Adapting the Social Force Model for Low Density Crowds in Open Environments

Manon Prédhumeau, Julie Dugdale, Anne Spalanzani

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Manon Prédhumeau[1,2,3][0000-0002-2003-1432], Julie Dugdale[1,3][0000-0002-9417-8701], and Anne Spalanzani[2,3][0000-0003-4813-4940]

[1] Laboratoire d'Informatique de Grenoble, LIG, Domaine Universitaire de Saint-Martin-d'Hères - BP 53 - 38041 Grenoble, France
[2] Institut National de Recherche en Informatique et Automatique, Inria, 655 Avenue de l'Europe, 38334 Saint Ismier, France
[3] Université Grenoble Alpes, 38400 Saint-Martin-d'Hères, France

Abstract. The Social Force Model (SFM) successfully reproduces many collective phenomena in evacuations or dense crowds. However, pedestrians behaviour is context dependent and the SFM has some limitations when simulating crowds in an open environment under normal conditions. Specifically, in an urban public square pedestrians tend to expand their personal space and try to avoid dense areas to reduce the risk of collision. Based on the SFM, the proposed model splits the perception of pedestrians into a large perception zone and a restricted frontal zone to which they pay more attention. Through their perceptions, the agents estimate the crowd density and dynamically adapt their personal space. Finally, the original social force is tuned to reflect pedestrians preference of avoiding dense areas by turning rather than slowing down as long as there is enough space. Simulation results show that in the considered context the proposed approach produces more realistic behaviours than the original SFM. The simulated crowd is less dense with the same number of pedestrians and less collisions occur, which better fits the observations of sparse crowds in an open place under normal conditions.

Keywords: Pedestrian dynamics · Multi-agent simulation · Crowd behaviour.

1 Introduction

To design pleasant cities in which to live, it is useful to model urban places that potentially involve crowds of pedestrians, such as public squares or large streets. To model pedestrian crowds, microscopic approaches use agents with behaviours defined at the individual level, allowing both a fine-scale and a larger scale study [1, 2]. These works very accurately reproduce individual movements and the emergent global behaviours caused by the interaction of agents, such as

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lane formation. Humans are social in nature, largely adhering to social norms. However, models that are based on particle flow dynamics do not adequately account for pedestrian social intelligence. The navigation of each pedestrian depends both on his own characteristics and on the surrounding pedestrians, who influence his trajectory. An interesting characteristic of crowds is that pedestrians interact with each other in a form of cooperation in order to avoid each other. Even in sparse crowds, interactions quickly become complex because each pedestrian interacts with many other people.

Multi-agent crowd simulation is one of the microscopic approaches that has been used. In existing models agents must move from one point to another, while avoiding collisions with other agents. It is in how to deal with these potential collisions that the models differ. Amongst others, cellular automatons, data-driven simulation, personality traits theory and geometric models based on velocity have been widely used to model pedestrian movements. In this article, we focus on one of the most famous crowd simulation techniques: the Social Force Model (SFM) by Helbing et al. [1]. This model uses physical forces to model local agent interactions. The forces represent the internal motivations of pedestrians to perform some actions. This model has been widely used to study very dense crowds or panic situations. It successfully reproduces many collective phenomena during evacuation. However, pedestrians adapt their behaviour to the situation and the SFM has some limitations when simulating pedestrian flows in open spaces under normal conditions. To simulate a sparse crowd (density < 0.3 p/m^2) in a large open area without panic behaviour where pedestrians are moving in an urban public square, adaptations are needed.

In this context, pedestrians tend to occupy the available space and seek to avoid dense areas in order to reduce the risk of collision [3, 4]. In this paper a modification of the SFM is proposed. The modification considers the visual perception of pedestrians; each pedestrian has a large perception zone and a restricted frontal zone to which they pay more attention. Using their perceptions, pedestrians estimate the density of their environment and dynamically adapt their personal space. Finally, the social force factors are tuned to reflect the perception and the assumption that in open spaces, pedestrians prefer to turn rather than slow down if there is enough space [3]. With these adaptations, the model better fits the characteristics of crowds in an open square place under normal conditions, as reported in the literature [3, 5–7]. The results show that in less dense crowds less collisions occur; this fits empirical observations in sparse crowds where rare bumping events are reported [8]. Moreover, our model is faster and provides a very simple way to vary the characteristics between agents.

