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Virtual Crowds Rheology: Evaluating the Effect of Character Representation on User Locomotion in Crowds

Jordan Martin , Ludovic Hoyet , Etienne Pinsard, Jean-Luc Paillat, Julien Pettré 

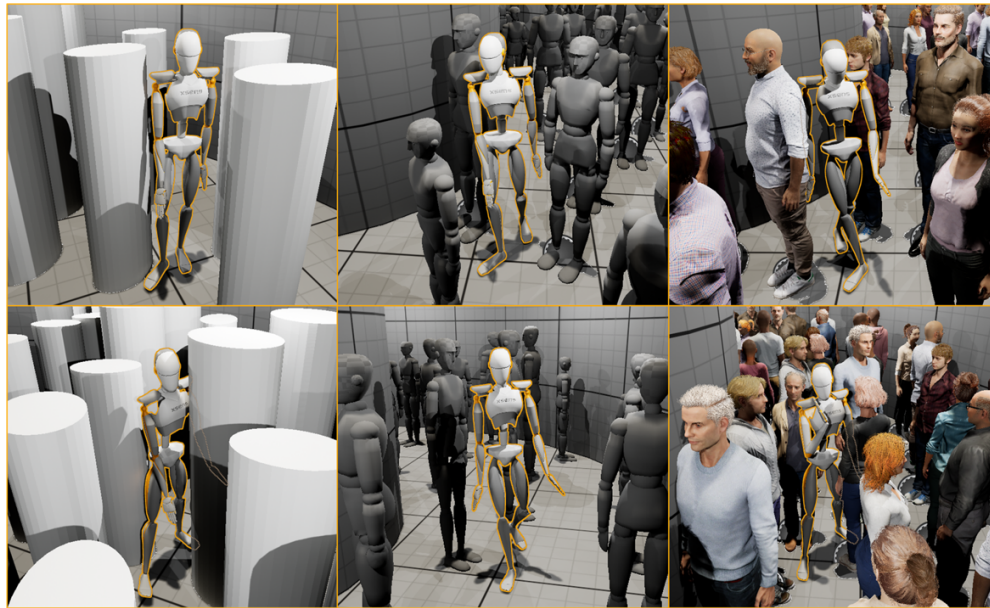


Fig. 1: Participant (yellow outline) moving through virtual crowds. Top-left: enclosing elliptic cylinder at $1.0 a/m^2$ (where a stands for agents); Top-middle: puppets at $1.0 a/m^2$; Top-right: realistic characters at $1.0 a/m^2$; Bottom-left: enclosing elliptic cylinder at $1.5 a/m^2$; Bottom-middle: puppets at $0.75 a/m^2$; Bottom-right: realistic characters at $2 a/m^2$.

Abstract—Crowd data is a crucial element in the modeling of collective behaviors, and opens the way to simulation for their study or prediction. Given the difficulty of acquiring such data, virtual reality is useful for simplifying experimental processes and opening up new experimental opportunities. This comes at the cost of the need to assess the biases introduced by the use of this technology. Our paper is part of this effort, and investigates the effect of the graphical representation of a crowd on the behavior of a user immersed within. More specifically, we inspect the virtual navigation through virtual crowds, in terms of travel speeds and local navigation choices as a function of the visual representation of the virtual agents that make up the crowd (simple geometric model, anthropomorphic model or realistic model). Through an experiment in which we ask a user to navigate virtual crowds of varying densities, we show that the effect of the visual representation is limited, but that an anthropomorphic representation offers the best trade-off between computational complexity and ecological validity, even though a more realistic representation can be preferred when user behaviour is studied in more details. Our work leads to clear recommendations on the design of immersive simulations for the study of crowd behavior.

Index Terms—Crowd, Human Interaction, Navigation, Visual Representation, Virtual Reality.

1 INTRODUCTION

Human collective movement datasets have shown their importance in the field of crowd modelling and simulation, and more specifically: crowd analysis [31, 64, 67], behaviour understanding [24, 70], detection of patterns [40], simulator calibration and evaluation [75], and more recently training of data-driven models [1, 74]. However, the various difficulties inherent in acquiring and processing crowd data to create datasets of high scientific value – whether in the laboratory or in the

field – have led to the use of virtual reality to achieve experiments [12, 57, 59]. Virtual reality (VR) is particularly relevant to decipher local interactions in crowds by observing interactions between a real user and a set of virtual characters [44]. While the use of virtual reality offers obvious advantages in terms of ethical, legal and logistical aspects of data acquisition, it also opens up numerous opportunities for setting experiments of a new kind, e.g., involving new types of data such as full body motion [77] or eye-tracking data [6]. However, the use of virtual reality raises the question of the ecological validity [28] of the data collected in this way, and a great deal of work has been carried out to assess the biases depending on the situations studied and the nature of the data acquired [3, 6, 7, 33, 34, 37, 39, 45, 79, 82]. This work is a continuation of that effort, where we explore an essential aspect of the study of crowd behaviour: navigation in crowds. We ask the following question: how do the methods used to graphically represent the agents of a virtual crowd, whose complexity can severely impact computational limitations, affect the formation of participants' locomotion trajectories, and more specifically, their locomotion speed

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and local navigation choices?

Crowds are often compared to fluids. Most crowd studies are therefore concerned with understanding how such “fluids” flow under different constraints and conditions [4, 17, 27, 68]. As we explore new ways to study crowd behaviour and collective dynamics with virtual reality, we wanted to entitle this article “Virtual Crowd Rheology” in reference to the branch of Physics that deals with the study of the flow of non-Newtonian fluids. As the second part of our title indicates, the general problem addressed in this work concerns the way in which the virtual crowd is graphically represented in these virtual reality studies, how this can influence the behaviours observed, and how we can better understand the ecological validity of such situations.

To address our question, we conducted an experiment in which participants were asked to navigate through crowds of agents whose representations varied. We use an original paradigm in which we ask participants to navigate continuously in a circular corridor, thus avoiding edge effects in our analysis and allowing us to collect a large amount of data in a short experiment. This situation is inspired by real laboratory experiments [20, 27, 29, 50] on crowds, with the benefit of avoiding the effect of spatial boundaries on trajectories. Note that the situation was also used in VR for other purposes, e.g., in the context of redirected walking [35] or of collecting crowd data [77]. Nevertheless, for the first time, we introduce the use of this situation to study navigation in stationary crowds, which we consider to be one of the original features of our approach in VR. We used three different representations: first, a simple elliptic cylinder representing the space occupied by the agents; second, a simplified anthropomorphic representation detailing the different limbs of the human body; and third, a detailed realistic representation whose geometry is refined and which also includes the use of realistic textures. We measured participants’ trajectories under varying conditions of character density and orientation, which are also known to influence behaviour. Our analysis shows a smaller effect of character representations compared to the initially expected one. The use of anthropomorphic representations seems sufficient to guarantee the ecological validity of the situations studied, and for studying crowd navigation. However, we still demonstrate the interest of using detailed realistic representation when user behaviour is studied in more details.

In this paper, we therefore propose the following contributions:

- We are laying out new ground for the study of crowd navigation in VR, by proposing an innovative experimental design, allowing navigation without distance or time limits. The results of our experiment set a new baseline for this topic.
- We propose new metrics for the study of navigation in crowds, in particular for the analysis of local choices for navigation in dense crowds. Beyond virtual reality, our metrics may be useful in the field of collective movement in a broader sense.
- We propose practical recommendations on how to model crowd agents to achieve a good trade-off between the computational complexity of immersive simulation, and the ecological validity of studying dense crowds in VR for navigation tasks.

