstrate that the higher the percentage of Canadians in the population the higher



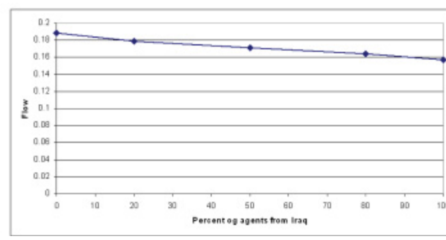
(a) Mean #Collisions



(b) Mean #Lane Changes



(c) Mean Speed



(d) Flow

Fig. 9. Differences between mixed cultures: Iraqians and Canadians.

the number of lane changes. Here again, the lowest number of collisions was found in population where 20% were from Canada and 80% from Iraq. Moreover, a significant difference was found in the number of lane changes between populations where 20% were from Canada and 80% from Iraq, and where 80% were from Canada and only 20% were from Iraq, according to the two-tailed t-test ($p < 0.01$).

Then, we examined the impact of mixed cultures on the pedestrians' speed. Figure 9(c) illustrates that the more Canadian pedestrians in the population the higher the mean population speed. The lowest mean speed was found in the population in which 80% were from Iraq and 20% were from Canada. As in previous experiments, a significant difference was revealed in the mean speed between a population with 20% Canadians and 80% Iraqis, and a population with 80% Canadians and only 20% Iraqis, according to the two-tailed t-test $p < 0.01$.

Furthermore, we examined the impact of mixed cultures on pedestrians' flow. The results presented in graph form in Figure 9(d) indicate that the highest flow was found in populations in which 80% were from Canada and only 20% from Iraq. The lowest flow was found in populations in which 80% were from Iraq and only 20% from Canada.

6 SUMMARY

In this article, we investigated the impact of micro-level, individual agent, cultural parameters on macro-level crowd behavior in urban settings. Building on existing literature that investigates culture in human crowds, we identified important cultural parameters in urban pedestrian movement. We extend a social agent algorithm previously used for pedestrian simulations, to accept individual cultural parameters reported in the literature. We use the agent model in simulations to measure their impact on crowd dynamics. The results of the simulation were quantitatively validated against data extracted from crowd movies in five countries. We then explored the effects of individual parameters in different cultures on global crowd phenomena.

While this article focused on pedestrian crowds in urban settings, it represents only a perspective on pedestrians under normative conditions. Other investigations have begun examining the effects of culture on crowd behavior under anomalous conditions, such as during evacuations (e.g., Schadschneider et al. (2009) and Tsai et al. (2011)). We believe such work in a necessary component in urban computing in general.

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