Social Crowd Simulation: Improving Realism with Social Rules and Gaze Behavior

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Figure 1: The left figure shows a photo of the social crowd simulation showing virtual agents interacting among them or with their cell phones. The right figure represents a top-down view of a similar scene.

Abstract

This paper proposes a novel approach to enhance the realism of a rule-based crowd simulation model by incorporating social rules and gaze-driven attention with consistent animations. Current crowd simulation models focus mostly on steering towards a goal while avoiding collision based on the agent's direction of movement. This leads to robot-like simulations since agents' appear to always have their attention perfectly aligned with the direction of movement. In the real world we observe that humans move in a crowd performing collision avoidance driven by attention, gaze, and non-verbal coordination with incoming traffic. In addition, humans exhibit different steering strategies based on whether they walk alone or in a group, whether they can look ahead and plan their best local movement, or react more abruptly because their gaze diverts from their direction of movement. Human gaze can be driven by movement but also by distractions such as being engaged in conversation with other people or using mobile phones. These human features are overlooked in crowd simulation leading often to perfectly smooth local movements of individuals. Our proposed method enhances existing crowd simulation frameworks by integrating social behavior models that affect both individual and collective dynamics, and drives gaze behavior to better simulate attention. By applying these models at both the steering and animation levels, we significantly improve the realism of the crowd simulation. A user study shows that our model was perceived as being more realistic and consistent with social behaviors when compared to a more traditional collision avoidance with just locomotion or with random animations.

CCS Concepts

• **Computing methodologies → Agent / discrete models**; **Collision detection**.

Keywords

Crowd Simulation, Collision Avoidance, Gaze Behavior, Social Rules

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1 Introduction

Crowd simulation serves various applications with different requirements. For instance, simulating evacuation scenarios or urban flow aims to mimic human-like velocities and densities. In computer graphics and entertainment, it is often necessary to simulate smooth collision avoidance, anticipation, and natural animation particularly for locomotion. Research has shown that including diverse animations [McDonnell et al. 2008; Molina et al. 2021] and group formations [Moussaïd et al. 2010] enhance realism, but these

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models ignore how other agents should perceive and react to groups. Researchers' efforts in the crowd simulation field, typically focus on local movement algorithms that deal with collision avoidance while respecting obstacle clearance, and then animations are added on top in an attempt to provide some perceptual realism to the final crowd simulation. However, they do not provide a consistent loop between behavior and animation. Moving on to other human aspects beyond local movement, researchers have shown that including psychological aspects [Pelechano et al. 2007] , personality [Durupinar et al. 2011; Guy et al. 2011] or simulating human perception [Oliva and Vilhjálmsson 2014; Ondřej et al. 2010] can further enhance realism.

The dynamics of a real crowd are quite complex and difficult to capture by simply moving agents towards a destination point while avoiding other agents and objects. Human avoidance maneuvers are also driven by the mutual understanding from subtle head movements or gaze that helps to indicate the intended direction for collision avoidance [Nummenmaa et al. 2009]. In addition, distractions such as mobile phone use can divert the individual's gaze, increasing the risk of collision [Murakami et al. 2021]. Recent advancements underline the trend towards incorporating heterogeneous elements such as social behavior, emotions, and characteristics into crowd simulation, aiming to enhance the steering accuracy and overall realism of these simulations [Pelechano et al. 2016]. This evolution signifies the field's move towards more nuanced and comprehensive models that can better replicate the complex dynamics of real-world crowds. Recently, many strategies have been developed to better represent how small groups of virtual people behave, by using real-life crowd observations to learn from them and use them to improve how these simulations represent human interactions and movements [Charalambous et al. 2023].

This paper aims to achieve a more holistic approach to crowd simulation by considering social behaviors that accurately simulate the interaction between local movement, grouping, and short-term decisions with attention models and social aspects that incorporate human perception and distraction in the simulation loop. These aspects are effectively intertwined with the animations to create a more realistic crowd simulation. The main contributions of our paper are:

- Gaze dynamics controlled by several focal points in accordance with social norms.
- A gaze driven Field of View model that dynamically adjusts to follow the agents' attention and determine collision detection.
- Collision avoidance force driven by the social situation and interaction with mobile phones or between individuals and groups.
- Animation triggered by gaze and social behavior that can better reflect the attention and social simulation to the viewer, thus closing the behavior-animation loop.

To validate the effectiveness and realism of our model, we conducted an experiment comparing three conditions: a traditional rule-based model with locomotion animations, the same model enhanced with random gaze and upper body animations, and our proposed social crowd model. The user experiment was designed to measure the perceived level of realism for each condition. The results showed that our model was perceived as being significantly closer to real crowd behavior and that users could correctly identify the intended social norms displayed in the simulation.

2 Related Work

Reynolds' seminal work [Reynolds 1987] showed that collective emergent behavior could be achieved through distributed rule-based models, enabling a flock to steer clear of obstacles while moving in alignment with nearby agents. Helbing et al.'s social forces model [Helbing et al. 2000] used imaginary forces to mimic real-life social and physical influences, such as reaching a destination, maintaining personal space, and avoiding collisions. Pelechano et al. [Pelechano et al. 2007] combined and extended these models by integrating geometric and psychological rules with social forces, resulting in the HiDAC model, which demonstrated diverse emergent behaviors based on situations and individual personalities. The RVO model used reciprocal velocity vectors to steer the agents [Snape et al. 2011], while vision-based models have utilized optical flow to imitate human perception steer agents based on it [Dutra et al. 2017b]. Most crowd simulation models focus on moving virtual agents towards a goal while avoiding collisions, but to create more plausible crowds for immersive virtual environments, it is necessary to incorporate social rules that better mimic human behaviour.

