



Modelling distracted agents in crowd simulations

Melissa Kremer¹ · Brandon Haworth² · Mubbasir Kapadia³ · Petros Faloutsos^{1,4}

Published online: 30 September 2020
© Springer-Verlag GmbH Germany, part of Springer Nature 2020

Abstract

Multi-agent simulations can provide useful insights into the movement of pedestrians in arbitrary environments for predictive planning and analysis. The fidelity of such agents is important for the validity of the associated analyses. Current methods tend to employ agent models that are largely homogeneous in both physical abilities and behaviours. However, actual pedestrians exhibit a wide range of locomotion abilities and behaviours. In this work, we take a first step towards identifying and modelling *distracted* behaviours, such as walking and texting on a cell phone. Our models relate reported changes to the locomotion patterns and sensory abilities of distracted pedestrians to the corresponding parameters of a commonly used crowd simulation steering approach. We demonstrate experimentally that accounting for even a few of these behaviours significantly alters the flow patterns of the simulated agents. This impact affects overall crowd behaviour and is reflected in several crowd statistics including flow rate, effort, and kinetic energy.

Keywords Crowd simulation · Behavioural modelling · Distracted behaviours

1 Introduction

Simulating virtual pedestrians provides an effective way to estimate and analyze the movement and flow patterns of people within existing or to be constructed environments, for urban planning, architecture, emergency response and similar domains. Most current work in this area focuses on largely homogeneous agents with similar sensory and locomotion abilities. Although the size and desired velocity of the agents

can be parametrized, sensing and locomotion are both normative. Recent work has shown that including non-normative gaits in pedestrian simulations results in significant differences in various measures derived from the movement of the simulated crowds [13]. Others have shown that implementing heterogeneous crowds in terms of emotion and personality, physiological characteristics, psychology, cultural diversity, and many other variables [2,5,10,32,41,46] has huge impact on the overall flow of simulated crowds. This points to the need to carefully and intentionally include various forms of heterogeneity in multi-agent crowds simulations.

State-of-the-art research in behavioural modelling for simulated agents focuses primarily on deliberate, domain-specific behaviours and narrative creation [19,45]. In this paper, we take a first steps towards understanding and modelling distracted behaviours, particularly those involving engagement with personal devices such as smartphones. Such behaviours have become commonplace in today's world. It is therefore timely that they are included in the relevant dynamic analysis and visualization tools.

Distracted behaviours are surprisingly diverse. They can be classified based on the cognitive load they require, the sensory deprivation they affect, and the resulting changes in gait patterns they produce. We devoted significant effort in distilling the relevant studies and observations into parameters that can be used in a crowd steering simulator.

Electronic supplementary material The online version of this article (<https://doi.org/10.1007/s00371-020-01969-4>) contains supplementary material, which is available to authorized users.

✉ Melissa Kremer
mkremer@cse.yorku.ca

Brandon Haworth
bhaworth@uvic.ca

Mubbasir Kapadia
mk1353@cs.rutgers.edu

Petros Faloutsos
pfal@eecs.yorku.ca

¹ York University, Toronto, Canada

² University of Victoria, Victoria, Canada

³ Rutgers University, New Brunswick, NJ, USA

⁴ Toronto Rehabilitation Institute, University Health Network, Toronto, Canada

The contributions of this work can be summarized as follows:

- We summarize a large body of research on the effects of distractions on the locomotion patterns and sensory abilities of pedestrians and use it to construct an initial taxonomy grounded in literature of distracted behaviours for multi-agent simulation.
- We implement this taxonomy in a state of the art crowd simulation technique.
- We demonstrate experimentally the impact of these behaviours both quantitatively by computing common analytical measures of crowd movement, such as flow, effort and kinetic energy, on a large set of simulated scenarios, as well as qualitatively by simulating specific scenarios that are often used for such demonstrations in this domain.

The main purpose of this work is to show that simulating distracted agents has both visual and measurable effects, using short and controlled experiments. The proposed models are not complete as they do not include visual attention models and refocusing behaviours. However, the effect of distraction on an agent's locomotion and sensory abilities reflects the ground truth that has been reported in the related literature.

2 Related works

The related work in this area largely covers two areas of the literature. The modelling of crowds and various behaviours as well as the study of the impacts of distraction on human movement, perception, and navigation. This section focuses on the former, while the latter is delegated to Sect. 3 where the models are described with respect to findings in the literature.

2.1 Crowd simulation

A variety of methods and approaches related to crowd simulation and agent interaction have been proposed. The earliest method, Boids, used simple rules for velocities resulting in a net velocity which combined agent navigation and collision avoidance while maintaining flock cohesion behaviour [38]. Physical force-based methods use attractive and repulsive forces to maintain comfortable distances between agents and obstacles while steering towards a goal [14]. Predictive force-based models compute future trajectories free from collisions for some time window based on current trajectories and were used in this paper [21]. An example of this is Predictive Avoidance Model (PAM), which uses forces like those in the Helbing's Social Forces model to maintain comfortable distances between agents as well as a piecewise predictive

force that anticipates future collisions and makes small avoidance manoeuvres well in advance for minimal effort obstacle avoidance. Similarly, velocity space geometric methods compute a collision-free space for an agent in a future time window and have been used to demonstrate emergent crowd behaviours such as congestion avoidance [9]. An overview of these and many other methods can be found in [20].

2.2 Behaviour modelling

Various behaviour models have been proposed and integrated into crowd simulations to produce higher fidelity simulations concerned with more than steering and collision avoidance. Cognitive modelling approaches allow agents to plan for high-level tasks which are then carried out through lower level controllers [7]. Decision networks for simulating and animating interactions between multiple agents with different personalities also provide fidelity in this area [44]. Important work has been done in modelling personality factors and their impact on behaviour [6]. Data-driven approaches have also been used to learn and recreate realistic crowd behaviours [18,26].

2.3 Gaze and attention modelling

Modelling gaze behaviour is also an important problem in building realistic and robust simulations with an important component of distraction behaviour. Some navigation algorithms simulate vision to some extent without gaze behaviour [24,33]. Rule-based perception models allow characters to focus attention based on stimuli from the environment [15,22].

Environment-centric saliency maps, where gaze is drawn to the most noticeable (salient) objects, invert this problem [16]. More direct approaches isolate gaze in personal face-to-face situations [3]. Some approaches implement models that simulate agent gaze in crowds as in [8], but does not alter gait or investigate the effects of altered gaits due to distraction. Other methods model this interaction with real users in interactive environments [23,29]. However, to the best of the authors' knowledge, crowd simulators do not include cell phones, distraction specific modelling, or investigate the impacts of this phenomenon on crowd outcomes.

