The Impact of Culture on Crowd Dynamics: An Empirical Approach

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ABSTRACT

In agent-based social simulation, crowd models are used to generate agent behaviors that should correspond closely to human crowds. Despite significant progress in this area, many existing crowd models do not yet account for important cultural factors in crowd behavior, and even more so, for mixed-culture crowds. Moreover, evaluation of crowd models accounting for culture is particularly difficult, e.g., as controlled experiments are more difficult to set up, due to lack of subjects from different cultures. In this paper we examine the impact of cultural differences on crowd dynamics in pedestrian and evacuation domains. We account for micro-level cultural attributes: personal spaces, speed, pedestrian avoidance side and group formations. We then quantitatively validate the macro-level predictions of an agent-based simulation utilizing these against data from web-cam movies of human pedestrian crowds recorded in five different countries: Iraq, Israel, England, Canada and France. Using the validated simulations, we investigate the impact of each micro-level attribute on the resulting macro level behavior. We also examine the impact of mixed cultures on macro-level behavior. In the evacuation domain, we use an established simulation system to investigate cultural differences reported in the literature, and additionally explore the resulting macro level behavior.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Experimentation, Measurement

Keywords

Social simulation, Crowd models

1. INTRODUCTION

In agent-based social simulations, high-fidelity crowd models generate synthetic crowd behaviors, that enable analysis, and that facilitate accurate predictions of macro-level crowd dynamics resulting from micro-level interactions. These are useful for training, safety decision-support systems, and traffic management.

Unfortunately, while many existing models of physical crowds can be parameterized for some basic micro-level parameters that vary with culture (e.g., speed), they do not yet account for important cultural factors such as the structure of groups and avoidance side. 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 (e.g., pedestrian flow). As a result, it is difficult to qualitatively validate models against social science observations.

The problem is further exacerbated as quantitative validation of agent-based simulation is particularly difficult, due to reduced accessibility to videos of human crowds in different cultures, and the obvious logistical challenges involved in setting up controlled experiments controlling the culture of the subjects.

In this paper we take a step towards treating culture in models of physical crowds. We examine the impact of cultural differences on crowd dynamics in pedestrian and evacuation domains, using proven agent-based simulations of the two domains. We introduce cultural individual-level parameters into the simulations, and then examine the effects of these individual level parameters on the emergent crowd dynamics. Moreover, we examine the effects of mixing individuals from different cultures in the same crowd.

In the pedestrian domain we relate the resulting culturally-aware simulation to pedestrian data which we recorded from web-cams of pedestrians in five different countries: Iraq, Israel, England, Canada, and France. We characterize the data in these locations along four individual-level parameters: personal spaces, speed, avoidance side (i.e., which side is preferred when avoiding an oncoming pedestrian), and group formations. We use established macro-level quantitative measures (e.g., flow, number of collisions, and mean speed) to identify crowd-level effects. We show that the model can faithfully replicate the crowd dynamics in these videos.

In the evacuation domain, we examine individual cultural parameters (documented in social science literature) as to how seriously people treat possible threats, their tendency to notify others, and their tendency to form groups. We then use the simulations to explore the impact of these on the resulting crowd behavior (measured quantitatively in evacuation time, panic levels, etc.).

2. BACKGROUND

Social sciences literature reports extensively on cultural differences in individual interactions. For example, Hall [10, 11] was one of the first to define *proxemics*, which examines the *personal spaces* that people maintain from each other in different contexts and cultures. Beaulieu [3] examined cultural differences in personal spaces. Levin and Norenzayan [14] examined the cultural differences in the *pace of life* (including mean walking speed) in 31 countries. They showed people in England and France walk faster than people in Jordan or Syria.

Similarly, Andrée and Eriksson [1] examined Swedish and Australians in evacuation scenarios. Their results show that Australians took alarms more seriously. Bryan [5] compared different parameters such as participants' awareness of the incident, their first ac-

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tion, etc. The study showed that different cultures differ in individual tendency to notify others about the existence of the event.

Many pedestrian crowd models can, in principle, account for simple cultural parameters such as proxemics and walking speed (e.g., [9, 12, 16, 17]). However, none of these models explicitly explore cultural differences, especially with respect cultural attributes such as grouping and avoidance side. Moreover, while these models relate micro-level parameters on macro-level crowd behavior (e.g., flow), the impact of cultural mixes within a specific crowd in these is not explored .

There have been several investigations utilizing quantitative comparisons between simulated crowd behavior and real human crowds, though not specifically focusing on culture. For example, Daamen and Hoogendoorn [6] performed controlled experiments in which subjects wore specially-colored caps to enable automated tracking by machine vision algorithms. The data was used to quantitatively examine pedestrian flow under a variety of conditions. Johansson et al. [13] utilized automated tracking of pedestrians where most subjects did not know their motions were tracked. However, the experiments were carried out indoors. In contrast to these and similar investigations, we utilize videos from completely uncontrolled settings, from different locations around the world. This real-world data, however, proved inaccessible to automated tracking, and so we used manual tracking instead.