2.1 Social Crowd Simulation

In recent years, efforts in crowd simulation have not only aimed to improve the accuracy of collision avoidance, but also to create simulations that more closely resemble real-life scenarios. Lerner et. al. [Lerner et al. 2009] introduced a data-driven method to fit behaviors to simulated pedestrian crowds by tagging agent trajectories with actions. Moussaïd et al. [Moussaïd et al. 2010] improved the social force model by incorporating group dynamics. This advancement recognized the fact that most pedestrians tend to walk in groups and engage in social interactions. Douglas Ivo et al. [Ivo et al. 2021] created a model to better represent social groups, like families or friends, in crowd simulations. This model allows for customizable group structures and dynamics, capable of simulating different sizes and levels of cohesion among group members, and grouping after separation. Karamouzas et al. [Karamouzas and Overmars 2012] developed a model to simulate small groups of people walking together. Zhang et al. [Zhang et al. 2022] studied how people move in two directions under different crowd sizes.They discovered that large groups often split into smaller ones when they meet people walking in the opposite direction, and small groups tend to detour around the opposing flow. Oliva et al. [Oliva and Vilhjálmsson 2014] introduced social path following. Their method considers the social environment and carves trajectories that reflect awareness of other human beings and their social activities, such as being engaged in conversation. Kremer et al. [Kremer et al. 2021] developed a model for simulating distracted agents, such as those walking and texting. This model adjusts locomotion patterns and sensory abilities of distracted pedestrians, significantly altering flow patterns and overall crowd behavior.

2.2 Studies and Models of Gaze Behavior

Some researchers have proposed saliency-based gaze simulation for virtual agents with the purpose of increasing the realism of the crowd. Several aspects taken from perception studies are included, such as distance and speed [Grillon and Thalmann 2009], and personality features [Ağıl and Güdükbay 2018]. By doing a weighted sum, the best point of interest is selected for the gaze direction. In addition, Kremer et. al. [Kremer et al. 2022] developed a parametric model for generating real-time saliency maps from the perspective of virtual agents

However, those early works are limited to simulating gaze, and such gaze is not used to influence the steering behavior. Our model incorporates these gaze dynamics found in the literature with social rules to provide more plausible virtual crowd simulations, where attention-driven gaze and steering behavior are intertwined to better resemble human behavior.

Research on gaze behavior, both from humans to virtual agents and from virtual agents to humans, highlights the importance of incorporating accurate gazing into simulated crowds. Berton et al. [Berton et al. 2020] used gaze tracking to compare human gaze behavior on real and virtual crowded streets, finding that gaze focuses on the visual center as density increases, though specific gaze paths were not provided. Raimbaud et al. [Raimbaud et al. 2023] analysed the users' gaze and movement behavior as well as social anxiety when virtual agents stare at them in a crowd. These findings highlight the importance of considering virtual agents' gaze when creating populated VR experiences.

2.3 Human Local Movement and Gaze

Recent sociological studies highlight how distractions affect pedestrian perception and movement. For example, smartphone use reduces the field of vision and slows walking speed, with users showing limited side-to-side eye movement [Agostini et al. 2015; Maples et al. 2008; Yoshiki et al. 2017]. In addition, Radau et al. [Radau et al. 1994] and Foulsham et al. [Foulsham et al. 2011] found that people typically turn their head and body rather than just their eyes to look around, suggesting a more comprehensive adaptation in response to visual stimuli. Hollands et al. [Hollands et al. 2002] also found that the direction of gaze indicates a person's intended path, highlighting the predictive nature of gaze behavior. Nummenmaa et al. [Nummenmaa et al. 2009] found that people navigate in the opposite direction to where others are looking to avoid collisions, effectively using gaze direction to predict movement.

Murakami et al. [Murakami et al. 2021] emphasized that avoiding collisions is a cooperative process, complicated by distractions like smartphone use, which divert attention and gaze. Jovancevic-Misic et al. [Jovancevic-Misic and Hayhoe 2009] highlighted the focus on avoiding potential collisions, with metrics like Distance at Closest Approach (DCA) and Time to Collision (TtC) used to quantify this behavior [Dutra et al. 2017a; Olivier et al. 2013, 2012]. Building on this framework, Meerhoff et al. [Meerhoff et al. 2018] showed that gaze is influenced by collision risk, with individuals focusing on those with the smallest DCA and TtC values, which indicate a higher perceived risk.

Foulsham et al. [Foulsham et al. 2011] observed that people are more likely to gaze at passersby from a distance than up close. This observation is consistent with Hessels et al. [Hessels et al. 2020], who found a decrease in gaze likelihood as pedestrians approach within 5 to 3 meters, suggesting an intentional avoidance of eye contact to prevent social interaction [Hessels et al. 2022].

These studies show the importance of head movement and gaze direction for safe navigation and collision avoidance, with people typically looking where they are walking and monitoring others, but averting their gaze to avoid close interactions. These observations have been modelled in the gaze simulation of our social crowd model.

3 Social Crowd Simulation Model

In this section, we discuss the social crowd model developed, starting by introducing the base model for steering behavior including group dynamics in Section 3.1, the attention model in 3.2, the gaze dynamics in Section 3.3, and finally, the animation dynamics in Section 3.4.

3.1 Steering Dynamics

Our social crowd model is based on a traditional rule-based model, which has been extended to incorporate group forces and attention models. The main novelty is how we regulate the impact of each force in the final movement based on a combination of attention, Field of View and direction of movement.

The forces in our model include:

- **End-Position-Seeking Force ($\mathbf{f}_e$)**: Steers agents towards their end position.
- **Collision Avoidance Force ($\mathbf{f}_c$)**: steers agents to avoid imminent collisions with other agents.
- **Anticipatory Collision Avoidance Force ($\mathbf{f}_a$)**: Triggered to simulate anticipation of collision against individuals and groups when there is no danger of immediate collision.
- **Group Dynamics Force ($\mathbf{f}_g$)**: Mimics natural grouping.
- **Wall Repulsion Force ($\mathbf{f}_w$)**: Steers away from walls.

The movement direction for agent i is determined by a weighted sum of these forces:

$$\frac{d\mathbf{w}_\mathrm{i}}{dt} = w_e\mathbf{f}_\mathrm{e} + w_c\mathbf{f}_\mathrm{c} + w_a\mathbf{f}_\mathrm{a} + w_g\mathbf{f}_\mathrm{g} + w_w\mathbf{f}_\mathrm{w} \tag{1}$$

where w_e, w_c, w_a, w_g, w_w are the respective weights for each force driven by the social rules which include attention, gazing direction and grouping behavior, enabling fine-tuned control over the final crowd movement (in our simulation, we use: $w_e = 1.5$, $w_c \in [2.4, 2.7]$, $w_a \in [0.3, 0.5]$, $w_g = 0.3$, $w_w = 0.3$).