2.4 Distraction gait analysis

Previous studies have examined the effect of dual-task cost and difficulty on gait. One study showed that the type of distracting activity is directly related to the task cost [40]. The type of activity can be visual, motor, or cognitive, and the study suggests that cognitive tasks are usually the most distracting, followed by motor and then visual. Another study [37] suggested that cognitive and visual demand during cell-

phone use affects gait, while gross motor does not, although it did not draw any conclusions about the effects of fine motor tasks such as tapping and texting movements. Other studies have examined whether the difficulty of the secondary task affects performance. In a study on talking on the phone while driving [31], results showed a more complex conversation was more distracting and increased reaction time more than a simple one. Another study [36] showed that the gaits of older adults in particular are more affected by more difficult secondary tasks, especially while navigating obstacles. More research may be needed to examine the full effect of task difficulty on gait.

3 Methodology

In this section, we describe a subset of possible distraction behaviours, which we focus on throughout the paper, and how we model them in the context of a popular crowd simulator.

3.1 Distraction types

We consider three types of distracting activities that agents may perform while walking: texting on a smartphone, talking on the phone, and reading an article or browsing the internet on a smartphone. We classified these behaviours according to their task type into visual, motor, and cognitive tasks with their related task costs. Examples of how activities, including these, may be classified in this taxonomy can be seen in Fig. 1. For example, walking and talking on the phone has no fine motor component. Any gross motor component it may have has been shown to have no significant impact on gait [37], so we have therefore classified it as a cognitive-only activity. These are only examples of how tasks may be classified, and some of these may be classified differently depending on the circumstance and the exact nature of the activity. Our models have a foundation in the literature on real-world distracted walking studies. Data from these studies suggest various gait and perception characteristics change when walking while distracted on a smartphone. This is due to the division of attention between walking activity and smartphone activity.

Based on the literature outlined in Sect. 2.4 and our taxonomy, we would suggest that texting while walking has high motor and visual demands and medium to high cognitive demands depending on the topic of conversation. Talking on the phone has low to no motor or visual demand but often high cognitive demand. Reading an article or browsing would have low to no motor demand, high visual demand, and medium to high cognitive demand.

3.2 Distraction modelling

Each distraction model is implemented as a separate layer above the steering layer. Once a behaviour is activated by the



Fig. 1 An example taxonomy of behaviours, categorized into visual, motor, and cognitive tasks to understand their relative task costs. Behaviours may have various types of loads predicated on their underlying task. Cognitive tasks are the most distracting, followed by motor and then visual. This figure contains several examples from every day life (including those modelled here) to exemplify how one might think about task costs. In reality, the boundaries and placement of these tasks can be fuzzy or vary based on context. For example, dancing can include a wide range of precision and contexts. In this paper, the context of distracted behaviours is crowds during everyday casual navigation tasks

behaviour trigger, it sends a message to the distraction model to make the agent distracted dependent on the interaction and state. Each distracted behaviour has a corresponding method in the distraction module that is called when the behaviour trigger activates. This method, in turn, sets the locomotion parameters in the steering model accordingly. An overview of this model can be seen in Fig. 2. Our experiments use PAM for agent steering and navigation. In general, the distracted behaviour can be set to trigger either randomly or when some external event occurs.

The literature on distracted walkers suggests that because people are looking down at their device instead of towards their goal, they have to rely on their spatial memory, proprioception, and peripheral vision to guide them towards the goal and may not have a completely accurate idea of where it is. This can cause lateral deviation from a straight path [17,25,39]. Sufficiently distracted pedestrians may even forget to turn where they are meant to. Therefore, in addition to setting the locomotion parameters, the distraction layer also implements a novel “fuzzy” goal for distracted walkers. Upon becoming distracted, instead of heading straight towards the actual waypoint, a random point within some radius of the actual waypoint is chosen and used as the waypoint instead. We then use a simple raycast to ensure the agent can still reach this point, and it is not on the other side of a wall or in an unreachable area. The radius is determined by the current distance of the agent to the actual waypoint and the distraction type (related to the cognitive task load). If an agent reaches a fuzzy goal while distracted, in most cases they do

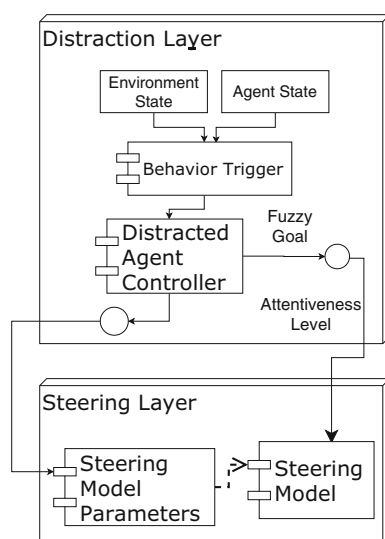


Fig. 2 An overview of the distraction module architecture

not go towards the actual waypoint to prevent backtracking if it is behind them. Instead the actual waypoint is updated as usual to the next waypoint if it is within sight. Again a simple raycast is used to determine if the agent can see the next waypoint. If they can't see it, the path is recomputed. Once the next actual waypoint is determined, the waypoint can be made fuzzy again if the agent is still distracted. If there is no next waypoint because the agent is almost at the goal, then the actual waypoint is set to the goal even if there is a little backtracking, which we believe is a realistic behaviour. This fuzzy waypoint approach probabilistically models some lateral deviations and forget-to-turn behaviours dependent on if the fuzzy waypoint is set further than the actual waypoint or laterally to the waypoint.

3.3 Parameter setting

Once a distracted behaviour is triggered, our distraction module adjusts the following parameters and passes them to the steering module: preferred speed, field of view, and neighbour distance. It also adjusts the waypoint “fuzziness” and passes it as the current waypoint to the steering layer. In the PAM algorithm, field of view is a settable float parameter representing the degrees of the agent's horizontal field of view as a cone aligned with the forward direction of the agent. Any obstacle outside of this cone is considered outside the field of view for that agent and is not considered for avoidance manoeuvres. Similarly, no obstacle further than the specified neighbour distance is considered when calculating avoidance manoeuvres.