Our paper is structured as follows. In Section 2, we review the state of the art on issues related to our study and show that previous work cannot answer our question, and therefore our results are complementary and go beyond existing knowledge on this topic. In Section 3, we provide a detailed description of our experiment. Section 4 gives a detailed explanation of the analyses we performed on the data collected in our experiment. Section 5 presents the results, which are discussed in the context of the state of the art in Section 6, before concluding in Section 7 with suggestions for future work.

2 RELATED WORK

Crowd simulation models are based on the principle that the behaviour of a crowd, and therefore its movement, emerges from local interactions between individuals [41, 76]. This fundamental concept has been translated into a number of different algorithms [73, 74], including social forces model [25], velocity space models [71–73], vision-based models [32, 49] or data-driven models [81]. All these algorithms are

inspired by observations of real crowd behaviour. From raw data as presented in [51], the field has produced more carefully analysed data from controlled experiments [24]. Their purposes are to validate the fundamental principles of a given model [55], to calibrate and evaluate its performance to replicate crowd behaviours [75], or more recently, to generate data-driven simulation models [1, 15, 30]. Controlled crowd experiments replicate and compare simplified real situations, such as one-dimensional flows [2, 29], bottlenecks [26, 69], navigation with obstacles [21, 63], going through a crowd [46], etc. It is worth noting that one aim of all these experiments is to quantify pedestrian flows in these specific situations, and more especially, different kind of relationships between density and velocity. However, laboratory experiments are still rare compared to the huge number of situations and variables that are of scientific interest, due to the many logistical, technical and even ethical difficulties that stand in the way.

VR offers opportunities to overcome some of the experimental difficulties, and has been used to perform crowd studies in the recent years [47]. Crowd behaviour experiments in VR have focused on interpersonal interactions [3, 7, 33, 48, 54], individual-group interactions [12, 58, 59], or even directly on the process of acquiring datasets in VR and evaluating their ecological validity [77]. As a conclusion, many studies show that using VR to study human behavior is relevant, even if there are some limitations due to biases introduced by the use of VR. These experimental biases were assessed in the studies cited above, and a general conclusion seems to have emerged: studied behaviors are qualitatively similar in VR but not always quantitatively equal to their real counterparts. Participants generally move slower in VR [42], do more head movements [7] to compensate for the eventually reduced field of view, and misjudge the distance [56], even though these differences can be influenced by the VR setup [7, 22]. However, participants still keep clearance areas [3], perform similar trajectories [48], and take similar visual information [6, 23].

Among these various biases, one question arises that relates more specifically to the quality of the simulation used to create the virtual worlds. This is the question addressed by our study. We focus on the 3D representation used to represent agents (i.e., the virtual humans composing virtual crowds). We explore how much the employed 3D representation influences participants behaviours, and, is there an interest in using detailed and realistic 3D models since they are costly in terms of required computational performances?

In our work, we explore different 3D representations ranging from simplistic geometry proxies (elliptic cylinders) up to realistic characters with detailed shape and texture. We explore the effect of these models on user motion at close proximity of characters, that we relate to speed-density relations, body movements as well as local navigation strategies. Close to our topic, stylization of characters was studied by Zell et al. [79], who showed that shape and material impact differently character realism and appeal, while other researchers explore the effect of character appearance on participants emotional reactions [37] or on their perceptions of characters [82]. From a crowd perspective, a few experiments studied collision avoidance while varying rendering style [39, 45] or animation and graphical models [33, 38]. In particular, Lynch et al. [33] performed an experiment close to our questions, exploring how different graphical models of a character (from really abstracted to a full-body character) convey different information about its motion and can affect the kinematics of inter-personal interactions. While not exploring appearance, methods for rendering physical contacts [5, 78] have been studied to induce realistic behaviors when navigating through crowds (vibration, audio, belief).

In contrast with previous work, we evaluate the effect of using different types of character geometries (human-like or not) during crowd navigation, whilst previous studies focused on situations one-to-one interactions. The study of navigation in more or less dense crowds leads to fundamental differences. In previous studies, the avoidance distance was a degree of freedom (and a variable studied as a metric). In our case, the interaction distances are imposed by the density of the crowd and we can therefore observe the effects on the speed of locomotion, which allows us to characterise the flows in the same way as in studies of collective dynamics. To our knowledge, no similar

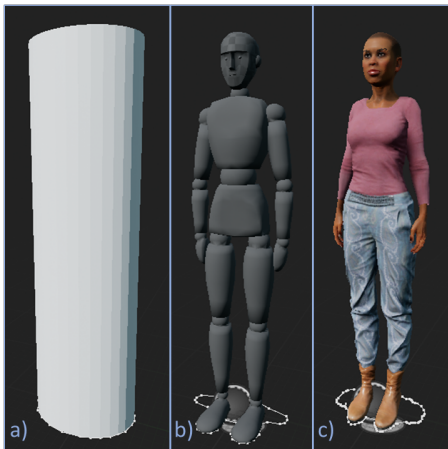


Fig. 2: The three different types of graphical representations (3D models of agents) we studied: a) an elliptical cylinder-shape representation (**CYL**), b) puppet-like characters (**PUP**), c) realistic human characters (**RHC**). Their projection on the ground are marked with a white 2D outline.

experiment was performed and reported in the literature.

3 EXPERIMENT

3.1 Research Question and Hypotheses

Our general objective is to understand how the graphical representation of human agents in virtual reality may affect users' locomotion through virtual crowds of changing density. We took inspiration from train stations, where most people are waiting for an announcement, and may hinder the movement of others navigating through the crowd.

To this end, we performed an immersive experiment where users were asked to walk along a circular corridor in a clockwise direction, filled with static virtual crowds (see Fig. 1). We controlled the level of density, the orientation of virtual humans as well as the graphical representation of agents. More specifically, we studied 7 levels of density, linearly increasing from 0.5, where we start to see an impact from density on speed in real data [13], to $2 a/m^2$, after which it is difficult to navigate without interactions with virtual agents, in $0.25 a/m^2$ steps (a stands for agent). We combined this with 2 orientations: aligned, facing the clockwise direction (**CLO**), or random (**RAN**) since character orientation may have an impact [3]. Finally we also considered 3 types of graphical representations for agents, as illustrated in Fig. 2: cylinder-shaped figures (**CYL**), (b) puppets displaying anthropomorphic characteristics (**PUP**), and (c) realistic human characters (**RHC**) approximately following a demographic distribution of height. Static characters were chosen instead of idle animations to ensure consistency between representations (as we could not animate cylinders). Thus, to focus on the effect of the graphic representation, we opted for unanimated characters. We analyzed first how the relation between user speed and crowd density is affected by the orientation and graphical representation of agents, second, how body movements can also be affected, and third, local navigation strategies.

We also make the following hypotheses:

H1 Speed-density relations. As in reality, we expect to find that speed decreases with density, whatever the studied conditions. However, we expect that the relation between speed and density is modulated by the graphical representation of agents, i.e., that participants will move more cautiously among agents that have a more realistic representation. Thus, speed should decrease faster with density for **RHC** agents compared to **PUP** or **CYL** agents [3]. Orientation of characters can also play a role since humans tend to avoid close proximity in face-to-face situations [65,66]. More manoeuvres to take more distance in these situations may also make speed decreasing faster with density in the **RAN** conditions compared to **CLO**.

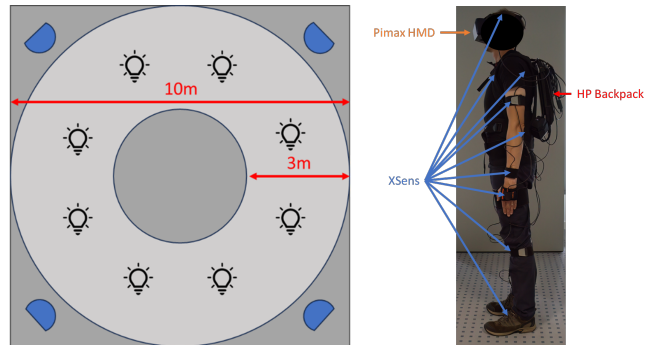


Fig. 3: Left: layout of the virtual scene, with the position of the lights and base stations (blue). Right: Side view of a participant fully equipped with the devices used for the experiment.

