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Guided by gaze: Prioritization strategy when navigating through a virtual crowd can be assessed through gaze activity

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ABSTRACT

Modelling crowd behavior is essential for the management of mass events and pedestrian traffic. Current microscopic approaches consider the individual's behavior to predict the effect of individual actions in local interactions on the collective scale of the crowd motion. Recent developments in the use of virtual reality as an experimental tool have offered an opportunity to extend the understanding of these interactions in controlled and repeatable settings. Nevertheless, based on kinematics alone, it remains difficult to tease out how these interactions unfold. Therefore, we tested the hypothesis that gaze activity provides additional information about pedestrian interactions. Using an eye tracker, we recorded the participant's gaze behavior whilst navigating through a virtual crowd. Results revealed that gaze was consistently attracted to virtual walkers with the smallest values of distance at closest approach (*DCA*) and time to closest approach (*TtCA*), indicating a higher risk of collision. Moreover, virtual walkers gazed upon before an avoidance maneuver was initiated had a high risk of collision and were typically avoided in the subsequent avoidance maneuver. We argue that humans navigate through crowds by selecting only few interactions and that gaze reveals how a walker prioritizes these interactions. Moreover, we pose that combining kinematic and gaze data provides new opportunities for studying how interactions are selected by pedestrians walking through crowded dynamic environments.

1. Introduction

As with collective animal behavior (Couzin & Krause, 2003), movements of human crowds emerge from the combination of the local interactions between neighboring pedestrians in the crowd (Moussaïd et al., 2012). The effect of single interactions on the formation of human locomotion trajectories has been extensively studied, for example during collision avoidance (Croft & Panchuk, 2017; Knorr, Willacker, Hermsdörfer, Glasauer, & Krüger, 2016; Olivier, Marin, Crétual, & Pettré, 2012), following (Lemercier et al., 2012; Rio, Rhea, & Warren, 2014), or grouping (Moussaïd, Perozo, Garnier, Helbing, & Theraulaz, 2010; Rio, Dachner, & Warren, 2018). However, the notion of an interaction neighborhood needs to be developed to fully explain the structure of the collective motion. Interaction neighborhoods in human crowds are typically designed somewhat arbitrarily according to the modeler's beliefs, based on for example distance (Helbing & Molnar, 1995), topology (Van den Berg, Guy, Lin, & Manocha, 2011), or vision (Ondřej, Pettré, Olivier, & Donikian, 2010). These assumptions are necessary as the high number of potential interaction sources make it nearly impossible to infer any causality based on the combined interactions. An interaction neighborhood is a formalization of which neighbors are likely to have an effect on the walker's trajectory. A formalization solely based on kinematics cannot be achieved without arbitrary hypotheses, therefore additional measurements are required to fully understand the process.

Gaze activity, in addition to kinematics, may provide a good indication of where humans get their (visual) information from for the control of human locomotion (e.g., Patla, 1997; Warren Jr, 1998; Nummenmaa, Hyönä, & Hietanen, 2009). Marigold and Patla (2007) showed that gaze is drawn towards task relevant aspects of the environment, as walkers fixated on locations where they would eventually step arguably to maximize the amount of information available for a safe foot placement. Moreover, gaze behavior changes depending on the risk of collision (Jovancevic-Misic & Hayhoe, 2009). In an experiment where participants came across confederates that would either seek collision or avoid collision, Jovancevic-Misic and Hayhoe (2009) showed that participants adapted their gaze behavior depending on which confederate was approaching them. The risky confederates would draw more attention, whereas the confederate that did not pose a collision risk was gazed at less. Additionally, gaze behavior provided