It has been observed in the literature that the walking speed of pedestrians tends to decrease by some fraction while distracted on a smartphone. We set the preferred speed during each distracted behaviour to the average of per-

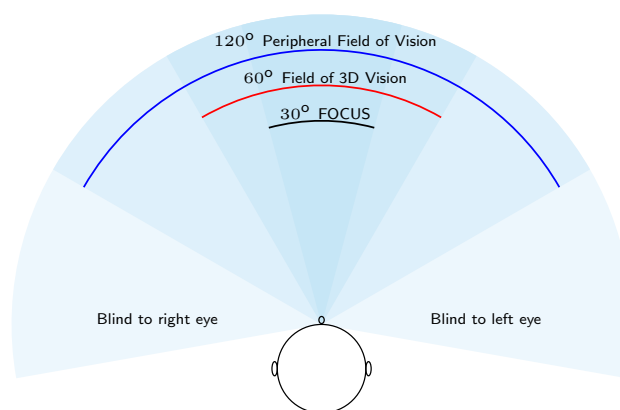


Fig. 3 Indicative range in degrees of key sectors of the normative human visual field, from top

centage reduction in speed reported in distracted walking studies which result in an average speed reduction of 20% [1,4,11,27,34,35,37,39,43]. Since non-distracted normative agents have an average preferred speed of 1.3 m/s, during walking and texting behaviours, agents were set to 80% of this value or 1.04 m/s. We repeated this process for the talking (phone call) as well as reading (or browsing) behaviours, setting their preferred speed values to 1.066 m/s (82%) [37] and 1.144 m/s (88%) [30,39] respectively.

The field of view is an important factor in the locomotion of distracted walkers. A depiction of various aspects of the normal human field of view is seen in Fig. 3. Literature suggests that not only is the horizontal field of view reduced as a result of the angle of the head being tilted forward in the sagittal plane, but also the amount of information processed within that field is reduced. A study measuring the field of view of someone talking on a cell phone showed that peripheral vision is reduced by 7–10% for large to small targets [28]. Since we assume that other pedestrians are a large target, we have therefore reduced the field of view for the talking on the phone distraction by 7%, resulting in a decrease from the default value of 200° – 186° . Another study showed that walkers that were distracted on a cell phone had a lateral range of eye movement of about 18° [42]. Studies of exactly how much peripheral vision is lost during cell phone use are lacking, but we assume from the normative model, Fig. 3, that there is at least 30 degrees lateral field of focus in every gaze direction, so we have set a total tentative value of 48° for the field of view during head-down distracted behaviours which in the current study includes texting and reading behaviours.

Real-world studies regarding neighbour detection distance while walking are limited, but we assume for the talking behaviour that this is not changed from the default since the field of view is still relatively wide vertically and horizontally. For the other distracted behaviours, where the gaze is directed down at the device, we have set an assumed value of 1m for the neighbour distance.

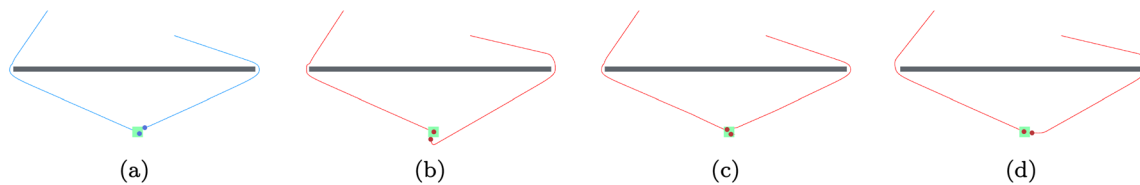


Fig. 4 The paths taken in the simple wall scenario by **a** two normative agents, **b** two distracted agents reading, **c** two distracted agents talking on phone, and **d** two distracted agents texting

The fuzzy goal radius for texting and reading behaviours has been set to 10% of the current distance between the agent and the actual waypoint, based on reported lateral deviation data [25,39]. In the current study, we set a relatively large maximum of 3 m as a cut-off for this distance to ensure the goal is not unrealistically “fuzzy” in simple paths. No fuzzy goal is used for the walk and talk behaviour as it is assumed there is no significant deviation when the goal is in sight. More research in this area may be required to find data-driven values as prior studies are concerned with walking in a straight line (without environment or people interactions).

There are several approaches that one can use to describe behaviours in a computationally convenient manner. In a complete model description, we may model agent–agent, agent–environment, and agent–focus interactions through a behaviour tree. However, to remove confounding factors in the following experiments, the distracted behaviour triggers at the start of each session and remains active for the duration for experimentation purposes. The experiments are also short and well-constrained subsections of larger environments and scenarios, which further limits unnecessary complexity.

4 Experiments

In the following experiments, we examine the importance of distraction modelling from the perspective of common multi-agent scenarios. In particular, we examine simple interactions, crowd egress, crossing groups scenarios. First, we qualitatively examine simple interactions in comparative crowd analysis to understand the impacts of distracted modelling at a micro scale, as impacts in micro-movement often produce emergent macro-behaviours in crowd simulation. We then examine crowd egress and crossing groups scenarios from both quantitative and qualitative perspectives with respect to past literature in comparative crowds analysis, multi-agent modelling, and dynamic environment analysis of safety critical scenarios.

4.1 Qualitative experiments

In this section, we conduct a number of experiments to qualitatively examine the impact of distraction modelling on

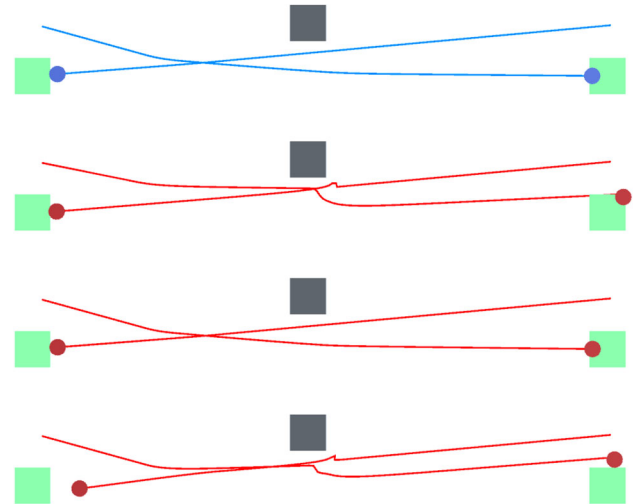


Fig. 5 The paths taken in the oncoming obstacle scenario from top to bottom: two normative agents, two distracted agents reading, two distracted agents talking on the phone, and two distracted agents texting

common scenarios from comparative crowd analysis literature. For qualitative analysis, we chose a handful of common scenarios often used to test the robustness of steering algorithms: the simple wall, oncoming obstacle, surprise and diametric goals scenarios.