H2 Body movements. To get a better understanding of the effect of the studied factors, we also inspect body movements. Since we expect participants to be more cautious among realistic characters, for instance, we expect a greater twisting of the shoulders at the narrowest points between more realistic characters (**RHC** vs. **PUP** or vs. **CYL**). We also expect participants to visually explore differently the scenes that result from different graphical representations, reason why we inspect participants' head motion.

H3 Local navigation. We expect the graphical representation of agents to also have an impact on some local navigation choices. For instance, still because humans tend to avoid close face-to-face navigation [65,66], and as proxemics is affected by graphical representations [33], we expect the successive selection of gaps between characters (i.e., the route participants take among multiple agents) to be affected by the studied conditions.

3.2 Apparatus

The experiment took place in a physical room large enough to contain the full $10 \times 10 m$ scene illustrated in Fig. 3. The experiment took place in a virtual $3m$ -width circular corridor (inner radius: $2 m$; outer radius: $5 m$) delimited by $3m$ -high walls (without texture). The scene was lit by 8 regularly spaced sources.

Participants were equipped with three devices (Fig. 3, right) and immersed in a virtual environment designed in Unreal Engine V5.0.3. For the Head-Mounted Display (HMD), we used a Pimax 5K (specifications: 90 Hz, 200° fov, 2560×1440 resolution) to display the virtual environment, which provided a wide field of view beneficial for our situations involving close proximity with other characters. It was used with 4 SteamVR 2.0 base stations, positioned at each corner of the room. During the experiment, we recorded participants' body motions using an Xsens Link motion capture system (composed of 17 IMU sensors), which was used both to display the participants' motions in real-time on their avatar for embodiment (which is known to impact avoidance behaviors [38]), as well as for later analysis of the experimental data. Since the experiment required to walk through the entire corridor, we equipped participants with an HP Z VR G2 backpack (specifications: NVidia RTX 2080, Intel Core i7-8850H processor, 32GB RAM, weight=4.66kg, width=333mm, height=60.9mm, depth=236mm), on which all the devices were physically connected.

3.3 Task

Participants were instructed to walk the circular corridor populated with static virtual agents, as illustrated in Fig. 1. They were asked to walk at their preferred speed, and to avoid colliding obstacles, as they would if they were walking in a real corridor among people. They were asked to start from a position shown by a green arrow, and to turn clockwise in the circular corridor. For information, while it is known that the apparatus might influence participant's behavior [43], we chose not to give any specific instruction about how participants should account for the worn apparatus to avoid influencing their reactions.

3.4 Population

Participants were recruited through internal mailing lists, resulting in 26 volunteers (19♂, 7♀, 7 were aged between 18 and 24 years old, 10 between 25 and 34, 8 between 35 and 44, and 1 between 45 and 54). They were all naive to the purpose of the experiment, had normal or corrected-to-normal vision, and gave written and informed consent prior to the experiment. The study conformed to the declaration of Helsinki. According to our questionnaire (see Section 3.7), most of participants were familiar with Virtual Reality (19 declared to be familiar with VR, 6 had little experience and 1 had no experience) and Video Games (15 declared to be familiar with it, 9 had a little experience and 2 had no experience). Finally, the data of two participants was discarded because of technical issues preventing the completion of the experiment.

3.5 Experimental Design

On arrival, each participant started the experiment by filling in three different forms: a consent form, a personal data questionnaire, a Simulation Sickness Questionnaire SSQ (see section 3.7 for details). Additional short SSQ questionnaires were completed during breaks (2 breaks during the experiment, which was designed to last 30 minutes). The participants were then equipped with the Xsens motion tracking suit, the Pimax HMD and the VR backpack computer (see Fig. 3 for an illustration). We then calibrated the Xsens motion capture system following the procedure provided by the manufacturer, to ensure motion capture quality and to resize the avatar to the participant’s dimensions.

Participants then performed the experiment, which was separated into three equal blocks each separated by a break (duration to the discretion of each participant, with a minimum amount of time for answering the short SSQ). In each trial, participants walked through half of the circular corridor filled with agents depending on the studied condition, i.e., it required two trials to walk fully through the whole circular corridor, during which participants experienced two different conditions. At the beginning of the experiment, participants first performed four training trials to become familiar with the virtual environment, the task, and the various conditions. They first performed a trial without any character, followed by three trials displaying in the following order CYL (density: 0.75), PUP (density: 1.25), RHC (density: 1.00). They then performed directly the 42 trials of the experiment: 3 Representations (CYL, PUP or RHC) \times 2 Orientations (RAN or CLO) \times 7 Densities (0.5, 0.75, 1.0, 1.25, 1.5, 1.75, 2.0 a/m^2). Participants were exposed to each condition once, presented in a pseudo-random order (randomised once, then presented in the same order to all participants). Since our experiment focuses on continuous walking, we deemed important that the participants were in the same conditions near the start and the end of each trial. After each break, the previous trial was however re-performed by participants to ensure continuity with the upcoming trial, and its data was then discarded. It is also important to mention that a new trial t_i started when participants entered a new half of the circular corridor (which was already populated with agents), which automatically triggered populating the corridor for trial t_{i+1} so that participants would not see agents suddenly appearing when approaching the next boundary. In this way, participants experienced a continuous navigation through the corridor, experiencing a different condition after walking through half of the circular corridor. They therefore walked through the whole circular corridor 23 times (twice for training, and 21 times for the experimental trials).

3.6 Stimuli Creation

In this section, we detail how we created the virtual scenes where participants performed their virtual task. Animated examples are presented in the supplementary video for illustrative purposes.

3.6.1 Graphical 3D models of human agents

The three different types of agent representations can be seen in Fig. 2. These representations were inspired by the literature with the following conditions: an object with human-size CYL [33], a simplified human shape PUP [33, 39, 45] and a realistic character RHC [39, 45]. Let us first describe how we created the human characters with the most

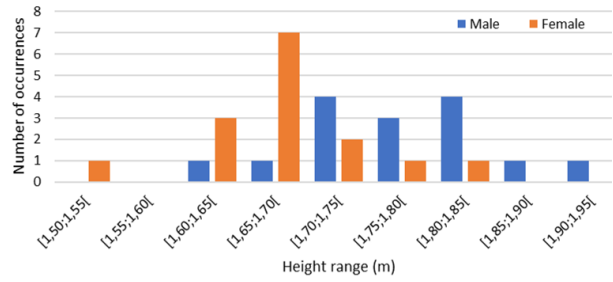


Fig. 4: Distribution of character heights in our experiment.

realistic appearance (RHC). Using Character Creator 3.4¹, an artist created for the purpose of the experiment 30 different characters looking in front of them with a neutral expression to avoid conveying emotions that may influence the participants [10], 15 with female and 15 with male attributes, varying corpulence, skin color, clothes with the goal of maximizing visual variety. In particular, as character height can also have a direct impact on the visibility of the participants in the scene, we created characters with different heights to approximately follow demographic statistics (considering those described in [60]), as illustrated in Fig. 4. The gender of the crowd may have an influence on the behavior [62] is mainly visible within RHC, however CYL and PUP are resized to the gendered RHC (height, width, depth), thus taking simplified gender-related attributes.