One of the key contributions of our work is in exploring mixed crowds. We believe we are the first to focus on mixed cultures. However, certainly others have examined crowds that are heterogeneous along other dimensions. Blue and Adler [4] used cellular automata to simulate collective behaviors, in particular pedestrian movement. Toyama et al. [20] expanded the model by adding different pedestrian characteristics, such as speed, gender, repulsion level, etc. This allowed examining heterogeneous crowds, in pedestrian and evacuation behavior. Similarly, Durupinar et al. [7] explore heterogeneous crowd simulations in which individuals have varying personality traits, such as *extroversion* and *openness*.

We use two agent-based simulations in our work. ESCAPES [21] is a an evacuation simulation, incorporating four key features: (i) different agent types and ages; (ii) emotional interactions; (iii) informational interactions; (iv) behavioral interactions among agents. SCT [8] is a general model of group behavior which has been successfully applied to pedestrian and evacuation simulations. Both investigations explore a variety of individual and social factors, but do not yet account for cultural differences.

3. PEDESTRIAN CULTURES

In modeling pedestrians, and based on the literature, we focus on the following individual (micro-level) cultural parameters: personal space ([3, 10, 11]), base walking speed ([14], avoidance side ([15]) and group formations (in particular gender-heterogeneity, size, and shape, e.g., whether side-by-side, or one gender in front [16]). We quantitatively measure these in movies taken in five different cultures: Iraq, Israel, England, Canada and France. Then we use a pedestrian simulation to show the impact of these cultural attributes on the resulting macro-level crowd dynamics.

3.1 Video Analysis of Pedestrian Dynamics

Overall, we collected over a hundred hours of pedestrian footage in different locations. In some, we only have a few minutes of video. In others, we have many hours. The movies from France were recorded in Paris from the top of the Eiffel tower. The movies from Canada were video taped from one of the streets in downtown Vancouver in the morning and also in the afternoon. The movies from Iraq were recorded from a web camera overlooking the yard in front of the Hussein mosque in Karbala.

The movies from Israel were similarly recorded from a web camera overlooking The Western Wall in Jerusalem. The movies from England were video taped in London in two different locations: From the London Eye, and from the Millennium Bridge. For the purposes of the analysis, we used randomly-cut 3-minute excerpts from different locations, for a total of 45 minutes.

To extract the group formations, speed, and avoidance side parameters from the videos, we asked four subjects to analyze the movies. Each movie was analyzed by two different subjects and we used the mean value for each measure in our results. For example, 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 it is a man or a women. For each group the subjects were asked to specify the size of the group; couples, three people or more and also the gender- and age- mix of each group; two women, two men, men and woman, woman with child, etc. To estimate speed, the subjects sampled 10 pedestrians in each movie, counting their steps within 15 seconds. To convert steps to an estimated velocity measurement, we can use the known average human step length for adults ($75cm$).

To determine the personal spaces between people in the movies, we used aerial photography techniques which involve the estimation of size from images. To be able to measure the length, width and perimeter of specific object successfully, it is necessary to know the scale of the photo. To do this, we measure the size of a few well-known objects to give a comparison to the unknown object. In each movie we tried to estimate personal spaces with two techniques: Using "Google Earth" to determine object sizes, or estimate size based on the known size of familiar objects (such as cars or sports-field dimensions). If only one technique was feasible, then we used only one measure; otherwise, we took the mean value between the two measures.

For example, in one Iraq movies there is a truck that passes among the pedestrians (Figure 1). A standard truck size if 8ft (2.44m). We measured the size of truck width on the screen (marked yellow) and found out it was 0.98cm. We then drew a line between the two people in the movie (marked red) and found out it was 0.15cm on the screen. We then deduced that the distance in reality is: $(0.98/0.15) \times 2.44m = 37cm$.

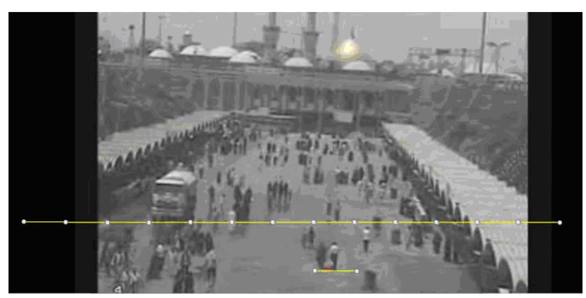


Figure 1: Personal space estimation using familiar objects.

To verify, we use another method. Using "Google Earth" we found that the width of the area is 38m (including the white shades; Figure 2). Each segment in the 16-segment yellow line is therefore 2.375 meters. Again, simple math shows the distance is approximately 36 centimeters.

3.2 Results of Video Analysis

The results show that indeed the five countries differ from each other in the four cultural parameters. For lack of space, we present here only a subset of the estimated cultural parameters resulting

Figure 2: Personal space estimation using Google Earth.

from the video analysis. Our intent here is to demonstrate that these parameters actually vary between the cultures. Thus although some of the trends found are consistent with the literature, we do claim that they are representative of the culture in question.