We use exemplary screen captures and trajectory rendering to compare the paths of distracted agents with non-distracted (normative) agents. Trajectories for the simple wall environment can be seen in Fig. 4. Trajectories for the oncoming obstacle environment can be seen in Fig. 5. Trajectories for the surprise environment can be seen in Fig. 6. Trajectories for the diametric goals environment can be seen in Fig. 7.

There are clear differences between the distraction types for each scenario. In the simple wall scenario, the normative agents take the path of the least effort and head for the goal as efficiently as possible. The reading and texting behaviours both have wider, less efficient turns. They also may end up deviated from the goal and have to make a small adjustment at the end to get to their goal. The talking behaviour is close to the normative behaviour in this scenario because they do not exhibit lateral deviation and the path taken is unaffected

Fig. 6 The paths taken in the surprise scenario by **a** two normative agents, **b** two distracted agents reading, **c** two distracted agents talking on phone, and **d** two distracted agents texting

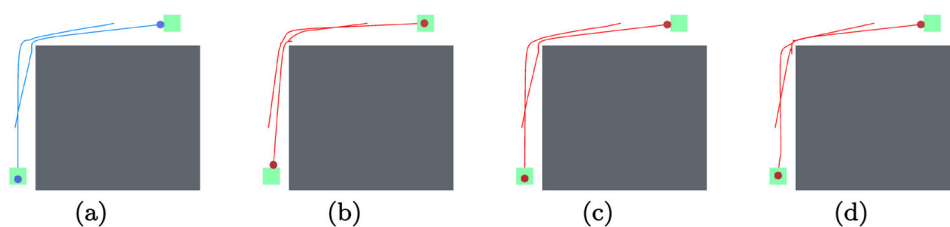
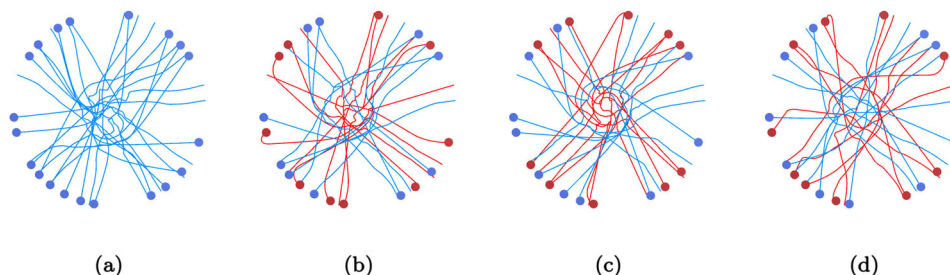


Fig. 7 The paths taken in the diametric goals scenario by **a** 20 normative agents, **b** 10 normative and 10 distracted agents reading, **c** 10 normative and 10 distracted agents talking on phone, and **d** 10 normative and 10 distracted agents texting



by their slower speed and slightly reduced field of view when no other agents are near them.

In the oncoming obstacle scenario, the normative agents avoided each other flawlessly. In comparison, the texting and reading behaviour paths both show where the agents failed to avoid each other and bumped when navigating around the obstacle. Again the talking behaviour paths look similar to normative agents.

In the surprise scenario, both the reading and texting behaviours had a collision between the agents at the corner, and the collision was more forceful for the texting behaviour. The no distraction and talking cases appear to be similar once again in this scenario, largely because the scenario is a visual challenge.

In the diametric goals scenario, there are some deviations for the reading behaviour. It can be difficult to interpret the entangled paths, but in general the talking paths seem smoother in the middle area. The texting paths are smooth as well, and the difference between this and the reading is mainly from the random fuzzy waypoints chosen and the differences in speed of these types of distracted agents, as normative agents would have reached the centre ahead of distracted agents and already leaving the centre when distracted types reached it.

4.2 Quantitative measures

For our quantitative experiments, we use common measures related to the movement of the agents. These are the flow rate F_r (the number of agents divided by the total simulation time), effort $E(S)$ (estimated total metabolic energy expenditure over the path integral of all agents), and kinetic energy $K(S)$ (total kinetic energy over the path integral of all agents). The measures are described in more detail below.

Flow rate is defined as the rate at which all agents A complete their goals in the scenario S .

$$F(S) = \frac{|A|}{T_s} \quad (1)$$

where T_s is the total simulation time. Then the average total effort $E(S)$ is defined as the average of all agent effort path integrals (integral over the total path of an agent $a \in A$) over all A in the S .

$$E(S) = \sum_A \frac{m \int (e_s + e_w v_i^2) dt}{|A|} \quad (2)$$

where $e_s = 2.23$ and $e_w = 1.26$ are the continuous energy expenditure rate and moving energy expenditure rate of the average human, respectively, v_i is the agent's instantaneous velocity, and m is the mass of an agent, usually set to 1 kg (to ignore mass). Total average kinetic energy $K(S)$ is defined as the average of kinetic energy over all agents' path integrals.

$$K(S) = \sum_A \frac{\int 0.5 m v_i^2 dt}{|A|} \quad (3)$$

In this way, all quantitative measures capture crowd wide impact of distraction in that particular scenario.

4.3 Egress

In Sect. 4.1, we highlighted how distraction modelling impacts the movement of individual agents in the simplest of environments. In particular, in scenarios where agent-agent and agent-environment interactions are involved and where agents gather and disperse. If these interactions are affected by distracted behaviours, what is the impact of distracted

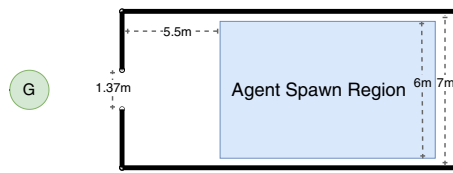


Fig. 8 Blue print of the egress scenario. Agents spawn in a hallway and share a goal region outside of a single egress point. This scenario represents a common subsection of building designs during a group egress situation, e.g. an evacuation

behaviours on group bottleneck egress points in building environments?

We use a common benchmark from the comparative crowd analysis and environment safety literature—the uni-directional bottleneck egress [12]. The exact layout of this scenario can be seen in Fig. 8. This scenario is simulated with an increasing proportion of each of the distracted model types—texting, reading, on call—keeping the remaining agents homogeneous. The distracted agents are using the parameters from their descriptions in Sect. 3. The remaining agents use the default parameters for PAM and a desired speed of 1.3 m/s, the average speed of human walking. Each proportion scenario is simulated 20 times with random initial conditions for the 50 agents. All distracted agents exhibit the same distraction type for each trial, so that we may compare across behaviours (we do not examine mixed behaviour crowds).

