Collective Dynamics

Asymmetries in Group-Individual Collision Avoidance due to Social Factors

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Received: 29 September 2023 / Last revision received: 1 February 2024 / Accepted: 12 April 2024
DOI: 10.17815/CD.2024.150

Abstract This research centers on analyzing frontal encounters between dyads (two-person groups) and individuals, aiming to measure each participant's role in avoiding collisions based on their deviation from their intended path. To achieve this, we establish the intended trajectory of each party by taking into account their walking direction leading up to the encounter. The largest discrepancy between this intended path and the observed path can be interpreted as the pedestrian's maximum lateral deviation.
We show a noteworthy discrepancy in deviation between group members and individuals in face-to-face encounters. Furthermore, we conduct an in-depth analysis of how the intensity of interaction among group members impacts collision avoidance dynamics. Notably, the contrast in deviation between individuals and group members is most pronounced when the level of interaction within the group is high. Ultimately, our findings consistently indicate that higher levels of interaction lead to more substantial deviations in the trajectories of encountered individuals and underscore the significant role of social dynamics in influencing pedestrian behavior during frontal encounters.

Keywords Microscopic pedestrian dynamics · social groups · collision avoidance

1 Introduction

With the progress of autonomous navigating agents for smart vehicles, assistive robots and drones and the pursuit of more accurate model of crowds, research attention towards collision avoidance has increased rapidly in recent years [1–4]. Researchers have explored different approaches to model this capability [5–7]. In the early stages, the Social Force Model [8] introduced a repulsive force between particles (representing pedestrians) to account for collision avoidance. These models have demonstrated promising results, particularly when coupled with path-finding algorithms for navigating autonomous agents [9].
Recent studies have delved into the specifics of pairwise avoidance during face-to-face encounters among pedestrians, leveraging trajectory data from uninstructed individuals [10–12]. These investigations have studied the deviations exhibited by pedestrians from their initially projected, undisturbed paths when coming into contact with others, examining both one-on-one and one-versus-many scenarios. The findings of these studies were compared with those of a Langevin-like physics model, revealing, for instance, that interactions involving multiple approaching pedestrians are more accurately characterized by the non-linear combination of short-range contact avoidance forces.
In order to improve our comprehension of the impact of groups on the broader crowd dynamics, it is also necessary to study the specifics of collision avoidance between groups and individuals. In particular, our recent works have revealed that collision avoidance between dyads and individuals is more pronounced when the dyad has a stronger social bond (e.g., couples or friends over colleagues, or engagement in a conversation) [13–15]. However, these conclusions were drawn based on an analysis that focused solely on the relative distance between the dyad and the individual. Therefore, this approach does not provide insight into the specific contributions of each party involved to the observed collision avoidance, since pedestrians do not necessarily follow the action-reaction principle of Physics [16]. It is plausible to assume that the dyads may become absorbed in their own social interaction, potentially making them less attentive to the pedestrians around them. As a result, individuals might need to be more proactive in avoiding collisions, either to compensate for this or due to adherence to a social norm. To put this hypothesis to the test, our study examines natural trajectories of uninstructed pedestrians.

2 Data and Methods

The data set used in this work is the DIAMOR data set [17]. It contains trajectories of uninstructed pedestrians recorded in an underground pedestrian street network of a commercial district of Osaka, in Japan. Trajectories are derived from depth information recorded using multiple laser ranger finders. The recording duration spans two weekdays for a total of eight hours of data, encompassing approximately 200 m^2 and allowing continuous tracking along a stretch of about 50 meters. The trajectories contain the position of each pedestrian and we compute the velocity by taking a first order derivative of the position.
Furthermore, video data was captured and employed for annotating social parameters.

Human coders were tasked with annotating both groups and individuals (those not affiliated with a group). These coders also marked whether or not dyad members were involved in interaction (verbal communication, potentially accompanied by non-verbal cues like gestures or eye contact, as defined by Knapp et al. [18]), as well as gauging the intensity of the interaction on a scale of four levels, ranging from 0, denoting no interaction, to 3, indicating strong interaction. Previous works using this data set [19] have generally focused on quantifying and modeling the impact of social interaction on the dynamics and spatial properties of social groups.

2.1 Data preparation

Given that the data is gathered in an ecological environment, the tracked trajectories may encompass various behaviors such as waiting or running which are not pertinent to this study. To filter out atypical or non-characteristic observations, each trajectory is processed in the following manner.

We focus particularly on two-person groups, i.e. dyads, since they are the most represented groups in the data set, and because they have been shown to generally have stable spatial structures [20]. Formally, let a dyad be defined as an unordered pair consisting of two members, denoted as p and q, i.e., $d = (p, q)$, and let i represent an individual. For simplification purposes, we condense a dyad to a single mobile agent during the data preparation phase. Specifically, the dyad's location is denoted by the center of mass of the group, while its velocity is represented by the dyad velocity $\mathbf{v_d}$. More precisely, $\mathbf{r_d}$ and $\mathbf{v_d}$ denote the average positions and velocities of p and q at each time step, respectively.