3.1.1 Group Simulation. The agents within a group simulation update their desired velocity vector according to the following rules similar to the original Reynold's model [Reynolds 1987]:

1. *Cohesion*: Draws agents towards the collective center of the group, promoting unity.
2. *Repulsion*: Generates a dispersing force to maintain comfortable spacing between agents, ensuring they do not get too close to each other.
3. *Alignment*: Encourages agents to move in a unified direction, aligning with the group's overall orientation for coordinated movement.

Additionally, the simulation adjusts the magnitude of their velocity so that agents can walk side-by-side with other members of the group, thereby better resembling human behavior.

To simulate such human behavior, first the group collision force, $\mathbf{f}_g$ is calculated (as in [Reynolds 1987]) and applied to the agent's velocity vector, and then the magnitude of the velocity vector is adjusted according to the following social rules:

- *Forward Acceleration*: Activated to increase the agent's speed when the agent is falling behind the center of mass of the group which shares the same social attributes.
- *Deceleration When Following*: As above, but to reduce the speed in order to better align with the position of the group.
- *Average Speed Alignment*: Our model enables agents to adjust their speed depending on their distance from the group's *CoM*. Upon entering a predefined distance threshold from the *CoM*, an agent's speed will adjust to match the average speed of its group.

3.2 Attention Model and Velocity

As mentioned in the related work, pedestrians experience a reduction in their field of view when using smartphones or talking to others. To replicate this dynamic FoV, our model simulates the perception of an agent, i, with a FoV which we implement as a sector centered along the agent's gaze direction $\hat{\mathbf{g}}^i$, with an angle, α^i which represents the horizontal FoV, and a radius r^i (distance from the agent) that represents the vertical FoV. Both the vertical and horizontal fields of view are affected by human factors, e.g. the horizontal FoV is reduced when the agent is talking to other agents, and even further reduced when using a mobile device as mentioned in the literature review. The radius of the sector should be shorter when looking down, and at its maximum radius when the agent is looking straight ahead. Therefore, our attention model is represented as a sector that changes direction based on gaze, and dimensions based on attention and social behavior (see Figure 2).

Although several studies have investigated the human FoV, precise measurements of its reduction are still lacking. Therefore in our system we have empirically chosen the FoV to 120° for walking, 60° for talking, and 30° for using a smartphone. Consistent with empirical findings, agents using a smartphone in our model exhibit decreased walking speeds[Agostini et al. 2015; Yoshiki et al. 2017]. Our attention model simplifies human FoV to trigger collision avoidance strategies. This enables agents to anticipate collisions and perform smooth local movements when obstacles are detected early, but react abruptly or even collide when the FoV does not provide enough time to react.

3.2.1 Avoidance Driven by Collision Area and Field of View. A key novelty in our method is that we separate direction of movement from gazing direction, thus our social model considers two different areas and checks for their intersection to trigger immediate collision avoidance. This behavior is inspired by the fact that human movement combines vision (based on gaze and FoV), with the perception of collision risk based on their movement relative to nearby agents.

In our model, each agent, i, has two areas: a collision avoidance area A_c^i and a field of view (FoV^i) (see Figure 3). The collision avoidance area A_c^i is a blue rectangle aligned with the agent's heading direction (velocity vector $\mathbf{v}^i$) and represents the immediate path, so any obstacle or agent in this rectangle represents a collision risk. The FoV^i is a sector as defined in section 3.2. Collision avoidance is triggered when another agent j enters the area defined by $A_c^i \cap FoV^i$, simulating natural human perception where one must see an obstacle within their gaze before avoiding it.

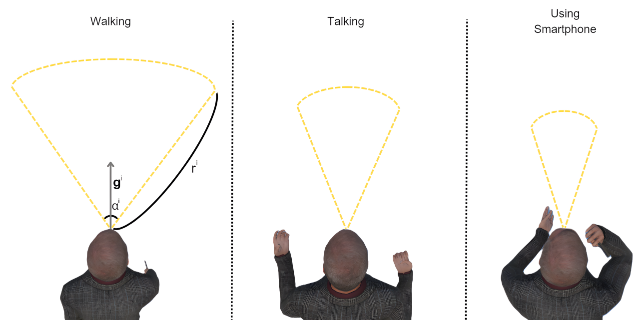

Figure 2: The yellow sector represents the agent's FoV. The one on the left is when the agent is performing a walking animation, the middle one is when the agent is performing a talking animation, and the one on the right is when the agent is using a smartphone.

In Figure 3, agent k, represented as a black sphere, is within the perceived area, FoV^i, but outside the collision avoidance area, A_c^i, indicating its presence is noted but does not necessitate immediate action. However, agents l and j are positioned within both the FoV^i and the collision avoidance area, A_c^i, therefore agent i needs to consider the risk of collision against agents l and j.

To accurately determine which agent require the most immediate evasive action, the collision avoidance force takes into consideration the Time-to-Collision (TtC) for each agent l and j. The algorithm prioritizes the agent with the lowest TtC. Assuming agent j has the shortest TtC, the collision avoidance force shown with a red vector $\mathbf{f}_c^i$ will be applied to agent i.

3.2.2 Collision Avoidance Force Calculation. The Collision Avoidance Force, f_c, is calculated using positional and directional vectors. Let p^j represent the position of the agent j that the agent i must avoid. The position of agent i is denoted by p^i, while $\mathbf{v}^i$ indicates the agent's velocity vector. The vector from the agent i towards the avoidance target j, $\mathbf{w}^{ij}$, is calculated as:

$$\mathbf{w}^{ij} = p^j - p^i \tag{2}$$

The vector $\mathbf{w}_\text{u}$ that determines the direction of collision avoidance depends on the angle between the vectors $\hat{\mathbf{w}}^{ij}$ and $\hat{\mathbf{v}}^i$, and is calculated as:

$$\mathbf{w}_u = \begin{cases} \mathbf{w}_\text{up} & \text{if } \hat{\mathbf{w}}^{ij} \cdot \hat{\mathbf{v}}^i \geq \tau_R, \\ \hat{\mathbf{w}}^{ij} \times \hat{\mathbf{v}}^i & \text{otherwise.} \end{cases} \tag{3}$$

where $\mathbf{w}_\text{up}$ is defined as the upward vector and the threshold $\tau_R = 0.9748$ (approximately 13.4°) is based on [Pelechano et al. 2007], and gives the agents a slight preference towards moving to the right to give way in frontal collisions, as in most learnt social behaviors.