We begin by examining groups and their makeup. Table 1 presents the percentage of pedestrians walking in groups in each culture. Table 2 shows the group size distribution. The results show that in Iraq there is a tendency towards larger groups.

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

Table 1: Group formation: individuals versus groups

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

Table 2: Group formation: group size

We turn to examining individual speed, and its variance based on gender and grouping in the different cultures. The speed units is the number of steps per 15 seconds (we avoid the conversion to meters per second, as the use of mean step length is not needed here, and only adds uncertainty). Table 3 shows that men walk faster than women in all examined cultures. Between cultures, Iraqi pedestrians are the slowest (this agrees with previous research [14]).

Next, we examine the effects of grouping on speed. Table 4 shows the mean speed of pedestrians that move as individuals, or in groups. The results show that in all cultures people as individuals move faster than people in groups.

Cultures also differ in their preferred pedestrian avoidance side. Table 5 presents the results. The first column correspond to right or left avoidance side and then we presents the distribution of each examined cultures.

Finally, the video analysis shows that there are cultural differences in personal spaces. Table 6 shows the personal spaces within groups, as well as the mean personal space. It examines whether there is a differences in personal spaces kept by men and women in the same group. Here we distinguish between gender heterogeneous groups, men homogeneous groups and women homogeneous groups. The results show that in Iraq, Israel and France women keep less personal space than men. The biggest gap between group of men and group of women is observed in Iraq.

3.3 Impact on Pedestrian Dynamics

After establishing that the parameters chosen do indeed vary significantly between cultures, we turn to agent-based simulation to examine their effect on macro-level pedestrian dynamics. We used the popular OpenSteer [18] as the simulation platform. We simulated a sidewalk where agents can move in a circular fashion from

Gender	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

Table 3: Speed: men versus women

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 4: Speed: individuals versus groups

east to west, or in the opposite direction. Each agent has limited vision distance (beyond this distance it cannot see). Agents are not allowed to move through other agents, in a case of possible collision the agents are tried to avoid it. The base pedestrian model was SCT [8], which was implemented fully and then extended to support the parameters noted above. The modifications to the original algorithm are straightforward, and are omitted for lack of space.

In all experiments described below, we examine the impact of individual cultural differences on the resulting macro-level pedestrian behavior, as measured by the following standard measures: (i) *the mean number of collisions* between two agents, averaged over all agents; (ii) the *observed mean speed* over all agents (this is different from the set individual speed, which each agent may or may not be able to achieve; and (iii) the pedestrian flow, i.e., the number of agents that cross a certain area divided by the length of the area and the time this process takes.

To carry out the experiments, we translated the results of the video analysis to simulation parameters for each individual as follows. First, in situation of possible collision an agent chooses whether to avoid the other agent on the right or left side. Normally, this choice is arbitrary, but we modified the simulation such that each agent has a cultural preference of the avoidance side, initialized at simulation start.

To set the walking speed in simulation, we converted the observed speed units (number of steps in a 15 second interval) to meters per second. To do this, we took $75cm$ as the mean human step length [2]. To set the simulated speed of individuals, given the possible noise in speed estimates, we quantized the range of observed speeds into three discrete sub-ranges. We then found that by using following speed level in our simulation: 2.27, 2.62 and 3.01. we get the best match to human data.

Finally, the simulated personal space was similarly approximated. Hall tells us that individuals maintain four rings of personal space: intimate, personal, social, public [10, 11] Because of the limits of the simulation, we only model three of them: personal, social and public. Hall reported on two observed sets of values for these distances: Some people maintain *close distances* (on average, personal: $46cm$, social: $120cm$, public: $370cm$). Others maintain *far distances* (personal: $76cm$, social: $210cm$, public: $760cm$). In the videos, we could only measure distance between couples, assumed to be the personal distance. We thus use Hall's values for close and far distances, normalized to the lowest observed distances (i.e., $46cm$ is normalized to be the lowest observed distance, and all others are calculated from it).

We ran extensive simulations with the above values, totaling over 100 hours of simulation. All results below are the averaged value over 30 trials. For lack of space we present here only a subset of the results.

Avoidance Side	Iraq	Canada	Israel	England	France
right	62%	63%	41%	77%	45%
left	38%	37%	59%	23%	55%

Table 5: Avoidance side: results

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

Table 6: Personal spaces kept by men and women within the same group.

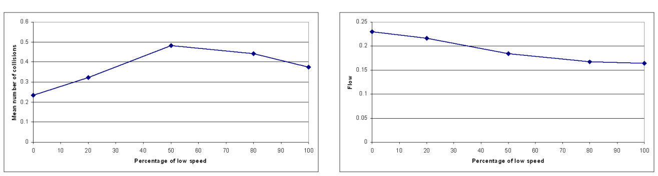
3.3.1 *Experiment 1: Impact of cultural parameters*

In this section we examine the impact of each cultural parameters on overall pedestrian dynamics. In all the experiments in this section, we fixed the sidewalk to be 110×20 and the number of agents to be 100. To account for group formations we divided our agents to be 30% individuals and 70% in groups as observed in some of the human movies, and also in [16]. We divide the agents to different group sizes and gender formations such as couples of women, 3 men groups, gender mixed couples etc.