We examine the impact of distracted behaviours on the common crowd-centric measures described above over the duration of each simulation.

We conducted an analysis as follows. The mean and standard deviation of all of our metrics are captured across the distracted agent models and their proportions in the crowd. A Kruskal–Wallis sign rank sum test and post-hoc Conover’s test with false discovery rate (FDR) and Holm corrections in the case of ties are used to isolate the significant dominances between the models across proportions in the crowd.

The metrics over all models and their proportions in the egress scenario crowd can be seen in Fig. 9. The statistical test results are summarized in Table 1.

This study reveals interesting artifacts in uni-directional bottlenecks with respect to distraction modalities. Texting does not particularly impact flow rate or the effort expended by the agents, but it does impact kinetic energy significantly when around 20% of the agents are texting. On the other hand, talking, which had little impact on simple scenarios with few agents, has a significant impact on both flow rate and kinetic energy when around 20% of the agents are on a call. In general, it seems that the distractions we consider in this paper have more impact on the measures around the 20% mark.

4.4 Group interactions

In Sect. 4.1, we highlighted how distraction modelling impacts the movement of individual agents in the simplest of environments. In particular, in scenarios where agent–agent and agent–environment interactions are involved and where agents pass and make collision avoidance decisions. If these interactions are affected by distraction behaviours, what is the impact of distraction behaviours on group crossing in building environments?

In this experiment, we examine the hypothesis that distraction behaviours, such as walking while texting, reading, or on a call, adversely affect crossing specific crowd measures like flow rate, effort, and kinetic energy. We follow this quantitative examination with a qualitative one, to see if distraction behaviours, such as walking while texting, reading, or on a call, adversely affect group specific qualitative artefacts of simulation such as lane forming in laminar flow.

Again, we use a common benchmark from the comparative crowd analysis and environment safety literature—the crossing groups hallway [12]. The exact layout of this scenario can be seen in Fig. 11. This scenario is simulated with an increasing proportion of each of the distracted model types—texting, reading, on call—keeping the remaining agent homogeneous. The distracted model agents use the parameters from their descriptions in Sect. 3. The remaining agents use the default parameters for PAM and a desired speed of 1.3 m/s, the average speed of human walking. Each proportion scenario is simulated 20 times with random initial conditions for the 50 agents. All distracted agents exhibit the same distraction type for each trial, so that we may compare across behaviours (we do not examine mixed behaviour crowds).

We examine the impact of distracted behaviours on multiple common crowd-centric outcome measures captured over the duration of each simulation. These are once again the flow rate, effort, and kinetic energy.

The same procedure is employed for the analysis of the crossing groups scenario as was described for the egress environment. We also capture a series of screen captures at exemplar moments to examine the qualitative impact of the models in this scenario.

The metrics over all models and their proportions in the crossing groups scenario crowd can be seen in Fig. 12. The statistical test results are summarized in Table 2. Qualitative examples with agent paths are shown in Fig. 13. An example of a high quality rendering with avatars using cellphones is shown in Fig. 14.

The results in the crossing groups scenario are deeply surprising. While the general hypothesis is that distraction disrupts laminar flow (something most city dwellers can attest to in their day-to-day lives), the level at which this occurs is extreme, an example of which is shown in Fig. 10.

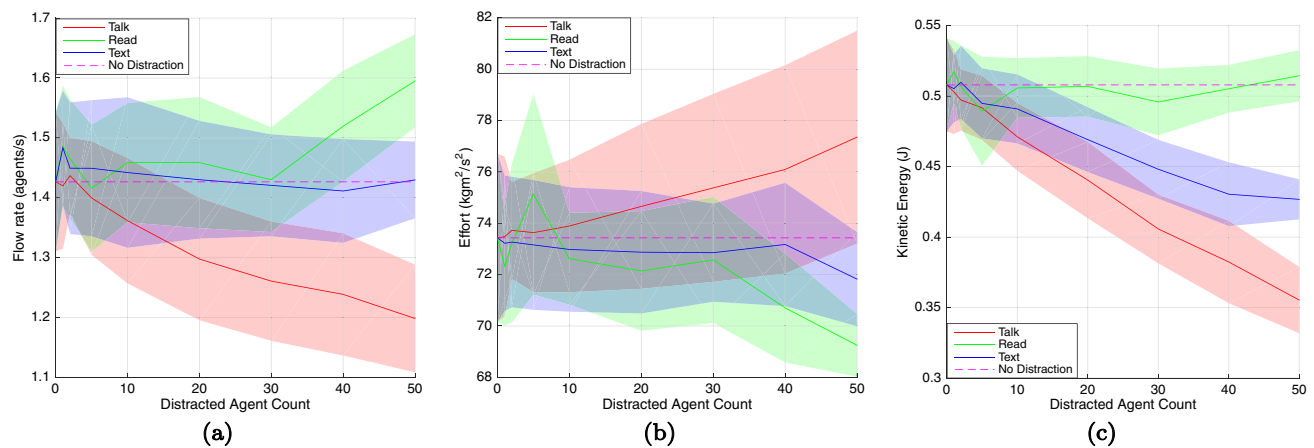


Fig. 9 The quantitative analysis of the egress scenario across all distracted models and their proportions of agents for **a** flow rate, **b** effort, and **c** kinetic energy

Table 1 Statistical test results indicating differences in crowd simulation measures for pairs of distracted activities and the number of distracted agents in the scene out of a total of 50 agents for the egress scenario. Checkmarks indicate a significant difference in dominance ($p < 0.05$)

	Flow rate								Effort								Kinetic energy									
	1	2	5	10	20	30	40	50	1	2	5	10	20	30	40	50	1	2	5	10	20	30	40	50		
No distraction/read	×	×	×	×	×	×	✓	✓	×	×	×	×	×	×	✓	✓	×	×	×	×	×	×	×	×		
No distraction/talk	×	×	×	✓	✓	✓	✓	✓	×	×	×	×	×	×	✓	✓	×	×	×	✓	✓	✓	✓	✓		
No distraction/text	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	✓	✓	✓	✓	✓		
Read/talk	×	×	×	✓	✓	✓	✓	✓	×	×	×	×	×	×	✓	✓	×	×	×	✓	✓	✓	✓	✓		
Read/text	×	×	×	×	×	×	✓	✓	×	×	×	×	×	×	✓	✓	×	×	×	×	✓	✓	✓	✓		
Talk/text	×	×	×	✓	✓	✓	✓	✓	×	×	×	×	×	×	✓	✓	×	×	×	✓	✓	✓	✓	✓		