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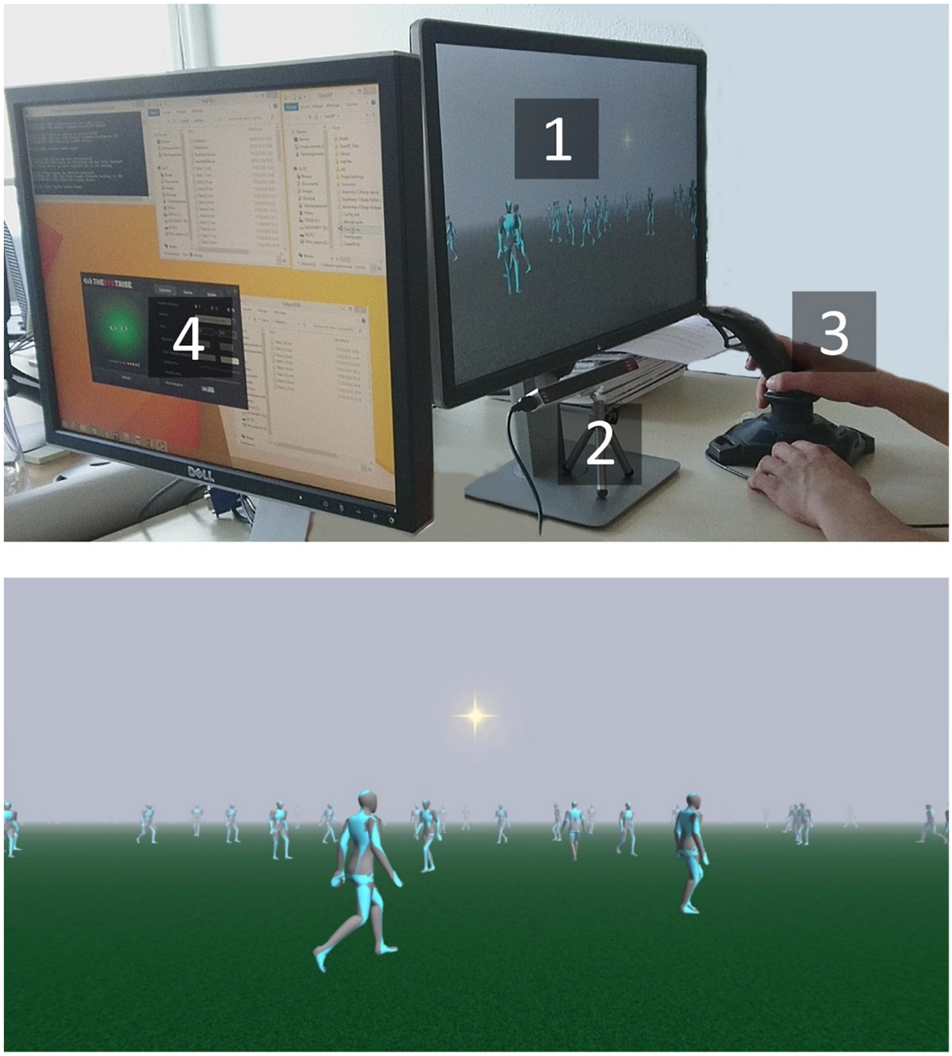

Fig. 1. *Top*) Participants sat in front of a 24″ screen (1). An eye tracker below the screen recorded participant's gaze (2). Participants moved through the virtual environment using a joystick (3). An additional screen (4) allowed the researcher to monitor the experiment. *Bottom*) Screenshot of the virtual environment through which participants navigated.

information about how a pedestrian engaged an interaction (Croft & Panchuk, 2017). In a collision avoidance task where an interferer crossed a participant's trajectory at 90°, Croft and Panchuk (2017) showed that the gaze behavior revealed whether the participant would cross in front or behind the interferer. Participants tended to pass behind when they looked at the interferer early in the interaction and when the duration of the fixation was long. It has even been shown that people use the gaze behavior of *others* to adjust their behavior (Dicks, Clashing, O'Reilly, & Mills, 2016; Colombi, Scianna, & Alaia, 2016; Colombi & Scianna, 2017), likely because it informs about the action intentions. Therefore, we focus on understanding how a person interacts with its environment based on its gaze activity. More specifically, it can thus be surmised that gaze activity may shed light onto which walkers prompt collision avoidance when walking through a crowded environment.

The risk of collision with another pedestrian can for example be quantified with distance- or time-based metrics such as the Distance at Closest Approach (*DCA*, also referred to as Minimal Predicted Distance; Olivier et al., 2012; Olivier, Marin, Crétual, Berthoz, & Pettré, 2013) and the Time to Closest Approach (*TtCA;* Dutra, Marques, Cavalcante-Neto, Vidal, & Pettré, 2017). Assuming that, at each time step, both pedestrians maintain their current heading and velocity, the future closest approach can be computed through linear extrapolation of each walkers' heading and velocity. *DCA* is then the predicted distance between these walkers **at**-, and *TtCA* the time **until**-, the instant of closest approach. As *DCA* and *TtCA* can be computed at every time step and simultaneously incorporate the action of two walkers, these metrics provide an interesting descriptor of the dynamics of an interaction between two walkers. In previous experiments, walkers have been shown to avoid collision when *DCA* is below a threshold of about 1 m in real-world conditions (e.g., Olivier et al., 2012, 2013), which has been replicated in virtual reality (Lynch et al., 2017). To avoid collisions, it is evident that typically lower *TtCA* or *DCA* values correspond to an increased necessity to interact to avoid collision. However, it is challenging to quantify this necessity to interact as it requires combining distance- and time-based metrics. Collision can be avoided with small continuous adjustments early in the interaction, but also with a late abrupt adjustment a short time before the closest approach. As such, in isolation neither *TtCA* nor *DCA* provides a full description of when a walker needs to respond to another walker. If there is not a lot of time left until the closest approach (i.e., low *TtCA*), it may well be that the distance at closest approach will be large (i.e., high *DCA*), and therefore no action would be required. On the other hand, it may be that the distance at closest approach is predicted to be small (i.e., low *DCA*), but with a lot of time left until closest approach (i.e., high *TtCA*) it may not (yet) be necessary to take action (due to the uncertainty of what