Speed. We first examine the influence of the individual speed on the produced pedestrian behavior. We initialized avoidance side of all the agents to right, the personal space of all the agents to *close*. We vary the percentage of agents with low speed (1.0) versus fast speed (1.33): 0% low speed, 20%, 50%, 80% or 100%. We examine the impact of the mixed speed population on the pedestrian's flow, collisions and speed.

Graph 3(a) shows the influence of mixed-speed populations on the number of collisions. The results show that the homogeneous-speed pedestrians have the lowest number of collision. The highest number of collisions is found in the mixed population where 50% move with low speed and 50% with high speed. There is in fact a significant difference between the number of collisions with homogeneous (low, high) speed, and the heterogeneous 50% population (two tailed t-test, $p < 0.01$ in both cases).

Graph 3(b) shows the influence of the mix speed population on the flow. It shows the highest flow has been found in population where all agents move with the highest speed and the lowest flow is in population with lowest speed. Note that the non-linear relation between changes in the population and changes in the flow, for example if we increase our population from 0% low speed to 20% low speed the flow will decrease in 6%. But there is only 1% difference in flow between population where all agent move with lowest speed and 80% of agents that move with lowest speed.



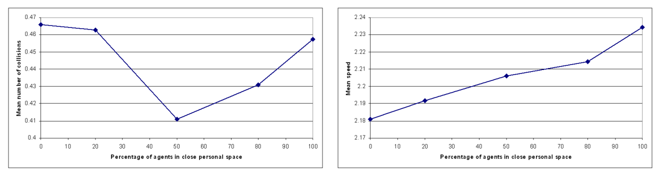
(a) No. of Collisions (b) Flow

Figure 3: The influence of mixed-speed population on flow and number of collisions.

Personal space. We now examine the impact of mixing agents of different personal spaces. We initialized avoidance side of all the agents to right, and their speed to the basic slow walk. We vary the percentage of agents with *close* personal space (versus *far* personal space) from 0% to 100% and examine its impact on the crowd.

Figure 4(a) examines how mixing pedestrians with different personal spaces impacts the number of collisions. The results show that there is a difference in number of collisions in the homogeneous *close* and *far* personal spaces. The difference between the mean number of collisions is small, but statistically significant (two tailed t-test, $alpha$ = 0.01). Surprisingly, given the earlier results for the impact of mixing individual speeds, the lowest number of collisions have been found in the 50%-mixed group. It is significantly lower than the homogeneous *far* group (two tailed t-test, $alpha$ = 0.01), and close to being significantly lower than the homogeneous *close* group (two tailed t-test, $alpha$ = 0.09).

Figure 4(b) similarly examines impact on the mean speed of the crowd. The results show that agents with close personal space have higher mean speed than agents with far personal space, although both of the groups were initialized with the same speed individually (so the effect is definitely due to just personal space preferences). Moreover, there is a significant difference between the *close*- and *far*- homogeneous groups (two tailed t-test, $alpha$ < 0.01). The differences in mean speed also have been found between the homogeneous groups and the heterogeneous 50%-mixed group (two tailed t-test, $alpha$ < 0.01 in both cases). The results for pedestrian flow follow the same trend shown in this figure, and so we do not display them for lack of space.



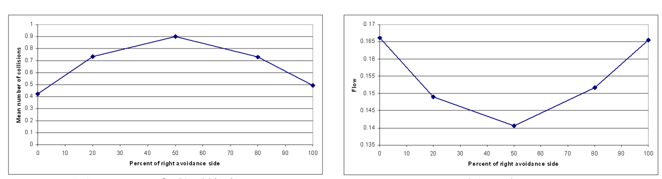
(a) No. of collisions. (b) Mean Speed

Figure 4: The influence of mixed personal-space on the number of collisions and crowd speed.

Avoidance side. We now turn to examining the effect of having pedestrians of mixed avoidance side preferences on the crowd. We initialized the speed of all the agents to slow walk, and the personal space of all the agents was set to *close*. We vary the percentage of agents with right-hand avoidance side (versus left-hand avoidance side) from 0% to 100% and examine the impact of these mixes the crowd's flow and mean number of collisions.

Figure 5(a) shows impact on the number of collisions between pedestrians. The lowest number of collisions is found in homogeneous groups (all agents have the same avoidance side preference). The highest number of collisions is found in heterogeneous group where 50% of agents with right avoidance side and 50% with left avoidance side. In fact, there is a significant difference between homogeneous groups and the heterogeneous 50% group (two tailed t-test, $alpha$ < 0.01 in both cases).

The results (Figure 5(b)) also show that homogeneous groups have an increased crowd flow, compared to the heterogeneous groups. The same trend was also observed in the mean speed of the respective groups.



(a) No. of Collisions (b) Flow

Figure 5: The influence of mixed avoidance side on the number of collisions and crowd flow.