Consequently, we handle both a dyad d and an individual i in a similar manner, initially assessing the adequacy of the number of trajectory data points. If there are more than 8 seconds of observation, we deem the trajectories to possess a satisfactory amount of data for characterizing locomotion while trajectories with fewer samples are excluded.

Furthermore, due to our focus on studying collision avoidance behaviors, we require that the dyad and the individual approach sufficiently close to each other. Therefore, we only consider trajectories where the following condition is verified: $\exists t \mid d_{di}(t) \leq 4$ m, where t denotes time and d_{di} is the instantaneous distance. The choice of a 4 m threshold is motivated by previous research on collision avoidance. Cinelli and Patla discovered that the "safety zone", which is the area in which individuals allow a moving object to approach before initiating an avoidance behavior, averages around 3.73 meters [1]. Additionally, Kitazawa et al. demonstrated that pedestrians focus their gaze most intensely on other approaching individuals when they are, on average, approximately 3.97 meters away, rarely directing their attention to pedestrians at greater distances [21].

Lastly, as our focus centers on understanding how the social attributes of the dyad influence collision avoidance, it is crucial that the pedestrians involved have sufficient visual access to each other. Thus, we stipulate that the dyad and the individual must have a frontal view of each other, indicating that they are moving in opposing directions. In this arrangement, they will be able to observe the approaching party and discern its social characteristics.

To guarantee a frontal view, we determined the relative motion direction of d and i, only

considering those pairs that are moving in opposite directions. Let ϕ denote the angle between the velocity vectors $\mathbf{v_d}$ and $\mathbf{v_i}$ at a given moment, $\phi = \arccos \frac{(\mathbf{v_d} \cdot \mathbf{v_i})}{(||\mathbf{v_d}||||\mathbf{v_i}||)}$. Then, d and i are regarded as moving in opposite directions, if $3\pi/4 \leq \phi < \pi$.
It is possible that other pedestrians may be present in the vicinity of the dyad and the individual, potentially influencing their behavior but we do not filter these to avoid reducing the sample size. We argue that such effects are likely to be averaged out and that most of the deviation will be due to the actual encounter between the dyad and the individual.

2.2 Maximum lateral deviation

In a previous study [2], Huber et al. studied the adjustments of path and speed made by a pedestrian when crossing with a non-reacting interferer at varying angles. Although the present study differs in purpose and nature of data/experiments, we expect to find similar behaviors in real world data, with pedestrians deflecting laterally to avoid a collision.
In quantifying the level of such adjustments, Huber et al. define the "lateral deviation" from the planned path of pedestrians, when avoiding collision with an "interferer" (an instructed pedestrian walking on a straight path, intersecting with the subject's path). In particular, this deviation is defined as the maximum Euclidean distance between the points on the actual (i.e. observed) trajectory and the straight line passing through its initial and final points. Nonetheless, in real world trajectories, it can be expected that after deviation from their initial trajectory, pedestrians stay on the new lateral position rather than returning to their original position. This assumption is validated in the work of Corbetta et al. [10], where pedestrians are shown to maintain their lateral distance even after avoidance is ensured.
Consequently, we compute our "maximum lateral deviation" δ by measuring the maximum distance between the points on the trajectory during the encounter (i.e. when the dyad and the individuals are less than 4 m apart) and the line directed by the velocity of the individual (resp. dyad) at the beginning of the encounter, i.e. 4 m away from the incoming dyad (resp. individual) (see Fig. 1). We argue that this line constitutes a better approximation of the intended trajectory than the line going through the first and last point of the trajectory, since it does not make any assumptions on what happens after the avoidance phenomenon. To make the computation of this distance more robust against instantaneous fluctuations of the direction of the velocity vector of the pedestrian(s) that can arise from gait dynamics, we measure the velocity before the encounter by averaging the instantaneous velocities over 2 seconds.
It is important to note that the values for the dyads correspond to the average of the individual deviation of the dyad's members, i.e. $\delta_d = \frac{\delta_p + \delta_q}{2}$. Using the center of mass of the dyad, as defined and used in Sec. 2.1, to compute the deviation would result in artificially lower values, since it would tend to smooth the trajectories.

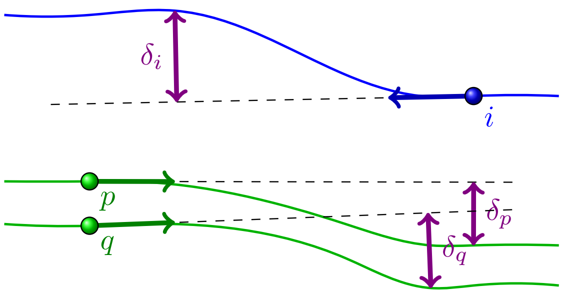

Figure 1 Illustration of the computation of the maximum lateral deviation δ for an encounter between a dyad $d = (p,q)$ and an individual i.