Based on these 30 realistic human characters RHC, we created the 3D puppet agents PUP by fitting the proportions of each puppet model (30 different ones) to each of the RHC agent, based on each character’s height, shoulder width, and torso thickness. We performed a similar procedure to create the 30 different 3D elliptic cylinder agents CYL, tightly bounding each of the realistic agents by adjusting the length and width of the elliptic basis and the height of the cylinder.

3.6.2 Orientation

Since agents’ orientation may impact avoidance movements [3], we considered 2 different orientations for agents: clockwise or random (CLO and RAN conditions). Clockwise orientation means that agents are aligned in the clockwise direction of the circular corridor, i.e., orthogonal to the radial direction of the corridor and facing the same direction that the participant is asked to move (this also means that the participants mainly see the back of agents). Clockwise orientation is meant to minimize the orientation impact, since all the characters are oriented towards the tangential direction of the corridor (Fig. 1, top). Random orientation means that each agent has its own orientation, generated randomly from a uniform distribution, thus introducing more orientation-linked behaviors (Fig. 1, bottom).

3.6.3 Density

Crowd density in our experiment took seven possible values ranging from 0.5 to 2 a/m^2 (a stands for agent), since a density lower than 0.5 a/m^2 has no impact on walking speed, while densities above 2.0 a/m^2 make it impossible to move among obstacles without provoking large collision volumes [61].

To generate crowds of controlled densities, we positioned agents according to a regular hexagonal pattern as shown in Fig. 5. By playing on the size of the hexagon – i.e., the distance between 2 agents – we directly control density. Note that $density = 2/(\sqrt{3} \cdot distance^2)$. For a given density, the global positions of agents stay the same amongst the different representations. Then, for each representation, we add some noise to the positions (relative to the distance between agents) to break pattern regularity while keeping the global density values the same, by including a random variation in a circle centered on the initial position. All densities, distance and positional noise values used in our experiment are reported in Table 1.

¹<https://www.reallusion.com/character-creator/>

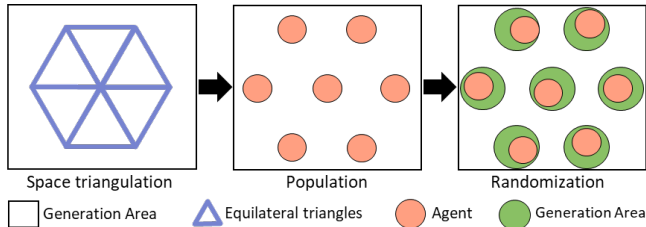


Fig. 5: Crowd generation process with controlled densities. Equilateral triangles (blue) position each agent (orange) with random repositioning in a local space (green) to create less uniformly distributed crowds.

Density (a/m^2)	Interdistance (m)	Random Variation (m)
0.5	1.51	0.3
0.75	1.24	
1.0	1.07	
1.25	0.96	0.2
1.5	0.88	
1.75	0.81	0.1
2.0	0.76	

Table 1: Parameters used to generate crowds of controlled density

This process is used to calculate the positions of the agents in the circle, while those outside the circular corridor or in collision with its walls are removed. Note that the resulting configuration will lead to local variations (due to free space limited by walls, noise in positions, and the removal process). The actual density obtained must therefore be evaluated locally, as explained in the next section.

3.7 Collected data

We first collected some personal data for demographics and statistical purposes. This includes age range, gender, experience in Video Game, and experience in VR. Additionally, biometric data was collected to calibrate the Xsens motion suit (height, arm span and shoe size).

We also collected answers to questionnaires. SSQ were used before and after the experiment: the first questionnaire serves as a reference to the second one, and might essentially help understanding participants' state evolution during the experiment and assess any potential risk of motion sickness. In addition, at each pause, participants filled a intermediary questionnaire to record their current state. The short questionnaire covers: dizziness and migraine, neck or back pain, stress and anxiety, inclusivity.

Finally, we collected participants' motion data during the experiment: we recorded Xsens raw data, as well as the body posture, HMD position and orientation as interpreted by Unreal Engine. With such motion data, we can fully recreate the full-body trajectories followed by participants within the virtual environment for each condition.

All collected data will be published as Open Data.

4 ANALYSIS

This section describes how we computed and analysed the collected experimental data.

4.1 Density estimation

In the study of collective behaviour, there is no consensus on the definition of crowd density and how it should be estimated. While a density term always reflects the relationship between the number of individuals and an area, many computation methods have been proposed [18]. We therefore used two calculation methods derived from [18] to ensure the robustness of our analysis. We also decided to consider only the local density. In contrast to global density, which reflects the average number of agents per (relatively large) unit of area (and which in our case is controlled in the experiment), the local density takes into account the variations due to the exact position and size of the agents in the corridor where the participant is exactly located.



Fig. 6: Shoulder orientation calculation. We first calculate the Delaunay Triangulation, of which the virtual agents are the vertices. Then, when participants cross any edge of any Delaunay triangle, we measure the angle $\in [0, 90]^\circ$ formed by their shoulder segment (left to right shoulder, computed from motion data) and the crossed edge.

The first method for computing local density is based on the so-called "Voronoi" method. The calculation is as follows: 1) we calculate the Voronoi diagram of which the virtual agents and the participant are the seeds (this calculation is therefore made at each time step according to the evolution of the participant's position). 2) When the Voronoi cell associated with the participant intersects the wall delimiting the corridor, the corresponding surface outside the corridor is removed. 3) The local density at the participant's position at time t is obtained with the formula $d_{v,t} = 1/s$ where s is the area of the participant's cell (calculated in step 2).

The second method is based on the use of a circle kernel. The calculation is as follows: 1) A $1m$ -radius circle is centred on the participant's position. 2) From the area of this circle, the area exceeding the limits of the corridor wall is removed. This gives the corrected area s of the circle. The number n of agents in the circle is counted. If the agent straddles the perimeter of the circle, only the proportion contained within the circle is counted based on the projection of the agent representation on the ground (as depicted in Fig. 2). Therefore, $n \in \mathbb{R}$. 3) The local density d_c at time t is obtained with $d_{c,t} = (n + 1)/s$. Note that we add 1 to the number of agents to take into account the increase of local density due to the presence of the participant himself.

4.2 Speed estimation

Since human locomotion speed is typically relatively slow, with a comfortable gait speed mainly between $1.15 m/s$ and $1.6 m/s$, [9, 19] and the sampling frequency of positions is comparatively high, we smoothed the recorded locomotion speeds to avoid the effect of noise on the analyses. We used a moving average approach, and calculated the smoothed instantaneous speed s_t at time t as the mean of the instantaneous speeds over a $0.4 s$ (about the duration of a step) sliding window centered on t .

4.3 Speed-Density relations

Our aim is to capture as simply as possible the relationship between density and speed, where previous work showed that speed decreases as density increases [61]. We expect this relation to be quite linear in the range of densities we studied. Consequently, we simply modelled the participants' speed density relationship by performing a linear regression on the speed density point cloud (d_t, s_t) .

An essential point of our experiment is to compare the effect of the graphical representation on this speed-density relationship (Hypothesis **H1**). To carry out this analysis we grouped for each participant i , by condition of graphical representation (CYL, PUP or RHC) and of orientation (RAN or CLO). We repeated the process for the two density calculation methods (d_v or d_c), resulting in the following collections of speed-density points $(d_{v|c,t}, s_t)_{CYL|PUP|HUM \times RAN|CLO}$. Thus, for each participant i we created 6 speed-density sets of points with 2 density calculation methods, i.e., 12 sets in total per participant. We then performed linear regression separately on each set of points and participant.