Group formations. Finally, we examine the impact of groups on the pedestrian dynamics. This is a complex parameters, as it involves not just the size of its group, but also its gender makeup. Also, as shown in Section 3.2, groups of different genders and sizes, walk in different speeds (thus indirectly varying the individual speed parameter). Table 7 presents the mean speeds of different formations, averaged over all five cultures (as analyzed from the videos). The results show, for instance, that in general individuals (groups of size 1) are faster than groups (groups of size 2 or more), and that individual men have the highest speed while group of women have the lowest speed.

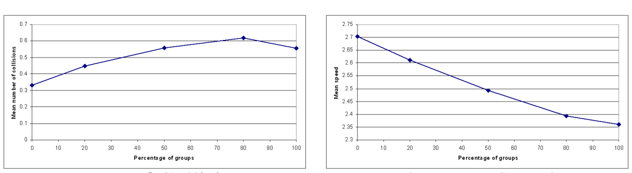
Formation	Mean speed
Individual men	27.3
Individual women	25.3
Mixed group	23.9
Men homogeneous group	25.9
Women homogeneous group	23.7

Table 7: Human video analysis: Mean speed of different formations

To address this complexity, we report here on a subset of the experiments, in which we initialize the speed of each agent in each formation (individual men, individual women, groups of men, groups of women and mixed groups) with the data taken from Table 7. We again initialized the avoidance side of all the agents to right and the personal space of all the agents to *close*. We vary the percentage of agents that move in groups (versus as individuals): from 0% (all individuals) to 100% (all groups of size 2 and above).

We first examine the impact of group formations on the number of collisions. Figure 6(a) shows that individuals agents have the lowest number of collisions. The highest number of collisions was examined in mixed population where 80% of agents move in groups and 20% as individuals (mean value: 0.63) which is significantly higher (one tailed t-test, $alpha < 0.01$) than in homogeneous population where all agents move in groups (mean value: 0.57).

Then, we examine the influence of groups on the mean crowd speed. Figure 6(b) shows that higher number of groups cause lower mean speed, which is expected given the general rule-of-thumb found in Table 7. There is a significant difference in mean speed between population where all agents are moving in groups and population where all agents are move as individuals (two tailed t-test, $alpha < 0.01$). Moreover, there is also a significant difference between the homogeneous population where all agents are moving in groups or as individuals and the heterogeneous population where 50% of agents move in groups and 50% move as individuals, according to two tailed t-test, $alpha < 0.01$ (in both cases). The crowd flow is not shown, since it follows the same trend as the speed results.



(a) No. of Collisions (b) Mean Speed

Figure 6: The influence of grouping on the number of collisions and crowd speed.

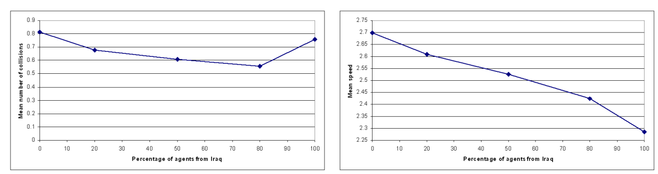
3.3.2 Experiment 2: Mixing Cultures

Now that we have some understanding of the effect of each individual cultural parameter, we examine complete bundles, i.e., complete cultures (each culture is a set of values assigned to the cultural parameters). To do this, we mix cultures on the same sidewalk. For example: if we mix the population such as part of it is from Iraq and another part is from Canada, and examine the impact on pedestrian dynamics.

For space reasons, it is infeasible to show here all the variations of cultures mixes, and we thus focus here on crowds mixing two cultures: Iraq and Canada. We vary the number of pedestrians in the crowd who are initialized with Iraqi cultural parameters, from 0% (pure Canada crowd) to 100% (pure Iraq crowd). As in previous section initialized each of the cultural parameters (frequencies of formations, speed, personal space and avoidance side) with the values extracted from real videos of this culture (Section 3.2).

We first examine the impact of mixed-culture pedestrian population on the number of collisions (Figure 7(a)). The results show that the higher the percent of Canadian in the population the higher the number of collisions—in mixed groups. The lowest number of collisions has been found in population of 20% Canada pedestrians. There is a significant difference between this population, and the population with 80% Canada pedestrians (two tailed t-test, $alpha < 0.01$). Interestingly, the number of collisions in the pure Iraq population jumps up, compared to the 20% Canada crowd.

We also examine the impact of the mixed-culture pedestrian population on the crowd mean speed (Figure 7(b)). The results show that an increased number of Canadian pedestrians in the population leads to higher mean crowd speed (indeed, Section 3.2 shows that the Canada pedestrians had higher mean speed than then Iraq pedestrians). The lowest mean speed has been found in population with 80% Iraq pedestrians. As in previous experiments, there is a significant difference in mean speed between the 80% Iraq population and the 20% Iraq population (two tailed t-test, $alpha < 0.01$).



(a) No. of Collisions (b) Mean Speed

Figure 7: Mixed Iraq-Canada pedestrians impact on the number of collisions and crowd speed.

3.3.3 Experiment 3: Comparison to human crowds

The previous two experiments focused on the use of simulation to investigate the effects of individual or bundled cultural parameters on overall crowd behavior. But an important underlying question is whether the fidelity of the simulation is sufficient to support conclusions as to human crowds.