The unit collision avoidance vector, $\hat{\mathbf{w}}_c$, is given by:

$$\hat{\mathbf{w}}_c = \frac{\mathbf{w}_u \times \hat{\mathbf{w}}^{ij}}{\|\mathbf{w}_u \times \hat{\mathbf{w}}^{ij}\|} \tag{4}$$

The magnitude of the avoidance force will depend on the type of obstacle and the distance. Our model handles two types of obstacles: a single agent, or a group of agents which is treated as a whole to simulate human social behavior of avoiding walking through couples or groups of agents when possible.

Let:

- S be a scaling factor based on the target's type (agent or group) . $S = 1$ for type=agent, and is calculated as defined in section 3.2.4 for groups.
- R represent the maximum possible distance between the agent and the avoidance target.

The final collision avoidance force, $\mathbf{f}_c$, is calculated as:

$$\mathbf{f}_c = S\left(1.0 - \frac{|\mathbf{w}^{ij}|}{R}\right)\hat{\mathbf{w}}_c \tag{5}$$

The collision avoidance force increases based on the obstacle's size and proximity, steering agents more strongly around larger groups and increasing as agents get closer. This mimics natural human behavior, adjusting detours based on distance to obstacles.

3.2.3 Anticipatory collision avoidance. In scenarios where there is no immediate collision risk, humans anticipate collisions with individuals in their field of view (FoV) to perform smooth detours of their trajectory. The anticipatory collision avoidance force, f_a, is activated for agents within FoV but outside the collision area A_c ($FoV \setminus A_c$). This force also calculates the TtC for these agents to determine activation. It follows the unaligned collision avoidance method from [Reynolds 1999] to anticipate collisions against other moving agents, by computing the future positions of each possible collider based on their current position and direction of movement. The anticipatory force is deactivated when the immediate collision avoidance force is active to prevent counteraction. The magnitude of this force is also scaled based on on the value of S to perform a stronger manouver to walk around a group instead of thorough it.

3.2.4 Collision Avoidance against a Group of Agents. In our system, agents with the same social attribute form a larger collective agent when they are within a certain distance. The social grouping behavior, defined in section 3.1.1, causes them to walk together, making it more likely that other agents will navigate around them rather than through the group.

Our group collision avoidance behavior is designed as follows: consider that agent i perceives agent j as the closest collider, and that agent j is walking along a group of N agents sharing group relationship. Define c as the center of mass (CoM) of all other group members walking with agent j, and d^{jc} as the distance of agent j from the c. The magnitude of the avoidance force that agent i needs to perform to steer around agent j and other nearby group agents is scaled by S, defined as:

$$S = \begin{cases} d^{jc} + 1 & d^{jc} \leq \frac{N}{2} \\ 1 & \text{otherwise.} \end{cases} \tag{6}$$

In this equation, agent j is part of a group if the distance from the group's CoM, c, is less than $\frac{N}{2}$. Otherwise, the agent is treated as a

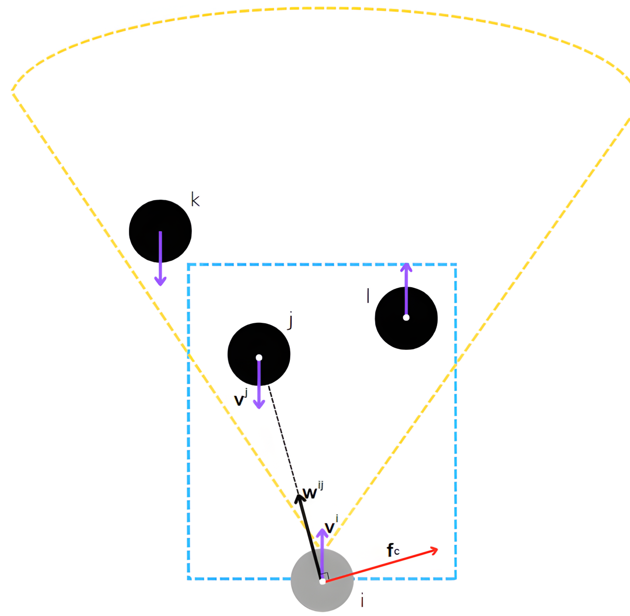

Figure 3: Each sphere represents an agent, with the blue borders indicating areas where collision avoidance for the agent i is activated. The yellow color represents the field of view (FoV^i). Agents are marked, with purple arrows indicating their direction of movement. The red line shows the collision avoidance force applied in this example.

single agent. The distance $\frac{N}{2}$ is based on Moussaïd et al.[Moussaïd et al. 2010], with a small adjustment to take the radius of the agents into account.

3.2.5 Shared Field of View for Agent in Group. In section 3.2.1, we discussed how the collision avoidance and anticipatory collision avoidance forces are triggered for agents walking by themselves. However, when agents walk as part of a group, the area for anticipatory collision avoidance is modified to consider social group behavior and attention.

Accurate collision avoidance is crucial for realistic simulation. However, if group members select different anticipatory avoidance targets, conflicting forces can arise, hindering effective collision avoidance. To avoid these situations and better simulate group steering, we propose a shared field of view model for groups, which ensures that agents within a group preferably select the same targets for anticipatory collision avoidance. This means that the choice of avoidance targets for agents within a group is given by the shared field of view of the group members (calculated as: $FoV^g = \bigcap_{i=0}^{N} FoV^i$). An agent i can thus choose an avoidance target that is not within its own FoV^i, as long as it is within the group's field FoV^g. Thus, if an agent starts steering due to anticipatory collision avoidance, the rest of the group will follow smoothly due to group behavioral forces. This concept reflects real-world dynamics where when walking with friends, you may be warned by them to avoid collisions with people or objects outside your FoV. This group FoV^g is not used for the immediate collision detection, as agents should only perform this behavior when the collider is within their individual FoV^i to correctly replicate real life situations.