This paper is organized as follows. In Section 2, the SFM and its prior adaptations are reviewed. In particular, the limitations of simulating sparse crowds in large open areas under normal conditions are addressed. Section 3 presents the proposed adaptations. Section 4 describes the simulation design, the scenarios and the criteria considered for the model evaluation. Section 5 describes the simulation results. Lastly, conclusions and future work are discussed in section 6.

2 Literature Review

2.1 The Social Force Model and its Adaptations

The SFM captures the motion of each pedestrian by Newtonian dynamics. In the original model, three forces describe the internal motivations of pedestrians. A desire force represents the agent's aspiration to move towards its destination. A repulsive force comes from other pedestrians (namely "social force") and from static obstacles so that the pedestrian can avoid them when they are too close. A third force models the attraction towards certain interest points (e.g. window displays). The resulting force applied to a pedestrian p is defined as:

$$\overrightarrow{F_p}(t) = \overrightarrow{F}_p^{des}(t) + \sum_{q \neq p}^{N_{ped}} \overrightarrow{F}_{pq}^{soc}(t) + \sum_b \overrightarrow{F}_{pb}^{repuls}(t) + \sum_k \overrightarrow{F}_{pk}^{attr}(t) + rand \qquad (1)$$

Where q represents another pedestrian among the total N_{ped} pedestrians in the scene. b is a wall or a static obstacle exercising a repulsive force toward p. k is an interest point for a pedestrian. $rand$ represents random variations that prevent the simulated agents from having a too rigid behaviour. Each force term is widely detailed in [1].

Some adaptations of the model that focus on specific contexts have been proposed. To match flow rates in very dense crowds, a respect area with a self-stopping mechanism has been added to prevent agents from continuously pushing over other agents [9]. A new force has been introduced to compute following behavior in pedestrian counter-flow situations [2]. In [10], anticipation has been added to the model by using predicted positions. The Headed Social Force Model considers pedestrians orientation into the dynamic model to prevent them from unrealistic movements [11].

Helbing et al. worked on several adaptations of their original model, for example simulating escape panic situations [12]. A new force models the physical force when a collision happens between two panicking pedestrians. This force prevents agents from physical overlapping when all other forces are very strong. The force combines a body force to represent the physical body and a sliding friction force to make colliding agents turn to opposite sides instead of pushing. The authors also worked on an unified model to represent normal and panic situations, with the addition of a nervousness parameter [5]. In [13], the authors proposed an interaction law from controlled experiments with pedestrians performing avoidance in a corridor.

2.2 The Reference Model and its Limitations

As pointed by Lakoba et al. [14], some SFM parameters can produce unrealistic behaviours if applied to a small number of pedestrians. They proposed modifications in order to avoid the following problems: unrealistic acceleration and deceleration; physical overlapping or too strong body force if a collision happens; social force independent of the density and of the pedestrians' orientation.

We reuse some of their ideas in the work described in this paper. Specifically the maximum acceleration was limited to 1.96 m/s^2 to fit with observations [15]. In addition a physical collision force was added in order to prevent overlapping pedestrians. In [12], the factors used for the body force and the sliding friction force are $k = 1.2 \times 10^5$ kg/s^2 and $\kappa = 2.4 \times 10^5$ kg/m/s respectively. These parameters make pedestrians very rigid and although this is suitable in the panic scenario, such values result in unrealistically high contact force in a sparse crowd. In [14], they reduced these parameters to $k = 2.4 \times 10^4$ kg/s^2 and $\kappa = 1$ kg/m/s. They validate their model with 100 pedestrians who have to exit a room by one door. In our context, these parameters are adapted as we do not want pedestrians to be projected during contact. After simulation tests, parameters values are set to $k = 12$ kg/s^2 and $\kappa = 24$ kg/m/s. The values were chosen by hand and can be refined with real data in future work. In real crowds, pedestrians simply rotate their shoulders in a shared effort to avoid the collision [16, 17].