Thus in this section, we examine whether the simulation can produce similar behavior to that of the observed human pedestrian crowd. We quantitatively compare the macro level measures (flow and mean speed) generated by the simulation to those of the crowds in the videos. We do not compare the number of collisions for this, as humans rarely collide—never in the video recordings—because they employ a more sophisticated obstacle avoidance algorithm than the simulation does.

To carry out the comparison, we recreated the initial settings in four of the videos in simulation. Specifically, we set the density of the pedestrian crowd (how many pedestrians per unit area); we set the individual parameters of agents and groups per the measured quantized values from the videos; and we ran the simulation for the same time as the videos. Note that we did not place simulated pedestrians in the initial locations of human pedestrians, as such fine-resolution placement should not affect macro-level crowd dynamics. Human subjects measured human crowd flow and mean speed by sampling pedestrians in the videos, and those sampled values were compared to the flow and mean speed analyzed direction from the simulated trajectory data.

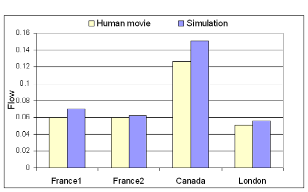
Flow in simulation and in human crowd videos. To compute pedestrian flow in the human pedestrian videos, we need to determine the sizes of the sidewalk or of the examined area. We can use the video analysis techniques described in Section 3.1 to do so. Indeed, we carried out the flow analysis in four different videos (two from France, one from Canada, and one from the United Kingdom (London).

First, we extract the density in these videos (which has a big impact on flow [19]). We sampled the number of pedestrians in defined area every 5 seconds, and averaged over all the samples, for a mean density which was used in the simulation. To do so, we normalized the person-width in the movies to the unit width in simulation, and expanded or shrank the area appropriately, to fit just as many simulated in the target simulated area, as there were (on average) human pedestrians in the target real-world area. The cultural parameters were set with the mean quantized values for the country in question, and the flow was then computed both in the simulation as well as in the real-world.

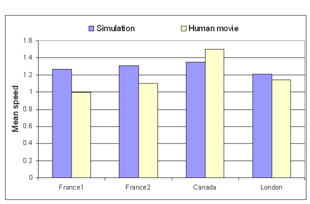
Figure 8(a) presents the results of the comparison. The x-axis marks the movie and the y-axis corresponds to the flow measurement. For each movie, we present two bars. The dark bar shows the flow that was extracted from crowd movie and the light-colored bar shows the flow that was computed from the simulation logs. The results show that in `France1` we get 15% error, in `France2` we get 4% error, the maximal error that we received is 16% in the `Canada` movie and in `London` we received 10% error. The mean error is 11%. Note that because the simulation is using low-resolution discrete results (e.g., only three values for speed) and mean values overall, a perfect match is essentially impossible.

Crowd speed in simulation and in human crowd videos. We also compare the emergent crowd mean speed produced by the simulation, to that measured in the four movies. This comparison was done in a similar fashion to the flow, though it is simpler to compute. The mean speed of the crowd in the videos is measured in units of steps per 15 seconds. This value was translated to the meters-per-second unit used in the simulation, by assuming a standard step is $75cm$ in length [2].

Figure 8(b) presents the speed comparison results. The x-axis shows the examined video and the y-axis measures the mean speed. For each video, we present two bars. The dark bar corresponds to the mean speed that was extracted from crowd movie and the light-colored bar corresponds to the mean speed that was computed from the simulation logs. The results show that in `France1` we get 21% error (the maximal error), in `France2` we get 16% error, in `Canada` we received 10% error and in `London` we received 6% error. The mean error is 13%.



(a) Flow



(b) Mean Speed

Figure 8: Comparison of simulation and real-world crowd flow and mean speed.

4. EVACUATION CULTURES

Cultural differences have been found in evacuation domain. For example, Swedish participants evacuated more in groups than Australians that evacuated more individually [1]. In this section we explore cultural parameters of individual evacuees (Section 4.1), and consider their impact on overall macro-level evacuation crowd behavior (Section 4.2).

4.1 Cultural Parameters in Evacuation

Based on our literature survey, we model the following cultural parameters of individual evacuees (evacuating agents). First, their tendency to notify others regarding an event that have caused them to evacuate. This differs, for instance, between the U.S. (higher tendency) and England (lower tendency) [5]. A second parameter complements the first, and addresses the seriousness with which people (agents) hearing about such an event take it (that is, whether they decide to evacuate too, as a result). For example, this differs between Australians and Swedish [1]. Finally, we model the tendency towards evacuating in groups or individually [1].

We implemented these parameters in the ESCAPES agent-based evacuation simulation [21] that models evacuation behavior in the International Terminal at Los Angeles International Airport (LAX). ESCAPES provides good results for modeling evacuation behavior [21], and received high praise from LAX security officials. ESCAPES simulates crowd behavior prior to the evacuation-causing event (e.g., explosion), as well as after. To evaluate the impact of these parameters, we used the scenario described in [21]. There are four areas (terminals) and four available exits; individuals and families wander freely in shops or in public areas, until the event. When the event occurs, and if they know of it, agents evacuate. The presence of authority figures (guards) is simulated, and their number controlled for experiments. Guard agents patrol (prior to the event), and inform evacuees about the event and available exits.