Figure 4 illustrates an example of group FoV^g. In this scenario, agent j detects agent k as an avoidance target within the group, while agent i does not detect k. Nevertheless, within the shared FoV, i will also consider agent k as an avoidance target, and thus also performs a detour moving away from k as if experiencing a collision avoidance force. The shared field of view model together with the scaling factor S allows us to replicate real world behavior, since humans walking in a group will avoid incoming traffic considering the group clearance and not just their own personal space.

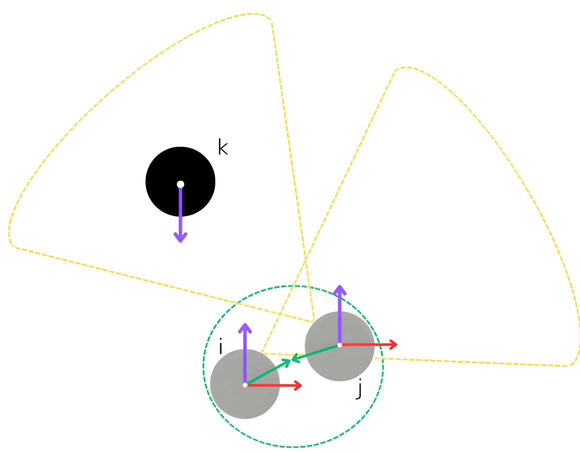

Figure 4: Grey agents i and j share the same social attributes. Green arrows indicate the force of group formation. Purple arrows show each agent's heading direction. Red arrows depict collision avoidance force. Yellow outlines represent the group FoV^g.

3.2.6 Collision Avoidance Coordination. If collision avoidance is treated individually, there can be situations where the symmetry of the avoidance forces lead the agents to unrealistic frontal collisions such as the one represented in figure 5 (top). This situation very rarely occurs in the real world, because humans are able of coordinating collision avoidance through non verbal communication and gaze [Nummenmaa et al. 2009]. To avoid unnatural maneuvers, our system coordinates avoidance sides between agents, reducing collision risk and creating realistic steering. When agents i and j have collision avoidance forces in the same side, a reflective vector q is calculated based on their relative positions, as shown in figure 5 (bottom).

The avoidance force after coordination, q, is calculated as follows: first agent i computes the vector towards the right with respect to its direction of movement $\mathbf{w}_\mathrm{R}$ as follows:

$$\mathbf{w}_\mathrm{R} = \mathbf{w}^{ij} \times \mathbf{w}_\mathrm{up} \tag{7}$$

Let θ be the angle between the vectors $\mathbf{f}_c^i$ and $\mathbf{w}^{ij}$, where $\mathbf{f}_c^i$ represents the collision avoidance force of agent i.

$$\cos\theta = \hat{\mathbf{f}}_c^{\,i} \cdot \hat{\mathbf{w}}^{ij} \tag{8}$$

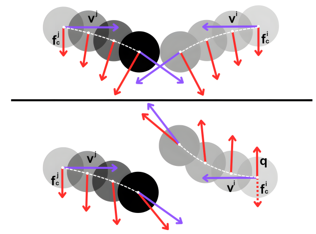

Figure 5: Diagram illustrating a collision avoidance scenario: The top represents the situation where both agents attempt to avoid the incoming collider by steering towards the same side. The bottom represents the avoidance after coordination.

Then the coordinated collision avoidance force is computed as:

$$\mathbf{q} = \begin{cases} 2\cos\theta\,\hat{\mathbf{w}}^{ij} - \hat{\mathbf{f}}_c^{\,i} & \text{if } \operatorname{sgn}(\hat{\mathbf{w}}_\mathrm{R} \cdot \hat{\mathbf{f}}_c^{\,i}) = \operatorname{sgn}(\hat{\mathbf{w}}_\mathrm{R} \cdot \hat{\mathbf{f}}_c^{\,j}) \\ \hat{\mathbf{f}}_c^{\,i} & \text{otherwise.} \end{cases} \tag{9}$$

3.3 Gaze Dynamics

Our model simulates social attention by having key focal points that are driven by the agent's behavior. This focal point determines the orientation of the central axis of the FoV, and are defined by:

- **Current Direction:** This represents the agent's intended walking direction, based on findings by Hollands et al. [Hollands et al. 2002].
- **Collided Target:** In case of an unavoidable collision due to distractions, agents briefly look at the other agent to acknowledge them.
- **Current Avoidance Target:** This is influenced by risk assessment, with a focus on agents that have a higher potential for collision. Jelena et al. [Jovancevic-Misic and Hayhoe 2009] highlighted the significance of the minimum TtC in identifying the most risky agent to collide with, leading individuals to pay attention to these agents. Additionally, Hessels et al. [Hessels et al. 2020] found that people tend to focus on farther agents rather than those closer to them. Building on their research, our model is designed to focus on the agent with the lowest TtC within the field of view. When agent j has the lowest TtC with agent i compared to other agents, agent i will look at agent j with a certain probability p, which is calculated as follows:

$$p = \frac{|\mathbf{w}^{ij}|}{R} \tag{10}$$

  According to research by Gallup et al. [Gallup et al. 2012a,b], people tend to avoid mutual gaze. Therefore, a function has also been implemented to disable the focal point when mutual gaze occurs.
- **Center of Mass:** This is relevant for group agents that focus on the collective position of others. Thus our social model aligns the direction of the agent's field of view toward the center of mass based on research by Moussaïd et al. [Moussaïd et al. 2010]. Furthermore, when agents within a group are engaged in a conversation, we have implemented a feature that sets this centre of mass as the focal point.

- **Collision Avoidance Coordination Target:** This focal point looks at the other agent's face during collision avoidance coordination.

3.4 Animation Dynamics

Finally, animations are added to help the simulated agents show their social behavior and gaze dynamics consistently, but also to modify the FoV accordingly to simulate attention driven steering. We divides the animations into two layers: upper body and lower body. Each layer is associated with specific animations. A detailed description of these animations is given bellow:

- **Upper Body:**
  - **Using a Smartphone:** This animation is performed at a random interval between 5 and 10 seconds with a 50% probability each time for the agents walking as individuals.
  - **Talking:** This animation is triggered when agents form groups, at a random interval between 5 and 10 seconds with a 50% probability each time. This animation is also triggered with a 5% probability when an agent collides with another agent.
  - **Walking:** This animation is the basic animation with the arms swinging in sync with the legs, and agents will default to this animation when they are not performing the smartphone animation or the talking animation.
- **Lower Body:**
  - **Walking:** Lower body locomotion animation using the motion matching implementation by Ponton [Ponton 2022].