Although most crowd models use a circle of 0.7 m diameter, it is more realistic to take into account the human form. The shoulder width and body depth of pedestrians follow uniform distributions respectively from 39 cm to 51.5 cm and from 23.5 cm to 32.5 cm [18]. These new shapes were used in the computation of social forces. Indeed, when walking through a crowd, pedestrians consider their own body size and the body size of other pedestrians to estimate the distance physically separating them. To calculate this physical distance, the distance between their positions was computed and the radius of each pedestrian ellipse was subtracted. Unlike a circle, the radius of an ellipse depends on the pedestrian's orientation angle. The following equation is used to find the radius of p, in interaction with a neighbour q:

$$r_p = \frac{\frac{w}{2} \times \frac{d}{2}}{\sqrt{(\frac{d}{2})^2 \times \sin^2(\alpha) + (\frac{w}{2})^2 \times \cos^2(\alpha)}} \tag{2}$$

with w and d the body width and depth of p and α the angle between p orientation and the direction from p position to q position.

The third problem identified by Lakoba et al. is that the social force is independent of the crowd density and the orientation of pedestrians. In the original SFM the selected parameters mean that the social force between pedestrians who are located only 50 cm away is very small, which is not realistic for a less dense crowd. In [14], the parameters are adapted to represent the fact that a pedestrian feels a greater social force from obstacles in front of him than from behind. Another approach to treat this issue is presented in section 3. We believe that as the crowd density increases, pedestrians are more willing to get closer to other pedestrians. Based on empirical observations from video data and on [3, 4], a second hypothesis is discussed: in sparse crowds, pedestrians are also more willing to turn rather than slow down as they approach a crowd. In brief, the base model used to build the adaptation presented in this paper is the SFM [13] including limiting acceleration plus a physical collision force to prevent overlapping [14] and an ellipse body shape.

3 The Proposed Adaptation

The baseline observation is that with the SFM, pedestrians in low crowd densities maintain very straight trajectories and many collisions occur, unlike in reality. The assumption behind this is that pedestrians slow down maintaining their trajectory rather than moving away, even if it means entering a dense area with a high risk of collision. However, our hypothesis is that in an open space, where pedestrians can spread out, they will tend to occupy the available space and seek to reduce density in order to reduce the collision risk [4]. To test this hypothesis, perception is added to pedestrians so they adapt their personal space to the crowd density and consequently modify their behaviour.

3.1 A Refined Perception

In the initial SFM, pedestrians perceive all other agents and the social force is lessened with the distance. To be more realistic, pedestrians were given a perception zone of 220°up to a distance of 7 meters [19], adding to a 360°1.5 meter wide zone. This represents the vision field of pedestrians, their auditory perception and the fact that they can rotate the head. Pedestrians do not pay the same attention level to all areas around them. Instead a lot of attention is paid to the "Information Process" zone [20]. Thus a finer zone is added in front of the pedestrians, called the attention zone, to which they pay more attention than the rest of the perception zone. This zone corresponds to a 90°4.5 meters wide zone plus a 360°1.5 meter wide zone. Therefore, pedestrians are more attentive to their close surroundings in their current direction (see Fig. 1).

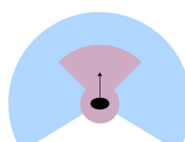


Fig. 1: Pedestrian perception zone in blue and attention zone in red

This new perception allows the pedestrians to differentiate between more important obstacles and the off-centered ones. In addition to increasing realism, by considering only the perceived neighbours the simulation time is reduced.