ESCAPES agents are complex, each having 14 available behaviors which it selects from, using a BDI architecture, and based on the agents knowledge of the world and other agents. Agents do *not* have a complete knowledge of the terminal layout, and in particular may not know about available exits, or the explosion taking place. ESCAPES models the certainty of each agent as to whether an explosion took place as a three-level ordinal variable, whose certainty values are either *low*, *medium*, or *high* (a *high* value will cause the agent to evacuate). Each agent also has three values of fear (integers between 0—no fear—and 2—high fear), which affect its actions (e.g., high fear increases speed). Each agent's fear is affected by several factors such as the agents proximity to the event (increasing the agent's event certainty and also the agent's fear), presence of authority figures (decreasing agent's fear) and more. Agents that decide to evacuate can also spread the knowledge about the event to their neighbors (the individual tendency to spread information is also controlled for experiments).

4.2 Evacuation Cultural Parameters: Impact

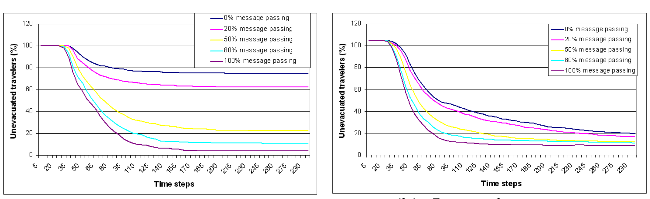
Using the ESCAPES simulation, we examine the impact of the individual cultural parameters on the resulting macro level crowd evacuation behavior. We measured the following evacuation crowd attributes: (i) *the evacuation time* (in fact, more accurately, the number of agents still in the terminal at any given time); (ii) *panic*, measured by the number of agents with *high* fear; (iii) the mean speed of the evacuating crowd; and (iv) the emergent clustering (grouping). Due to lack of space, we will report here only on a subset of the results, pertaining to the first two measures in the list above.

4.2.1 Experiment 1: The impact of notifying others

In ESCAPES, agents that are close to the event location have a full knowledge regarding the event, while agents that are far from the event are unaware about what happened (e.g., too far to hear the event). Agents that aware of the event may pass their event certainty and knowledge to other agents, physically close to them. By varying the number of other agents to which they communicate, we in fact vary the individual tendency to inform others. Also, since simulated guards in ESCAPES also notify others regarding the event, we examine the impact of notifying others with and without authority figures.

Figure 9(a) presents the agents' evacuation rate, with no guards present. The x-axis marks the simulation time steps. The y-axis marks the percentage of unevacuated agents. The results clearly show that the more agents communicate the faster the evacuation time. However, there was no significant difference between agents that pass the event knowledge to all close neighbors (100% message passing) and agents that pass the knowledge to 80% of close neighbors (80% message passing). There is a significant difference between 80% of message passing and 50% of message passing (two-tailed t-test, $alpha = 0.04$), and between 50% of message passing and 20% of message passing (two-tailed t-test, $alpha < 0.01$). Significant difference also exists between agents that pass the knowledge to 20% of close neighbors and agents that pass no knowledge at all (two-tailed t-test, $alpha < 0.01$).

Figure 9(b) presents the results for the same settings, except for the number of guards (here, five). The general trend is the same as in Figure 9(a). However, the authority figures cause almost no effect in evacuation time among fully communicable agents (100% notify others) in comparison to Figure 9(a). For example, the mean evacuation time in population with 5 authority figures and among 100% fully communicable agents is 24.5 while the mean value among same fully communicable agents but in population without authorities (Graph 9(a)) is 23.4, which is not significantly lower (according to one tailed t-test, $alpha = 0.42$). However, among non-communicable agents (0% notify others), the guards have a big impact. For example, the mean evacuation time in population of non-communicating agents (0% notify others), with five guards is 45.05, while the mean value for the same population without authorities (Figure 9(a)) is 80.2, which is significantly higher (one tailed t-test, $alpha < 0.01$).



(a) No guards (b) 5 guards present.

Figure 9: The impact of agents' knowledge passing on the evacuation time, in the presence of authority figures (guards).

4.2.2 Experiment 2: The Impact of Seriousness

The level of seriousness with which humans take events (e.g., the sound of alarm or explosion) affects participants' level of fear during the event. As fear affects the speed selected by evacuees, the result is that seriousness impacts overall evacuation crowd behavior.