4 Results

In this section, we first show some of the results obtained with our simulator (see the accompanying video for more results) and then introduce the user study that was performed for validation.

Figure 6 displays an example of the results of sharing the FoV in a group. The sequence shows two agents walking together that perform a steering around another incoming agent smoothly, even though the agent with the blue top is paying attention to his friend and cannot see the other agent within his FoV. Figure 7 shows on the left the group collision avoidance making other agents perceive it as a union and walking around, while on the right we show the effect of not using it and thus having other agents walking through groups. Figure 8 shows how the reduction of the FoV due to using a smart phone cannot correctly avoid collision and leads to a frontal collision against the agent walking in opposite direction. Finally, Figure 9 shows the result of avoidance coordinator, where two agents walking against each other and having both calculated their avoidance steering direction on the same side, can coordinate the maneuver to avoid collision. The agents will first gaze at each other so that the viewer can perceive this as a non-verbal form of communication and after changing the steering direction, gaze in their new direction of movement.

4.1 User study: experimental design

We conducted an online survey evaluating three conditions:

(1) **Dyn**: The first condition featured our developed model which incorporates dynamic social behaviors with gaze-driven attention, on top of a rule-based collision avoidance model. Consistent animations are then added to reflect social behaviors and gaze behavior.
(2) **Bsc**: The second condition is a basic rule-based collision avoidance model without the social rules and gaze dynamics described in this paper, and using only a walking animation.
(3) **Rnd**: The third condition used the same model as in Bsc but with randomly added animations, to include gestures such as talking, smartphone use, and gazing at randomly selected focal points.

4.1.1 Procedure. Participants first read and accepted an online consent form before providing demographic information (gender, age, country of employment, video game play frequency, and familiarity with crowd simulation technologies). Videos, each representing different conditions, were then shown in a randomized order using balanced Latin squares to avoid learning bias. After each video, participants rated the realism, group dynamics, and animation quality of the crowd simulation, as detailed in Table 1.

4.1.2 Measurements. We adapted the questionnaire from [Molina et al. 2021] and extended it by adding questions not only about the realism of the crowd simulation but also about group dynamics and animations. As shown in Table 1, it consists of six questions in total: R1 and R2 about the realism of the crowd, G1 and G2 about the functionality of the group dynamics, and A1 and A2 about the behaviour when using smartphones and the realism of the animation.

Table 1: Table 1: Questionnaire content. The scores are on a 7-Likert scale (1 = strongly disagree, 7 = strongly agree).

Realism	
R1	I find the behavior of this crowd simulation very realistic.
R2	I think that the movements and interactions in the simulation mirror those I would expect in a real world setting.
Group	
G1	The simulation effectively represents the dynamics of different social groups, such as families, coworkers, or friends.
G2	I can observe individual and group behaviors in the simulation.
Animation	
A1	Individual with a smartphone appear to behave differently.
A2	The animations in the simulation look realistic to me.

4.1.3 Participants. We collected data from 12 anonymous participants (4 women, 8 men) aged 18-55 years ($\mu = 31.75$, $\sigma = 9.35$). In terms of frequency of playing video games, the majority reported playing occasionally (a few times a month), with engagement ranging from daily to never playing. Knowledge of crowd simulation

Figure 6: Results from sharing the FoV within a group. From left to right, a pair of agents walking towards another individual agent. The agent with the blue shirt cannot see the incoming agent as it is paying attention to his friend, and thus it is not in his individual FoV. The two agents perform the avoidance detour correctly thanks to the shared FoV.

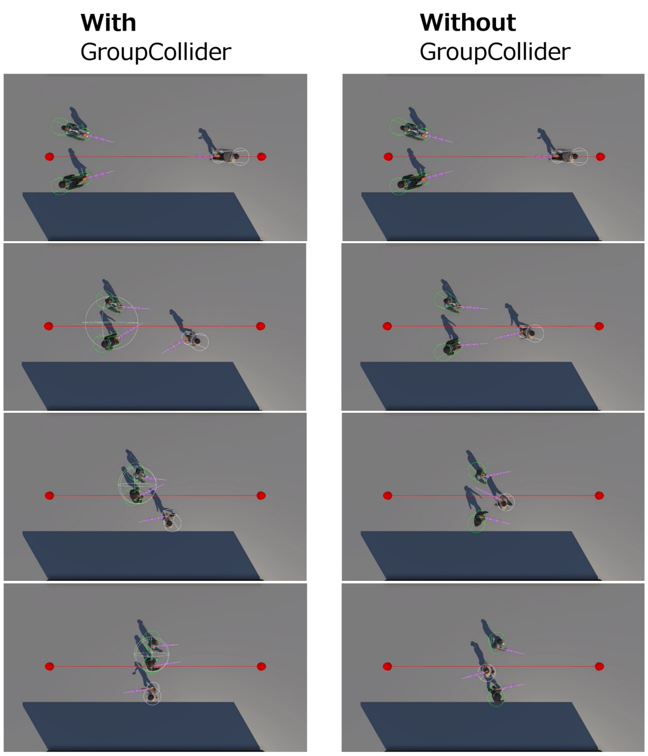

Figure 7: Results showing group collider avoidance. The column on the left shows how the agents walking together are perceived as a group by the agent walking in the opposite direction. Therefore the agent performs a larger detour to walk around the group. On the right column, there is no group collider and thus the agent walking in opposite direction walks through the group forcing it to split.