3 Results and Discussion

Table 1 Average maximum lateral deviation δ of individuals and dyads annotated with each intensity of interaction of the encountered dyad. p-value for the two-sample Welch's t-tests for the equality of means are also shown.

Intensity of interaction	# encounters	δ_i (mm)	δ_d (mm)	T-test p-value
0 (no interaction)	75	383 ± 236	382 ± 300	0.98
1	161	387 ± 287	326 ± 220	0.20
2	771	396 ± 305	334 ± 252	$< 10^{-3}$
3 (strong interaction)	208	450 ± 333	359 ± 250	$< 10^{-3}$
all	1215	403 ± 304	340 ± 251	$< 10^{-3}$

Tab. 1 shows the average maximum lateral deviation of individuals and dyads for various levels of intensity of interaction, as well as the average deviation for all individuals and dyads.

One first interesting result is that, based on the cumulated values, it is clear that individuals deviate more than dyads during frontal encounters. The statistical significance of the difference seen in lateral deviation values is demonstrated by the low p-value obtained from the two-sample Welch's t-tests for the equality of means ($< 10^{-3}$).

Moreover, it appears that this difference in deviation between individual and dyad depends on the intensity of interaction of the dyad. As a matter of fact, higher levels of interaction of the dyad (annotated as 2 and 3) are consistent with more significant deviations between individual and dyad (both p-values $< 10^{-3}$). On the other hand, for lower levels of interaction (0 and 1), the statistical significance is lost and the deviations present less pronounced disparities.

Finally, we observe that a higher level of interaction of the dyad is consistently associated with a stronger deviation of the individual. In other words, people tend to, perhaps unconsciously, give more space to incoming groups when they are strongly interacting. One may argue that individuals gauge their avoidance based on their expectation of how much the groups will act to avoid them, as previously modeled in [22]. Nevertheless, such relation could not be found for the dyad itself though, as the smaller deviations are found for the intermediate levels of interaction (1 and 2).

4 Conclusion and Limits

This study delved into the intricacies of frontal encounters between dyads and individuals, with a focus on quantifying each participant's role in collision avoidance based on their deviation from their intended path. By establishing the intended trajectory for each party, considering their pre-encounter walking direction, we identified the maximum lateral deviation as a key metric.

Unlike our previous works on the topic [13, 14], we did not limit ourselves to studying only relative distances but analyzed the position of each pedestrian involved in the collision avoidance, in the reference frame of the world. This decision was made to ensure that a direct comparison of the contributions of both parties to the collision avoidance dynamics was feasible. It also allowed for computing separate deviations for both members of the dyad to prevent any collateral smoothing resulting from using the center of mass of the group.

Our findings revealed a substantial discrepancy in deviation between group members and individuals during these encounters. Moreover, we conducted a thorough analysis of how the intensity of interaction among group members influences collision avoidance dynamics. Notably, the contrast in deviation between individuals and group members was most pronounced when the level of interaction within the dyad was high. Finally, our results demonstrated that higher levels of interaction between the members of the dyad led to more significant deviations in the trajectories of encountered individuals, but that no such relation could be found for the dyad itself.

This research underscores the pivotal role of social dynamics in shaping pedestrian behavior during face-to-face encounters, offering valuable insights for understanding and potentially improving collision avoidance strategies in various contexts, such as autonomous navigation and crowd management.

Nevertheless, there are certain limitations within the scope of this study. Firstly, we focused on encounter scenarios, but it would be valuable to contrast the deviations observed in these cases with a baseline of undisturbed situations, when neither dyads nor individuals are in proximity to any other pedestrian. Additionally, alternative metrics for quantifying the extent of deviation between the two parties could be explored. For instance, the straightness index, calculated as the ratio of the straight-line distance to the actual traveled distance, presents another viable option. Addressing these limitations will be a focal point in forthcoming works.

Acknowledgements This work was supported by the JSPS Grant-in-Aid for JSPS Fellows 22J-20686. This work was (in part) supported by JST Moonshot R and D under Grant Number JP-MJMS2011, Japan. This work was (in part) supported by JSPS Kakenhi Grant Number 23K11169.

Ethics Statement The experiment resulting in the acquisition of the DIAMOR data set has been reviewed and approved for studies involving human participants by the ATR ethics board.

Author Contributions Adrien Gregorj: Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Writing—original draft, Writing—review & editing / Zeynep Yücel: Conceptualization, Formal analysis, Data curation, Formal analysis, Methodology, Supervision, Writing—original draft, Writing—review & editing / Francesco Zanlungo: Conceptualization, Formal analysis, Methodology, Writing—original draft, Writing—review & editing, Project administration, Writing—review & editing / Takayuki Kanda: Funding acquisition, Project administration, Writing—review & editing.

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