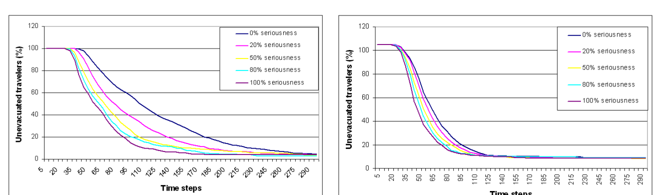
To model seriousness in ESCAPES, we modified the agent models as follows. As indicated above, each unmodified ESCAPES agent has a *certainty* variable which indicates the certainty of the agent in the occurrence of an event. Each agent also has a *fear* variable that tracks the agent's level of fear (*none*, *low*, or *high*). Normally, the certainty variable has a direct positive influence on the agent's fear: high certainty leads to high fear. To account for the cultural difference in seriousness, we defined a third variable for each agent, with three levels of seriousness: *not serious*, *semi-serious*, *serious*. Now, when an agent knows about an event (high certainty) the agent's fear going to be set based on the the agent's seriousness level: *serious* agents would have *high* fear, *semi-serious* would have *low* fear, and others would have fear set to *none*.

In the subset of experiments we report on below, we vary the percent of *serious* agents versus *semi-serious* agents, and examine the impact on the evacuation time and the crowd panic (measured by the percentage of agents with *high* fear). Since ESCAPES authority figures have a calming effect (they reduce the fear level of individual agents), we examine the impact of seriousness with and without authority figures.

We begin by examining the impact of individual seriousness on evacuation time. Figure 10(a) presents the results of the agents' evacuation time when no guards are present. Figure 10(b) shows the results in the presence of five guards. In both figures, the x-axis marks the simulation the time steps, and the y-axis marks the percentage of unevacuated agents. The results show that more serious agents evacuate faster. This is to be expected, as when agents have fear set to *high*, they increase their speed. Indeed, we find a significant difference in the case of no guards, between population of all serious agents (100% seriousness) and population of semi-serious agents (0% seriousness), according to two-tailed t-test with $alpha = 0.004$.

However, the results additionally show that guards cause have almost no impact on the evacuation time between serious and semi-serious agents. With five guards present, there is no significant difference between population of all serious agents (100% seriousness) and population of semi-serious agents (0% seriousness).

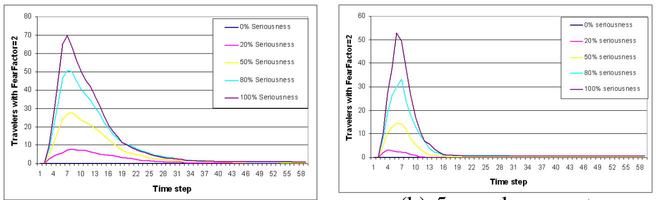
Moreover, the guards have no effect in evacuation time among serious agents (100% seriousness) in comparison to Figure 10(a). The mean percentage of unevacuated agents in simulations with 5 authority figures in the the 100% serious crowd is 24.5. For the same population, but without guard, the value is 23.4 (Figure 10(a)). However, among semi-serious agents (0% seriousness), authority figures have a big impact. The mean unevacuated percentage in the semi-serious population with 5 authority figures is 29.6. With no guards, this jumps significantly to 41.1 (one tailed t-test, $alpha = 0.03$). Thus the effects of guards on evacuation time is in fact dependent on the culture. This is because semi-serious agents take much more time to decide to evacuate.



(a) No guards (b) 5 guards present

Figure 10: The impact of seriousness on the evacuation time, in the presence of authority figures (guards).

We also examine the impact seriousness on the crowd panic level, as measured by the percentage of agents with *high* fear. We again contrast a case without authority figures, and a case with authority figures. Figure 11(a) presents the results for the no guards case. Figure 11(b) shows the results for a case with five guards. In both, the x-axis represents the time steps and the y-axis represents the amount of unevacuated agents with *high* fear. The results show that higher seriousness causes higher levels of panic. However, the authority figures successfully lower fear (contrast the two figures). For example the mean panic value in a crowd with 100% serious agents, and with five guards is 5.2. Without guards, the panic increases to 12.2.



(a) No guards

(b) 5 guards present

Figure 11: The impact of seriousness on fear, in the presence of authorities (guards)

5. SUMMARY

In this paper, we took first steps to explore the impact of micro-level, individual agent, cultural parameters on macro-level crowd behavior. Building on existing literature which investigates culture in human crowds, we identified important cultural parameters in two physical crowd domains (pedestrian movement and evacuation). We implemented these in established agent-based simulations for these domains, and used the simulations to measure their impact on crowd dynamics. We thus go beyond existing work, which focused on describing cultural parameters of individuals, without investigating their crowd-level effects.

In the pedestrian motion domain, we conducted three sets of experiments. The first explored first the effect of each parameter by itself, in mixed crowd settings (mixed, in the sense that the parameter in question was varied among the agents). The second explored mixing agents, each with a pre-set bundle of such parameters (i.e., a present values for each of the parameters, that match recorded videos from different countries and cultures. Finally, the results of the simulation were quantitatively validated against data extracted from videos of crowds in five different countries.

In the evacuation domain, we presented a subset of results which demonstrate how cultural parameters (such as the seriousness with which evacuees treat indications of the need to evacuate) affect evacuation time and panic levels. For these, we additionally examined the effect that authority figures can have on the evacuation measures. We found that in some cultures (in particular where agents treated evacuations seriously), guards did not speed up evacuations. In others (in particular where agents did not take evacuations seriously), guards had a calming effect (lowering panic), while still increasing the rate of evacuation.

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