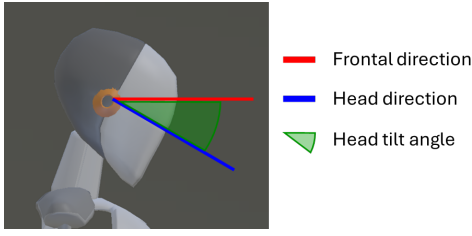


Fig. 7: Head tilt angle calculation.

With hypothesis **H1**, we expect a larger effect of density on speed when more realistic character representations are used. Therefore, we mainly compare the regression coefficient we obtain (i.e., the slope of the regression). We performed a 2-way Repeated Measures ANOVA for each density calculation method, for measuring the effect of our independent variables Representation (**CYL**, **PUP** or **RHC**) and Orientation (**RAN** or **CLO**) on slopes.

4.4 Shoulder orientation angle

In our study, we also inspected participants' shoulder orientation as they crossed the free space between two agents. This measure was used by Berton et al. [5], and can reveal whether participants prove to be more cautious when crossing these spaces. This analysis is related to hypothesis **H2**. To this end, we calculate the Delaunay Triangulation, of which the virtual agents are the vertices. When participants cross any edge of any Delaunay triangle, we measure the angle formed by their shoulder segment (left to right shoulder, computed from motion data) and the crossed edge (see Fig. 6). An angle of 0° therefore represent no shoulder rotation, while an angle of 90° would mean that the participants are crossing with their shoulders orthogonal to the segment between the two characters.

With hypothesis **H2**, we expect participants to display larger shoulder rotations when passing close to realistic characters. Because of the scarcity of such data, instead of performing linear regressions we decided to mainly compare average shoulder rotation angles across conditions, by performing a 3-way Repeated Measures ANOVA with within-subject factors Representation (**CYL**, **PUP** or **RHC**), Orientation (**RAN** or **CLO**) and Density (0.5 to $2 a/m^2$).

4.5 Head tilt angle

We also performed an additional head tilt angle analysis, to explore whether participants would explore the scene differently depending on our condition, since scenes are visually different. Even though we did not collect eye-gaze data, head tilt angle can be a good indicator of a difference in behaviour and more particularly in the process of visual acquisition of the scene (see Fig. 7).

With hypothesis **H2**, we expect a difference in how participants take visual information (i.e., head tilting) depending on character representations and density. We therefore performed linear regressions between density and head tilt angle, and compare the regression coefficients obtain (in that case the slope and intercept of the regressions). We performed a 2-way Repeated Measures ANOVA for each density calculation method, for measuring the effect of our independent variables Representation (**CYL**, **PUP** or **RHC**) and Orientation (**RAN** or **CLO**).

4.6 Local navigation strategy

A detailed and interpretable analysis of local navigation strategies in the case of this study is difficult. This is due to the use of a circular corridor. Very practical for continuous locomotion over long distances, it has a major influence on the local navigation strategy: it is likely that participants tend to stay close to the inner wall to reduce the length of the journey per turn, and also likely that this element of the strategy predominates and drowns out the other influencing factors. However, we believe that we can still reveal the influence of our conditions by inspecting the variability of the paths. Since we believe that the most realistic representations of our characters (**PUP** and **RHC**) add

constraints to navigation (as mentioned in hypothesis **H3**), we expect less variability in the paths than for the **CYL** condition.

To measure the diversity of paths resulting from different local navigation strategies, we use the Dice Similarity Coefficient [14] as a metric (note that this metric was previously used in [6]). As in our other analyses, we rely on a Delaunay triangulation (again with the virtual agents as vertices) and represent a participant's path as a sequence of cells traversed. We group all the participants paths by condition of Representation and Orientation (since we need the exact same position of virtual agents to make the DICE measure meaningful), and in each group compare the paths by pairs. We obtain a final score between 0 and 1, where 1 means that all the paths consist of the same set of cells, and 0 would mean that the paths have no common cell. Additionally, a score of 0.7 means that the paths consist of 70% of common cells. We compare the distribution of obtained scores per condition of graphical representations. There are 3864 possible pairs of paths, and as many DICE scores. Since the distribution of scores is non-normal, we performed Wilcoxon tests to compare them.

4.7 Statistical Analyses

For our analyses, we set the level of significance to $\alpha = 0.05$ and use the notations * (p -value < 0.05), ** (< 0.01) and *** (< 0.001) to highlight significant differences in the figures. Results are reported as mean \pm standard deviation. Normality was assessed using Q-Q plots and Shapiro-Wilk tests, and sphericity using Mauchly's tests. Greenhouse-Geisser adjustments to the degrees of freedom were applied when appropriate to avoid any violation of the sphericity assumption. In case of a significant main or interaction effect, we performed pairwise comparisons using post-hoc Tukey tests.

5 RESULTS

5.1 Speed-density relations

Figs. 8 to 10 graphically summarise our analyses of the regression coefficients applied to the speed-density point clouds acquired under different conditions and participants. Regarding the slope of the regressions, we found for both computation methods a main effect of Representation (Voronoi: $F_{2,46} = 8.69, p < 0.001, \eta_p^2 = 0.274$; Circle: $F_{2,46} = 7.03, p < 0.01, \eta_p^2 = 0.234$) and Orientation (Voronoi: $F_{1,23} = 9.09, p < 0.01, \eta_p^2 = 0.283$; Circle: $F_{1,23} = 8.15, p < 0.01, \eta_p^2 = 0.262$), as well as a Representation \times Orientation interaction effect (Voronoi: $F_{2,46} = 3.84, p < 0.05, \eta_p^2 = 0.143$; Circle: $F_{2,46} = 4.11, p < 0.05, \eta_p^2 = 0.152$).

For both calculation methods, post-hoc analysis reveals that the **CYL** condition is significantly different from **RHC** ($p < 0.01$), and significantly different from **PUP** only for the Voronoi calculation ($p < 0.01$), showing that speed decreases generally more quickly with density when navigating among **CYL** characters. For Orientation, our results show that speed decreases more quickly with density when navigating among characters oriented randomly (**RAN**), than when navigating among characters aligned with the corridor's direction. However, post-hoc analysis of the interaction effect showed that speed is influenced by density only in the **RAN** condition (Fig. 10), even though the results still display a slight trend in the **CLO** condition. We also observed for the Circle computation method that speed decreases more quickly with increasing densities in the **RAN** than **CLO** condition when navigating through **RHC** agents ($p < 0.05$).

Regarding the intercept of the regressions, we found for both computation methods a main effect of Orientation (Voronoi: $F_{1,23} = 23.86, p < 0.001, \eta_p^2 = 0.509$; Circle: $F_{1,23} = 14.26, p < 0.001, \eta_p^2 = 0.383$), showing in both cases a lower intercept value of the regressions for **CLO** than **RAN**.

These initial results, suggest that the method used to calculate density only slightly affects the speed-density relations.