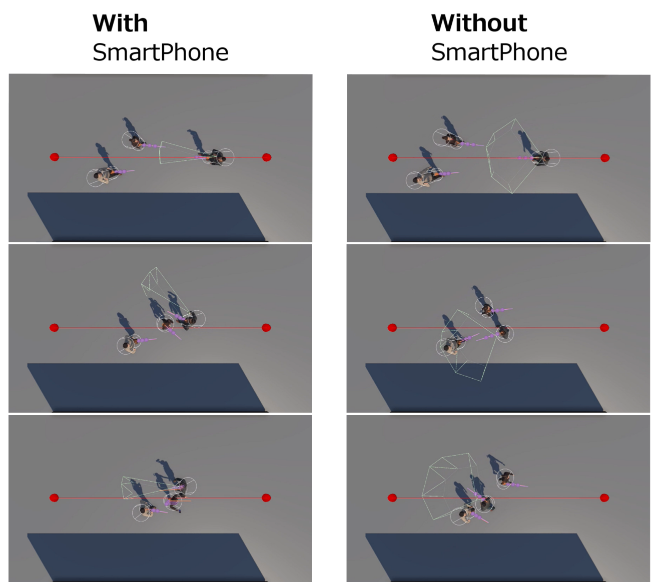

Figure 8: Results on the impact of having a reduced FoV due to using a smart phone. With this reduced FoV the agent detects the possible collider later, and thus performs and abrupt turn that is not enough to avoid the crash.

averaged 3.0 on a 5-point Likert scale ($\sigma = 1.60$), indicating moderate expertise.

4.1.4 Statistical Analysis. We analyzed the differences across our three conditions: Dyn, Bsc and Rnd. For all dependent variables, we established a significance level to $\alpha = 0.05$.

Normality of the data in each factor level was tested using the Shapiro-Wilk test, and the homogeneity of variances for each factor level was tested using Levene's test. Results from these preliminary tests indicated that while all groups displayed homogeneity of variances, several groups did not follow a normal distribution, notably in R1 (Dyn and Bsc conditions), G1 (Bsc condition), G2 (Dyn condition), and A1 (Bsc condition). Details are provided in the Supplemental Material.

4.2 User study: results

4.2.1 Realistic Behavior(R1). The R1 data analysis used non-parametric tests. A Kruskal-Wallis test indicated significant differences among conditions ($H = 9.02$, $p = 0.011$). H represents the Kruskal-Wallis test statistic, and p denotes the p-value indicating the significance level. Subsequent pairwise comparisons were performed using the Mann-Whitney U test with Bonferroni correction. In these comparisons, U represents the Mann-Whitney test statistic, and p denotes the p-value indicating the significance level. It was found that the score in the Dyn condition was significantly higher than in the Bsc condition($U = 122$, $p = 0.009$). No significant differences were

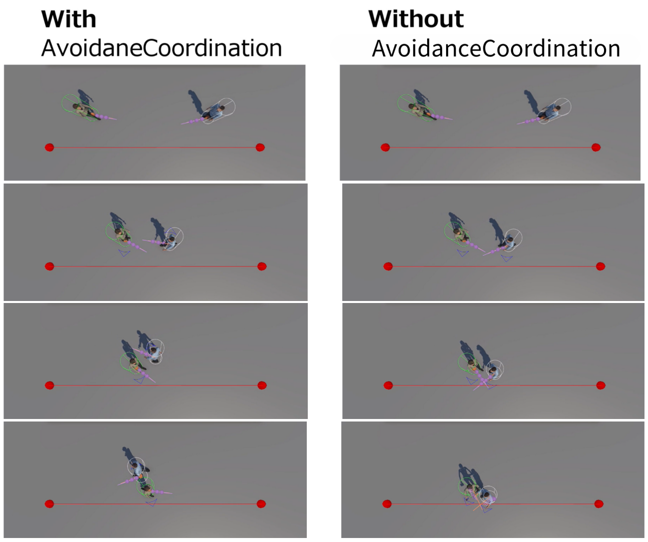

Figure 9: Results showing the avoidance coordinator. When agents are performing the avoidance maneuver on the same side, they can gaze at each other and coordinate sides so that they can smoothly avoid each other. On the right column the result of not activating this feature which can lead to unrealistic steering and increases the risk of collision.

found between the Dyn and Rnd conditions (U = 104, p = 0.179) or between the Bsc and Rnd conditions (U = 87, p = 1.000). Thus, crowd behavior in the Dyn condition is more realistic than in the Bsc condition, with no difference between the Dyn and Rnd conditions or the Bsc and Rnd conditions.

4.2.2 Realistic Movements and Interactions(R2). The R2 data analysis used parametric tests. An ANOVA test indicated significant differences among conditions ($F(2, 33) = 5.844, p = 0.007$). Tukey's HSD post-hoc test showed that the Dyn condition ($M = 4.667, SD = 1.303$) scored significantly higher than the Bsc condition ($M = 2.833, SD = 1.303, p = 0.007$) and the Rnd condition ($M = 3.250, SD = 1.485$, $p = 0.043$). No significant differences were found between the Bsc and Rnd conditions ($p = 0.741$). Thus, movements and interactions in the Dyn condition were more realistic than in the Bsc and Rnd conditions, with no difference between the Bsc and Rnd conditions.

4.2.3 Dynamics of Different Social Groups(G1). The G1 data analysis used non-parametric tests. A Kruskal-Wallis test indicated significant differences among conditions ($H = 10.13$, $p = 0.006$). Pairwise comparisons using the Mann-Whitney U test with Bonferroni correction showed the Dyn condition scored significantly higher than both the Bsc ($U = 121$, $p = 0.013$) and Rnd conditions ($U = 114, p = 0.045$). No significant differences were found between the Bsc and Rnd conditions ($U = 86$, $p = 1.000$). Thus, the Dyn condition more effectively represents the dynamics of different social groups compared to Bsc and Rnd, with no difference between Bsc and Rnd.

4.2.4 Individual and Group Behaviors(G2). The G2 data analysis used non-parametric tests. A Kruskal-Wallis test indicated significant differences among conditions ($H = 17.60$, $p < 0.001$). Pairwise comparisons using the Mann-Whitney U test with Bonferroni correction showed the Dyn condition scored significantly higher than both the Bsc ($U = 137$, $p < 0.001$) and Rnd conditions ($U = 122$, $p = 0.012$), with no significant differences between Bsc and Rnd ($U = 104$, $p = 0.190$). Thus, individual and group behaviors are significantly more observable in the Dyn condition than in Bsc and Rnd, with no difference between Bsc and Rnd.