Fig. 10 The paths taken in the crossing groups scenario by **a** 50 normative agents, **b** 40 normative agents and 10 distracted agents texting. In both cases, the initial positions and conditions were the same. This comparison shows how the presence of distracted agents breaks the laminar flow

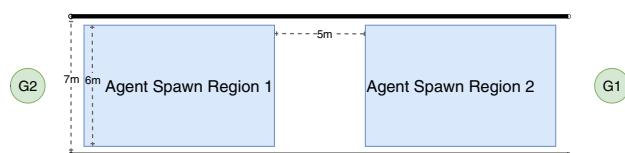


Fig. 11 Blue print of the crossing groups scenario. Agents spawn in a hallway in two regions with opposing goals. This scenario represents a common subsection of building designs during a group crossing situations

As little as one agent, in a crowd of 50, talking on their phone or texting can significantly alter the flow rate of two crossing groups. This includes reading at 2 agents, and includes all modes of distraction in the paper after as little as 5 agents. In addition, the mode soft distraction significantly differ from

each other after around 2 out of 50 agents. This is reflected in Fig. 13 where we can see paths are much smoother when no distracted agents are present. In particular, that agents who are distracted disrupt the formation of high value lanes (laminar flow) as the group meet, merge, and pass. Taken together, these results are evidence that simulating various modes of distraction is necessary, particularly in our modern world where personal devices are ubiquitous.

4.5 Discussion

One of the most interesting results of our study was that while the talking behaviour is considered the least distracting task, it produced interesting emergent artifacts related to the scenario. It has been previously observed that in bottleneck

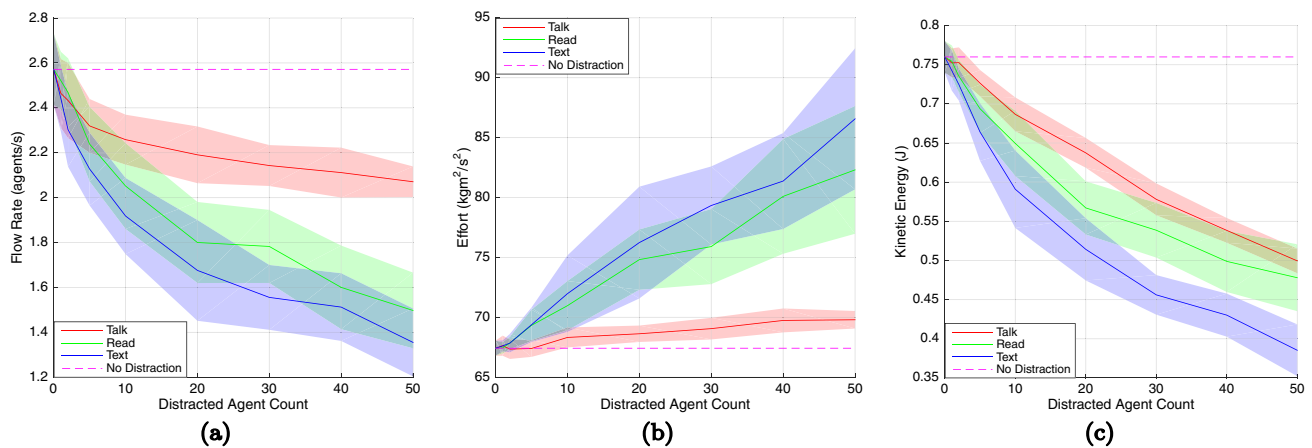


Fig. 12 The quantitative analysis of the crossing groups scenario across all distracted models and their proportions of agents for **a** flow rate, **b** effort, and **c** kinetic energy

Table 2 Statistical test results indicating differences in crowd simulation measures for pairs of distracted activities and the number of distracted agents in the scene out of a total of 50 agents for the crossing groups scenario

	Flow rate								Effort								Kinetic energy							
	1	2	5	10	20	30	40	50	1	2	5	10	20	30	40	50	1	2	5	10	20	30	40	50
No distraction/read	×	✓	✓	✓	✓	✓	✓	✓	×	×	✓	✓	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	✓
No distraction/talk	✓	✓	✓	✓	✓	✓	✓	✓	×	×	×	✓	✓	✓	✓	✓	×	×	✓	✓	✓	✓	✓	✓
No distraction/text	✓	✓	✓	✓	✓	✓	✓	✓	×	×	✓	✓	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	✓
Read/talk	×	✓	×	✓	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	✓
Read/text	✓	✓	✓	×	✓	×	✓	✓	×	×	×	×	×	×	×	✓	×	×	✓	✓	✓	✓	✓	✓
Talk/text	×	✓	✓	✓	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	✓

Checkmarks indicate a significant difference in dominance ($p < 0.05$)

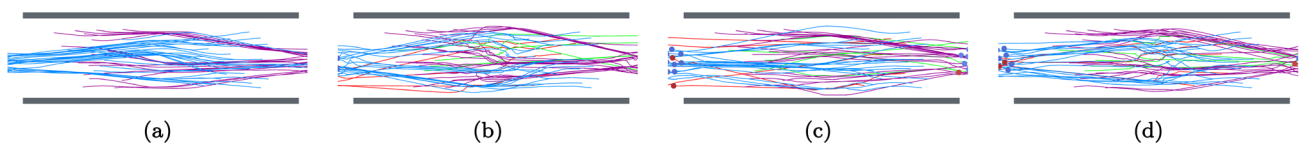


Fig. 13 The paths taken in the crossing groups scenario by **a** 50 normative agents, **b** 40 normative and 10 distracted agents reading, **c** 40 normative and 10 distracted agents talking on the phone, and **d** 40 normative and 10 distracted agents texting



Fig. 14 Qualitative rendering of a crowd with avatars using cellphones

egress scenarios, obstacles and slow moving agents can actually improve flow rate and effort. Thus, reading and texting may actually improve flow in some scenarios. However, the opposite is true in bidirectional flow scenarios. Because the

talking behaviour resembles normative agents, it produces laminar flow behaviours, which reduces effort and increases flow rate in crossing groups. Reading and texting in these scenarios disrupts laminar flow, increasing effort and reducing flow rate.