5.2 Shoulder orientation angle

For each condition, We computed the average shoulder orientation angle per participant, and performed a 3-way RM ANOVA on within-subject factors Representation, Orientation and Density. We found a main effect of Representation ($F_{2,34} = 11.47, p < 0.001, \eta_p^2 = 0.403$) and Density ($F_{1,64,27.96} = 27.71, p < 0.001, \eta_p^2 = 0.620$), as well as interaction effects: Representation \times Orientation ($F_{1,50,25.46} = 8.86, p < 0.01, \eta_p^2 = 0.343$), Density

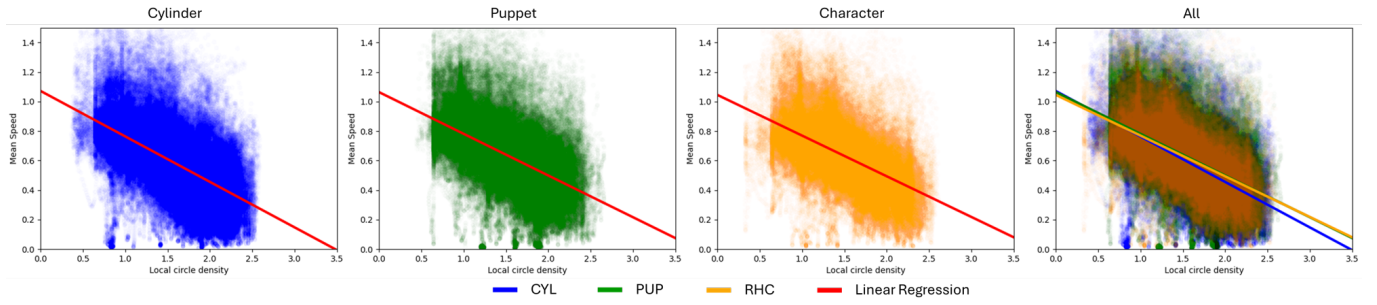


Fig. 8: Speed-density clouds of points for densities computed with the Circle method. From left to right: CYL, PUP and RHC conditions are displayed, the last plot on the right combines the same scatter plots and shows the 3 regressions to allow visual comparison of the slopes obtained. The displayed linear regression was computed from the slope and intercept averaged over the individual regression of each participant.

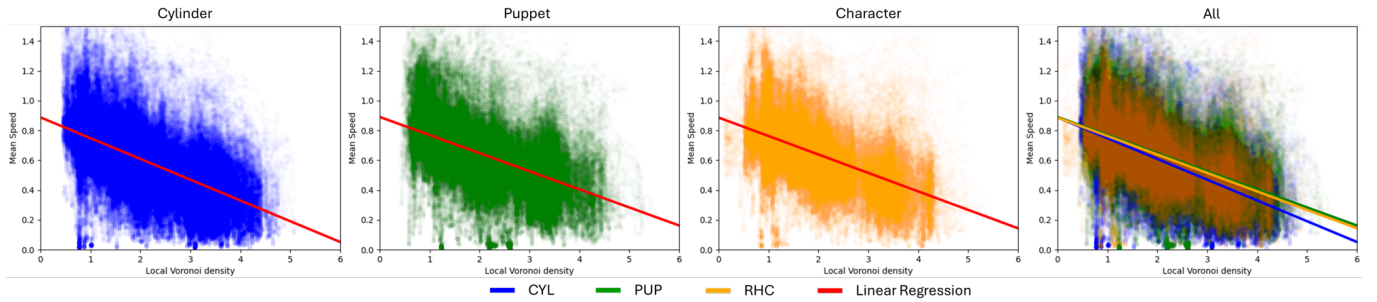


Fig. 9: Speed-density clouds of points for densities computed with the Voronoi method. From left to right: CYL, PUP and RHC conditions are displayed, the last plot on the right combines the same scatter plots and shows the 3 regressions to allow visual comparison of the slopes obtained. The displayed linear regression was computed from the slope and intercept averaged over the individual regression of each participant.

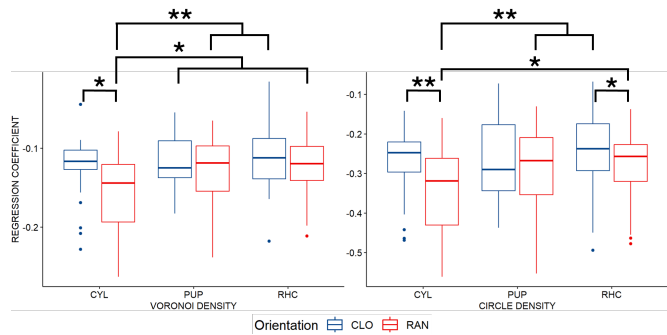


Fig. 10: Representation \times Orientation interaction effect of the speed regression slope coefficient, for the Voronoi (left) and Circle (right) density calculation methods.

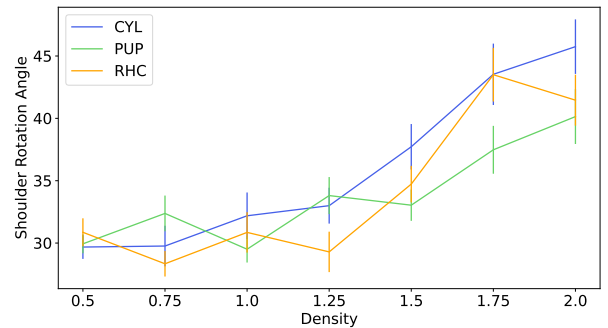


Fig. 11: Representation \times Density interaction effect for Shoulder Rotation angles

\times Representation ($F_{4,28,72.82} = 2.95, p < 0.05, \eta_p^2 = 0.148$), Density \times Orientation ($F_{3,39,57.70} = 3.37, p < 0.05, \eta_p^2 = 0.165$) and Density \times Representation \times Orientation ($F_{3,67,62.38} = 4.86, p < 0.01, \eta_p^2 = 0.222$). For information, we also explored for potential relations between shoulder orientation and the distance between the characters that users was crossing, but only found significant correlations in a minority of cases (less than 30%).

Regarding the effect of representation, post-hoc analysis showed that participants rotated on average more their shoulders in the **CYL** condition than in either **PUP** or **RHC** ($p < 0.05$). They also rotated them more with increasing densities, separated in three significant groups ($p < 0.05$): $[0.5, 1.25] a/m^2$ range, then $1.5 a/m^2$, and finally $[1.75, 2] a/m^2$. All representations (**CYL**, **PUP** and **RHC**) followed similar trends, despite some minor differences (see Fig. 11).

5.3 Head tilt angle

Fig. 13 summarises our analyses of the regression coefficients applied to head-tilt vs. density point clouds acquired under different conditions and participants. For both density calculation methods, we found a main effect of Representation (Voronoi: $F_{2,46} = 10.91, p < 0.001, \eta_p^2 = 0.322$; Circle: $F_{1,55,35.60} = 10.04, p < 0.001, \eta_p^2 = 0.304$) on the slope of the regression, as well as a main effect of Orientation (Voronoi: $F_{1,23} = 23.96, p < 0.001, \eta_p^2 = 0.510$; Circle: $F_{1,23} = 6.02, p < 0.001, \eta_p^2 = 0.207$) on the intercept of the regression. For Voronoi only, we also found a main effect of Representation ($F_{2,46} = 13.51, p < 0.001, \eta_p^2 = 0.370$) on the intercept.

For both calculation methods, post-hoc analyses show that, on average, participants looked down more with increasing densities in the **CYL** and **PUP** conditions than in the **RHC** condition (i.e., more negative slope $- p < 0.01$). Using Voronoi calculation for density, we also found a smaller intercept value for **CYL** than for **PUP** or **RHC** (i.e., participants look lower at low densities in **CYL** condition $- p < 0.01$). These results suggest that participants tend to look less towards the floor

in the **RHC** condition, and significantly more towards the floor in the **CYL** condition. We also found that participants tended on average to look slightly more towards the floor in the **CLO** than **RAN** conditions (difference of intercept of 2.4° for Voronoi, and 2.1° for Circle).

5.4 Local Navigation Strategies

Fig. 12 displays examples of the paths followed by participants according to the experimental conditions. This is a selection of 10 condition examples, chosen to illustrate different levels of similarity according to the DICE method (ranging from 0.3 to 0.94). The examples are shown in ascending order of similarity.