4.2.5 Behavior of Individual with Smartphone(A1). The A1 data analysis used non-parametric tests. A Kruskal-Wallis test indicated significant differences among conditions ($H = 11.65$, $p = 0.002$). Pairwise comparisons using the Mann-Whitney U test with Bonferroni correction showed the Dyn condition scored significantly higher than the Bsc condition ($U = 121, p = 0.012$), and the Rnd condition scored significantly higher than the Bsc condition ($U = 123$, $p = 0.009$). No significant difference was found between the Dyn and Rnd conditions ($U = 72$, $p = 1.000$). Thus, individuals with smartphones behave differently in both the Dyn and Rnd conditions compared to the Bsc condition.

4.2.6 Realistic Animation(A2). The A2 data analysis used parametric tests. An ANOVA test found no significant differences across conditions $F(2, 33) = 0.789, p = 0.463$. Consequently, no further post-hoc testing was conducted. Therefore, animation realism did not significantly differ across conditions.

5 Discussion

Under question R1, our findings indicated that Dyn is more realistic than Bsc. However, while there is a trend of Dyn being higher than Rnd, no significant differences were found. We had initially expected that the Dyn condition would be more realistic than the Rnd condition. However, no significant difference was found between them. Feedback indicated that the realism of our model was reduced due to a lack of animation variety, unnatural movements after collisions, and glitchy animations. This highlights that the quality, and quantity of animations significantly impact realistic crowd behavior which is consistent with previous work [Molina et al. 2021]. Our goal was to evaluate whether the crowd behavior appeared natural and the animations helped understand the social context, rather than just focusing on the quality and quantity of animations. Therefore, by increasing both the quantity and quality of animations, we could achieve a more nuanced assessment of their realism within a social context. For R2, Dyn was shown to better reflect real-world crowd movements and interactions than the other models. The Dyn condition showed a significant difference from Bsc and Rnd in G1 and G2, indicating our model's ability to differentiate individual and group behaviors. Considering the results from R2, G1, and G2, this finding is convincing, and the clear distinction between group and individual behaviors potentially enhances the overall realism of the crowd simulation. For A1, no difference was observed between Dyn and Rnd, but both differed from Bsc. This question aimed to assess whether animation-specific FoV and walking speeds affect steering behaviors, expecting individuals with smartphones to behave differently. However, no significant differences were found

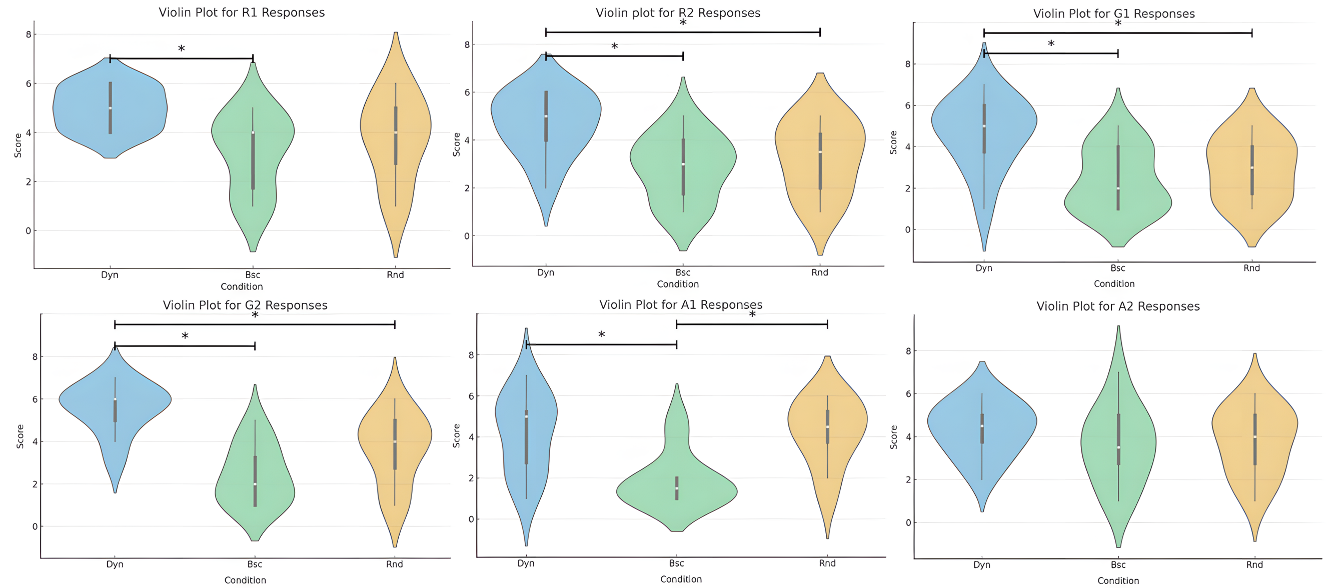

Figure 10: Violin plots of metrics obtained for the questionnaires. Asterisks represent the significance level: * (p < .05).

between Dyn and Rnd. This outcome occurred because participants interpreted the question as merely identifying whether agents with animations of smartphone appeared different from others with animations of walking or talking, based on open-ended feedback. Therefore, it seems necessary to refine the wording of the question to better align with the intended evaluation. For question A2, no differences were observed among the conditions. Additionally, the middle scores received in response to this question suggest that the realism of the animations themselves was lacking.

6 Conclusions and Future Work

We developed a crowd model that incorporates social behaviours, simulating interactions such as local movement, grouping, and short-term decision making, as well as attention models and social aspects that account for human perception. We then conducted a user study to evaluate the realism of our model. The results suggest that our model produces more realistic behaviours compared to models that only simulate random animation or walking. It was also suggested that our model was better at distinguishing between individual and group behaviours. However, it was noted that a lack of animation quality and quantity could reduce the overall realism of the model. Improving the overall realism of the crowd behavior involves many other aspects that could be tackled as future work. For example, adding even more animation variety or computing collision avoidance at the limb level instead of bounding cylinders for the whole character, could make crowd appear more plausible. In our examples, we have shown that gaze can help the viewer understand what the virtual agents is paying attention to. In this work we have limited the gaze to simply looking directly towards a point, however gazing involves many other issues such as saccade, blinking, or avert gaze, that could make the character's eyes appear even more realistic. Another important venue for future work would be to extend the model to include a wider variety of social behaviors such as giving way, or walking with kids or a pet that would exhibit a less predictable trajectory. Including more social behaviors to move past simple collision avoidance would help in advancing the field of crowd simulation to achieve more plausible populated virtual environments.

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