5 Conclusion

We have presented a first attempt towards modelling distracted behaviours for the purposes of pedestrian simulation. The parameters of the proposed model are based on a thorough survey of actual studies of distracted behaviours and thus reflect our best understanding to date of ground truth. The main goal of this paper was not to provide a com-

plete model of distracted pedestrians, but rather to show that accounting for even simple distracted behaviours does make difference in the resulting simulations both in terms of a qualitative and a quantitative point of view.

Going forward, we plan to investigate a richer taxonomy of distracted and deliberate behaviours, and at the same time model virtual pedestrians with diverse sensory and locomotion abilities. In the short term, we aim to model non-normative gaits, such as those related to cerebral palsy, and knee and hip ailments. We believe that developing more inclusive and diverse pedestrian simulators will significantly improve their fidelity and practical value in a number of important domains, such as urban simulation and computer games.

Funding Funding was provided by Ontario Research Foundation (Grant No. RE08-054) and National Science Foundation (Grant Nos. IIS-1703883, S&AS-1723869).

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Anonymity Grants are not listed yet for anonymity reasons.

References

- Agostini, V., Fermo, F.L., Massazza, G., Knaflitz, M.: Does texting while walking really affect gait in young adults? *J. Neuroeng. Rehabil.* **12**(1), 86 (2015)
- Allbeck, J.M., Badler, N.I.: Creating crowd variation with the ocean personality model (2008)
- Bailly, G., Raidt, S., Elisei, F.: Gaze, conversational agents and face-to-face communication. *Speech Commun.* **52**(6), 598–612 (2010)
- Cha, J., Kim, H., Park, J., Song, C.: Effects of mobile texting and gaming on gait with obstructions under different illumination levels. *Phys. Ther. Rehabil. Sci.* **4**(1), 32–37 (2015)
- Curtis, S., Guy, S.J., Zafar, B., Manocha, D.: Virtual tawaf: a case study in simulating the behavior of dense, heterogeneous crowds. In: *IEEE International Conference on Computer Vision Workshops (ICCV Workshops)*, pp. 128–135. IEEE (2011)
- Durupinar, F., Allbeck, J., Pelechano, N., Badler, N.: Creating crowd variation with the ocean personality model. In: *Proceedings of the 7th International Joint Conference on Autonomous Agents and Multiagent Systems*, vol. 3, pp. 1217–1220. International Foundation for Autonomous Agents and Multiagent Systems (2008)
- Funge, J., Tu, X., Terzopoulos, D.: Cognitive modeling: knowledge, reasoning and planning for intelligent characters (1999)
- Grillon, H., Thalmann, D.: Simulating gaze attention behaviors for crowds. *Comput. Anim. Virtual Worlds* **20**(2–3), 111–119 (2009)
- Guy, S.J., Chhugani, J., Curtis, S., Dubey, P., Lin, M., Manocha, D.: Pedestrians: a least-effort approach to crowd simulation. In: *Proceedings of the 2010 ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, pp. 119–128. Eurographics Association (2010)
- Guy, S.J., Kim, S., Lin, M.C., Manocha, D.: Simulating heterogeneous crowd behaviors using personality trait theory
- Haga, S., Sano, A., Sekine, Y., Sato, H., Yamaguchi, S., Masuda, K.: Effects of using a smart phone on pedestrians' attention and walking. *Procedia Manuf.* **3**, 2574–2580 (2015)
- Haworth, B., Usman, M., Berseth, G., Kapadia, M., Faloutsos, P.: On density-flow relationships during crowd evacuation. *Comput. Anim. Virtual Worlds* **28**(3–4), e1783 (2017). <https://doi.org/10.1002/cav.1783>
- Haworth, M.B.: Biomechanical locomotion heterogeneity in synthetic crowds. Ph.D. thesis, York University, Toronto, Canada (2019)
- Helbing, D., Molnar, P.: Social force model for pedestrian dynamics. *Phys. Rev. E* **51**(5), 4282 (1995)
- Hill, R.: Modeling perceptual attention in virtual humans. In: *Proceedings of the 8th Conference on Computer Generated Forces and Behavioral Representation*, pp. 563–573. Citeseer (1999)
- Itti, L., Koch, C., Niebur, E.: A model of saliency-based visual attention for rapid scene analysis. *IEEE Trans. Pattern Anal. Mach. Intell.* **11**, 1254–1259 (1998)
- Jeon, S., Kim, C., Song, S., Lee, G.: Changes in gait pattern during multitask using smartphones. *Work* **53**(2), 241–247 (2016)
- Ju, E., Choi, M.G., Park, M., Lee, J., Lee, K.H., Takahashi, S.: Morphable crowds. In: *ACM Transactions on Graphics (TOG)*, vol. 29, p. 140. ACM (2010)
- Kapadia, M., Falk, J., Zünd, F., Marti, M., Sumner, R.W., Gross, M.: Computer-assisted authoring of interactive narratives. In: *Proceedings of the 19th Symposium on Interactive 3D Graphics and Games*, pp. 85–92 (2015)
- Kapadia, M., Pelechano, N., Allbeck, J., Badler, N.: *Virtual Crowds: Steps Toward Behavioral Realism*. Morgan & Claypool Publishers, San Rafael (2015)
- Karamouzas, I., Heil, P., Van Beek, P., Overmars, M.H.: A predictive collision avoidance model for pedestrian simulation. In: *International Workshop on Motion in Games*, pp. 41–52. Springer (2009)
- Khullar, S.C., Badler, N.I.: Where to look? Automating attending behaviors of virtual human characters. *Auton. Agents Multi Agent Syst.* **4**(1–2), 9–23 (2001)
- Kokkinara, E., Oyekoya, O., Steed, A.: Modelling selective visual attention for autonomous virtual characters. *Comput. Anim. Virtual Worlds* **22**(4), 361–369 (2011)
- Kuffner, J.J., Latombe, J.C.: Fast synthetic vision, memory, and learning models for virtual humans. In: *Proceedings Computer Animation*, pp. 118–127. IEEE (1999)
- Lamberg, E.M., Muratori, L.M.: Cell phones change the way we walk. *Gait Posture* **35**(4), 688–690 (2012)
- Lee, K.H., Choi, M.G., Hong, Q., Lee, J.: Group behavior from video: a data-driven approach to crowd simulation. In: *Proceedings of the 2007 ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, pp. 109–118. Eurographics Association (2007)
- Licence, S., Smith, R., McGuigan, M.P., Earnest, C.P.: Gait pattern alterations during walking, texting and walking and texting during cognitively distractive tasks while negotiating common pedestrian obstacles. *PLoS ONE* **10**(7), e0133281 (2015)
- Maples, W., DeRosier, W., Hoenes, R., Bendure, R., Moore, S.: The effects of cell phone use on peripheral vision. *Optom. J. Am. Optom. Assoc.* **79**(1), 36–42 (2008)
- Narang, S., Best, A., Randhavane, T., Shapiro, A., Manocha, D.: PedVR: simulating gaze-based interactions between a real user and virtual crowds. In: *Proceedings of the 22nd ACM Conference on Virtual Reality Software and Technology*, pp. 91–100. ACM (2016)
- Niederer, D., Bumann, A., Mühlhauser, Y., Schmitt, M., Wess, K., Engeroff, T., Wilke, J., Vogt, L., Banzer, W.: Specific smartphone usage and cognitive performance affect gait characteristics during free-living and treadmill walking. *Gait Posture* **62**, 415–421 (2018)