As mentioned in Section 4.6, we computed DICE scores between each pair of participant trajectories, for each Representation \times Orientation \times Density, and performed a 3-way RM ANOVA on these factors, with participant pairs as subjects. We found a main effect of Representation ($F_{1,8,494.93} = 174.80, p < 0.001, \eta_p^2 = 0.389$), Orientation ($F_{1,275} = 5.65, p < 0.05, \eta_p^2 = 0.020$) and Density ($F_{4,51,1240.01} = 202.37, p < 0.001, \eta_p^2 = 0.424$), as well as a interaction effects: Representation \times Orientation ($F_{2,550} = 4.41, p < 0.05, \eta_p^2 = 0.016$), Density \times Representation ($F_{8,53,2345.19} = 98.07, p < 0.001, \eta_p^2 = 0.263$), Density \times Orientation ($F_{5,50,1513.49} = 121.97, p < 0.001, \eta_p^2 = 0.307$) and Density \times Representation \times Orientation ($F_{7,23,1989.48} = 108.99, p < 0.001, \eta_p^2 = 0.284$).

More specifically, post-hoc analysis showed that DICE scores were significantly higher on average for **RHC** (0.693 ± 0.250), then **PUP** (0.674 ± 0.261), then **CYL** (0.605 ± 0.295) ($p < 0.01$, see Fig. 14). We also observed a tendency for DICE scores to decrease with density, even though it was affected by the other factors to some extent.

6 DISCUSSION

In this section, we discuss the results of our experiment, put into perspective in the light of previous work. We give technical recommendations on how to carry out studies on crowd navigation in virtual reality. Finally, we put our conclusions into perspective with regard to the limitations of our studies, in order to open up avenues for future work.

6.1 Speed-Density relations

First, we return to the original question posed in this article. When studying crowd behaviour in virtual reality, is the use of different representations likely to introduce behavioural biases? To answer this question, we first chose to examine data that is essential for the study of collective movement: speed-density correlations. Our results show that, as expected by the **H1** hypothesis, the use of more or less realistic representations modifies how density influences speed. However, we expected that more realistic representations would slow down more participants, and our results do not seem to support this. It therefore seems difficult to simply characterise the effect of graphical representations on speed. On the contrary, we could say that the steepest decrease of speed when density increases is obtained in the **CYL+RAN** condition.

However, a more interesting result is that significant differences are obtained between anthropomorphic (**PUP** and **RHC**) and non-anthropomorphic (**CYL**) representations. Should we conclude that an essential recommendation for the design of virtual scenes for the study of crowd movement is to use anthropomorphic characters, regardless of their realism? At this stage, this is our first recommendation. And this is positive, because the computational cost of a **PUP** representation is significantly lower than that of a **RHC**, opening the way to VR experiences that can involve very large crowds without having to resort to specific modelling and rendering techniques.

These initial results can be compared with those in the literature. On the one hand, many previous studies used non-realistic anthropomorphic representations without questioning their possible influence on behaviour. This is the case of the pioneering work on the use of VR to study inter-individual interactions [48] (which investigated the role of locomotion interfaces): despite the non-realistic appearance of the characters, behaviour similar to reality was observed. Even the use of non-realistic but graphically detailed representations (zombies in [12], different body parts or geometries in [33], different appearances in [39]) show differences in interactions, that can be described as small.

How to interpret **H1** is not fully validated, and even opposite effect can be observed? While we have ensured that the **CYL**, **PUP** and **RHC** representations have similar dimensions and occupy comparable areas when their shape is projected on the floor, the total volume occupied by the cylindrical representation is larger. This means that each **CYL** agent takes up more of the scene visually. Thus, the density as perceived by our participants could be different from that measured by our two evaluation methods, which only consider the area occupied by the agents on the floor. As we previously mentioned, there is no consensus on the method of calculating density, but we do know that a visual definition of perceived density has not yet been explored [18]. While we know that locomotion is primarily guided by vision [52], the use of virtual reality as we practice it opens up new and unique opportunities to revisit these different notions of density. The ability to know precisely and continuously the eye-obstacle distances for any point in the visual field will allow us to compare different density calculations again. Would a visually-based definition of density explain better the observed speed adaptations? We left this question for future work.

6.2 Body movements

As stated in **H2**, we expected to gain a better understanding of the observations on speed-density relationships by examining body movements. In particular, we expected shoulder movements to be more important for more realistic representations, following the idea that participants would be more careful not to collide with more human-like figures. Note that a similar analysis was performed in [5]. Our examination of the shoulder orientation data did not allow us to confirm this hypothesis. However, there is still a significant difference in shoulder angles at the highest densities. Nevertheless, it is the **CYL** representation that causes the largest rotations (Fig. 11). We think that the massive and inanimate aspect of the cylinders may have played a prominent role: it is possible that the participants avoided to a greater extent a collision that would have caused a hard impact if the cylinder had been real, similarly to what can be observed with vision-based navigation algorithms [74]. Moreover, participants could have expected collaborative behaviors from the agents [11], thus it is important to remind that participants were informed that the crowd would be static, and experienced it beforehand during the training session, which should have limited their expectations. It is however not possible to confirm these new hypotheses on the basis of our current data, which we plan to address in the future with human perception and visual density defined as a depth map as it is used for robot navigation [8].

We also explored the head tilt angle: there was a significant effect of agent representation. In the **CYL** condition, participants look downwards very clearly when navigating between agents, less so in the **PUP** condition, and even less so in the **RHC** condition. **H2** is therefore partially validated. How should these results on head angle be interpreted? Very few studies to date have been able to explore visual activity in dense crowds. Existing studies [6, 7, 36] have shown that gaze activity is strongly linked to the collision avoidance task. However, the experiments were conducted in highly dynamic situations. It is difficult to compare our results directly with previous ones. Our interpretation is as follows. In a static situation that is denser than in previous studies, it seems that the eye's activity evolves towards the search for intervals between agents that are favourable for navigation. The differences in the volume occupied by the different geometric representations seem to have an impact on this visual exploration. Thus, in the case of the **CYL** agents, the exploration of the free surface of the ground seems to favour this search, whereas the visual space opened up by the shape of the shoulders and the head seems to allow a higher visual exploration, which explains the higher head angle observed for **PUP** and **RHC** representations. The question remains as to the difference between the **PUP** and **RHC** representations. Other elements may come into play here. A more visually realistic representation may lead to the search for other visual information, such as the interception of the characters' gaze. But it seems difficult to validate such hypothesis without, for instance, detailed eye-tracking data.

This interpretation brings us back to the previous point. Although the different graphical representations studied ultimately leave more or less

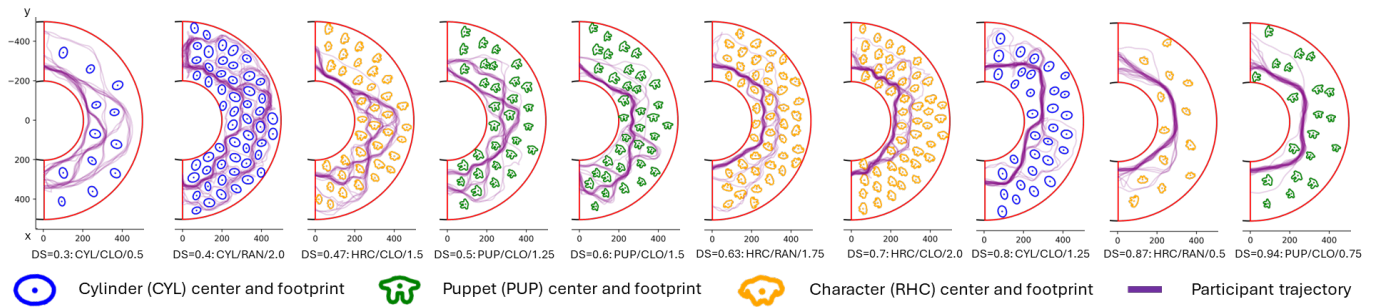


Fig. 12: Examples of sets of participants paths according to conditions, ordered from smallest (higher diversity) to highest DICE scores (higher similarity). DICE scores (DS) are indicated below each figure, followed by the selected Representation/Orientation/Density condition.