31. Patten, C.J., Kircher, A., Östlund, J., Nilsson, L.: Using mobile telephones: cognitive workload and attention resource allocation. *Accid. Anal. Prev.* **36**(3), 341–350 (2004)
32. Pelechano, N., O'Brien, K., Silverman, B., Badler, N.: Crowd simulation incorporating agent psychological models, roles and communication. Technical report. Center for Human Modeling and Simulation, University of Pennsylvania, Philadelphia (2005)
33. Peters, C., O'Sullivan, C.: Synthetic vision and memory for autonomous virtual humans. In: *Computer Graphics Forum*, vol. 21, pp. 743–752. Wiley Online Library (2002)
34. Pizzamiglio, S., Naeem, U., Abdalla, H., Turner, D.L.: Neural correlates of single-and dual-task walking in the real world. *Front. Hum. Neurosci.* **11**, 460 (2017)
35. Plummer, P., Apple, S., Dowd, C., Keith, E.: Texting and walking: effect of environmental setting and task prioritization on dual-task interference in healthy young adults. *Gait Posture* **41**(1), 46–51 (2015)
36. Plummer-D'Amato, P., Brancato, B., Dantowitz, M., Birken, S., Bonke, C., Furey, E.: Effects of gait and cognitive task difficulty on cognitive-motor interference in aging. *J. Aging Res.* **2012** (2012)
37. Prupetkaew, P., Lugade, V., Kamnardsiri, T., Silsupadol, P.: Cognitive and visual demands, but not gross motor demand, of concurrent smartphone use affect laboratory and free-living gait among young and older adults. *Gait Posture* **68**, 30–36 (2019)
38. Reynolds, C.W.: Flocks, herds and schools: a distributed behavioral model. *SIGGRAPH Comput. Graph.* **21**(4), 25–34 (1987)
39. Schabrun, S.M., van den Hoorn, W., Moorcroft, A., Greenland, C., Hodges, P.W.: Texting and walking: strategies for postural control and implications for safety. *PLoS ONE* **9**(1), e84312 (2014)
40. Tian, Y., Huang, Y., He, J., Wei, K.: What affects gait performance during walking while texting? A comparison of motor, visual and cognitive factors. *Ergonomics* **61**(11), 1507–1518 (2018). <https://doi.org/10.1080/00140139.2018.1493153>
41. Xue, Z., Dong, Q., Fan, X., Jin, Q., Jian, H., Liu, J.: Fuzzy logic-based model that incorporates personality traits for heterogeneous pedestrians. *Symmetry* **9**(10), 239 (2017)
42. Yoshiki, S., Tatsumi, H., Tsutsumi, K., Miyazaki, T., Fujiki, T.: Effects of smartphone use on behavior while walking. *Urban Reg. Plan. Rev.* **4**, 138–150 (2017)
43. Yu, K.H., Shim, J.H., Choung, S.D., Jeon, H.S.: Effect of using a cell phone on gait parameters in healthy young adults: Texting and texting while listening to music. *J. Korean Soc. Phys. Med.* **10**(4), 25–31 (2015)
44. Yu, Q., Terzopoulos, D.: A decision network framework for the behavioral animation of virtual humans. In: *Proceedings of the 2007 ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, pp. 119–128. Eurographics Association (2007)
45. Zhang, X., Schaumann, D., Haworth, B., Faloutsos, P., Kapadia, M.: Multi-constrained authoring of occupant behavior narratives in architectural design. In: *Proceedings of SimAUD* (2019)
46. Zheng, L., Qin, D., Cheng, Y., Wang, L., Li, L.: Simulating heterogeneous crowds from a physiological perspective. *Neurocomputing* **172**, 180–188 (2016)

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Melissa Kremer is a Master's student at York University in the Department of Electrical Engineering and Computer Science. Her research interests include human animation and crowd simulation, in order to develop tools for the creation of realistic behaviours in virtual human crowds. She is currently researching distracted agents and their impact in crowd simulations.



Brandon Haworth is an Assistant Professor in the Department of Computer Science, Faculty of Engineering; the Director of the Graphics, Artificial Intelligence, Design, & Games (GAIDG) Lab; and a Research Fellow in the Institute on Ageing and Lifelong Health at the University of Victoria. He received the B.Sc. Hons. degree in Computer Science from York University in 2013, M.Sc. in 2016, and Ph.D. in 2019. Brandon has also worked as a researcher and consultant with the University of Toronto, the University Health Network: Toronto Rehabilitation Institute, Teeple Architects, and other academic and industry partners. His research interests include crowd steering behaviours, artificial intelligence, digital game design, architectural optimization, assistive technologies, and rehabilitative technologies with a purpose to explore the intersections between visibility, representation, and decision-making in interactive technologies.



Mubbasir Kapadia is the Director of the Intelligent Visual Interfaces Lab and an Assistant Professor in the Computer Science Department at Rutgers University. Previously, he was an Associate Research Scientist at Disney Research Zurich. Kapadia's research lies at the intersection of artificial intelligence, visual computing, and human-computer interaction, with a mission to develop intelligent visual interfaces to empower content creation for human-aware architectural design,

digital storytelling, and serious games.



Petros Faloutsos is a Professor at the Department of Electrical Engineering and Computer Science at York University, and an affiliate Scientist at the UHN-Toronto Rehabilitation Institute. Before joining York, he was a faculty member at the Computer Science Department at the University of California at Los Angeles, where in 2002 he founded the first computer graphics lab at UCLA. Faloutsos received his Ph.D. degree (2002) and his M.Sc. degree in Computer Science from

the University of Toronto, Canada and his BEng degree in Electrical Engineering from the National Technical University of Athens, Greece.