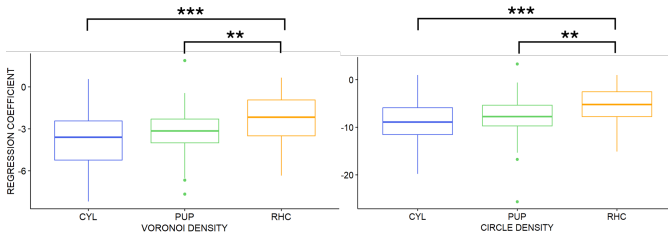


Fig. 13: Main effect of Representation on the regression slope coefficient for the tilt head angle vs. density, for the Voronoi density calculation methods.

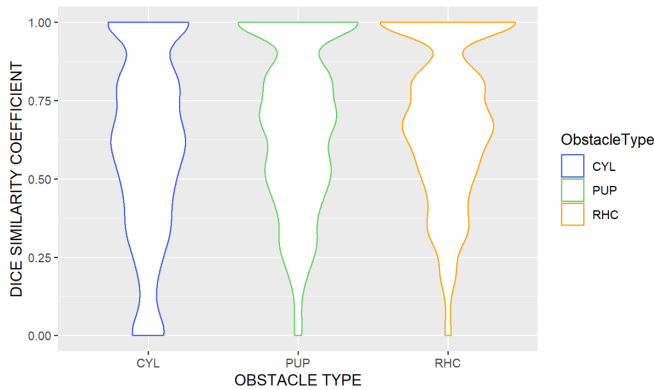


Fig. 14: DSC scores grouped by conditions of Graphical Representation.

the same space for navigation, the fact that they give rise to different visual spaces seems to affect not only speed-density relations but also strategies for visually exploring the environment. In the next section we discuss how these differences impact local navigation strategies. Nevertheless, it would be interesting to further explore the eye-head relation in the future, by analysing gaze activity using an oculometer integrated into a HMD.

We can here refine recommendations for the design of scenes for the study of collective movement. The space visually occupied by agent representations also seems to have an impact on detailed body movements and could influence participants' visual exploration strategies. Our analysis also shows that participants may modify their behaviour according to the physical properties they attribute to the agents, or even their ability to communicate or react. Thus, it is important to control the characteristics that participants attribute to agents (and this can be done in several ways) in the design of experiments. For future work, in addition to eye-tracking data mining, an experiment using simplified representations of agents with perceptible communication and response capabilities would support our discussion.

6.3 Local navigation strategy

Hypothesis **H3**, like the previous two, is based on the idea that the more realistic **RHC** appearance affects interactions between participants and agents, and consequently, their proximity [82] as well as the participants' trajectories. As far as local navigation is concerned, our hypothesis is that this factor has an impact on the route participants take (indeed, this route can be seen as a succession of gap selection to pass between specific agents). For agents represented by non-realistic criteria, such as the size of the gaps between agents so as not to have to sneak, but also, the distance travelled per turn by navigating closer to the inner wall. However, the variability inherent in human behaviour means that, although these criteria do come into play, not all participants will take exactly the same route under the same conditions. We can also imagine that, locally, one gap or the other would be very similar according to these selection criteria. We can appreciate these situations of local symmetry by looking in detail at some of the trajectories of the examples in Figure 12: there are points of separation between the trajectories where we can imagine that the two choices made were equivalent.

The idea of path similarity analysis using DICE methods is to explore whether additional criteria can play a role in the representation of realistic characters. Indeed, as mentioned above, in the interaction between two people, certain situations can be avoided that would not make sense when interacting with an object, such as close proximity in a face-to-face situation. Hypothesis **H3** was that local navigation strategies would be more constrained by criteria specific to the most realistic representations, resulting in greater similarity. Results confirmed this hypothesis. Thus, this analysis enables us to confirm the role of graphical representation in virtual crowd navigation and shows a fairly clear role for the level of realism used on local navigation strategies, with an effect that seems to us to be quite important. This result enables us to confirm the importance of using realistic representations when studying navigation. Finally, we note that an anthropomorphic but non-realistic representation (**PUP**) has an effect on similarity, but to a lesser extent. The similarity scores between **PUP** and **RHC** are close, showing once again the importance of not using oversimplified forms to represent agents.

7 CONCLUSION

The study of crowds in virtual reality opens up some very interesting prospects for disciplines that study the dynamics of collective behaviour. Virtual reality opens up new types of analyses by facilitating access to the measurement of parameters of interactions between individuals and the "crowd" environment that surrounds them. However, the ecological validity of the situations studied in VR is a crucial aspect in the implementation of this technology.

In this article we have conducted a study to better understand the influence of the graphical representation of agents in a crowd on user navigation behaviour. This study leads us to important conclusions for the design of VR environments. The representation of agents plays a very important role in locomotion in virtual crowds. We measured the

effects of representation on several aspects of locomotion, including density-dependent speed of movement, body posture, and presumably visual information intake for locomotion control, as well as local route choice and thus, by rebound, navigation. When computational resources are available, approximation to a realistic representation of humans obviously is the best option. However, these representations are costly and our study shows that the use of simplified anthropomorphic representations enable us to observe behaviours very close to those based on the most realistic representations. However, the use of proxy geometric forms that are too geometrically distant from human appearance should be avoided. These representations have a major impact on visual perception of the environment and adversely affect locomotion and navigation.

Through discussion we have identified immediate avenues for future work. First, we see an opportunity to revisit the notion of density for the study of crowd dynamics. VR enables us to easily work with the information available in a participant's visual field to better understand speed-density relationships. While we can clearly see correlations between speed and density, they remain noisy. Analysing the visual field would undoubtedly make it possible to obtain a definition of density that highlights more precise relationships, with very significant implications for the collective dynamics community. A second direction to follow concerns the analysis of oculometric data to further our understanding of the differences that can be generated by different representations. The clear effect of our conditions on head posture encourages us to do this. Finally, we have highlighted some promising results on route choice. The methodology implemented extends that introduced by Berton et al [5] and opens up the possibility of a detailed analysis of navigation strategies in crowds. Although this topic has received little attention so far, we believe that virtual reality opens up new opportunities that should be exploited immediately. It is this latter direction that we have decided to pursue immediately.

There are other, longer-term directions open to us that address the limitations of our experiment. First, we have studied stationary crowds, such as found in train stations, and our agents were non-reactive and static. One objective is to extend our studies to animated and reactive crowds. This raises the question of the level of realism needed for the animation, which is a difficult question. While we can hope that a behavioural model leading to realistic animation is paramount, it is also a costly element of simulation, and a preference for simplified approaches may soon prove necessary. Another difficulty is the so-called uncanny valley [80]. The use of detailed, realistic graphics can cause a feeling of repulsion when the agent starts to move. This is a phenomenon that could counterbalance the introduction of movement capabilities in the virtual crowd. This was a strong motivation not to originally include dynamic crowds in our study and to isolate the graphical representation alone in a first step. Nevertheless, our paper lays the groundwork for continuing this work. The impact of participants' height relative to the one of agents might also be a predominant factor [53], since it can create visual obstruction. Tightly linked to that topic is gender: the gender of participants in relation to the one of agents might have conditioned them for certain behaviors [62]. In this study, we did not address gender-related or sex-related variables although our data might capture some of their effects. A dedicated study is required to quantify them, for instance, by observing interpersonal distances we plan to consider cultural variables, in the same way Chattaraj and colleagues did [16].

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