3.2 A Scalable Personal Space

Humans have a personal space corresponding to the region surrounding them which they regard as psychologically theirs [19]. As crowd density increases, pedestrians are more willing to approach other pedestrians. In this work using their perceptions, pedestrians estimate the density of the crowd and dynamically adapt their ellipse size, representing their body shape and their personal space. In a dense crowd, there is no margin around the agents, the ellipse is equal to the body shape. If a pedestrian passes a few centimetres from another pedestrian, there will be no feeling of intrusion. This is what is observed in heavily crowded situations where pedestrians are willing to forego their personal space and accept being close to other pedestrians, even strangers. On the contrary, in a dispersed crowd, the margin around the agent increases: if there is enough space, pedestrians will not normally brush against each other. The ellipse corresponds to the agent's body and its extended personal space.

The agents estimate the crowd density by using their perception zone as in section 1. The perception area is computed by taking into account the 220°zone up to a distance of 7 meters and the 360°zone of 1.5 meter wide. Each agent perceives 96.7 m^2. To determine the perceived crowd density, the number of agents currently present in this perception area, which corresponds to their neighbours, is calculated. The surrounding density in pedestrians per square meter is obtained by dividing the number of neighbours by the perceived area.

To define the size of the personal space according to the density, we use the concept of Level of Service (LoS) [21]. The LoS is a qualitative measure of the traffic service quality, defined from A to F. A corresponds to a free flow where no adaptation is needed to avoid collisions and F represents a very crowded space. The level values have been corrected many times and several versions exist depending on the considered configuration. In this paper the values defined in the Highway Capacity Manual (HCM) are used [6], for the walkways and sidewalks. The LoS A corresponds to a maximum density of 0.18 p/m^2, LoS B is a maximum density of 0.27 p/m^2, LoS C has a maximum density of 0.45 p/m^2, LoS D corresponds to a maximum density of 0.71 p/m^2 and LoS E has a maximum density of 1.33 p/m^2. The LoS defined for walkways was used since it considers mainly frontal collisions. A more accurate ranking could be done if the same information was available for large pedestrian streets or public squares.

It is assumed that a pedestrian's personal space is egg shaped, as people are more exigent in terms of respecting their frontal space [22]. To represent this, a combination of two ellipses is used: a small ellipse for the back, when the angle is greater than 90°from pedestrian orientation and a larger ellipse for the front.

A function was defined that uses density to obtain the three margins around the agent body that represents the agent's personal space (see Fig.2). The LoS was used to get a maximum personal space in LoS A, and a non existent personal space in LoS E and F. On each side of the pedestrian, a space is defined between 0 cm to 10 cm, as pedestrians do not need a lot of lateral space between each other to cross. The space behind the pedestrian is more important than the side space because pedestrians do not follow each other too closely in the street: the back space is set from 0 cm to 15 cm. The front space is the largest space and is set from 0 cm to 60 cm. The personal spaces of two interacting pedestrians is considered; if they are aligned laterally the space in between them is twice the individual lateral space, i.e. maximum 20 cm. These values are inspired from the experiment of [22] and can be calibrated with real data in future work.

The personal space margins are added to the body shape discussed in section 2.2. When an interaction happens, the agent will take into account its own size and personal space plus the other agent's size and personal space.

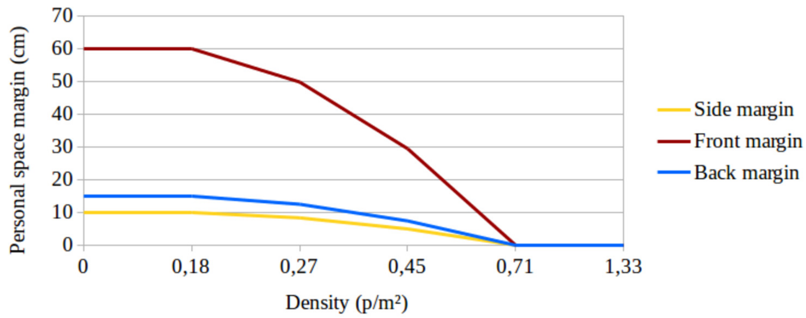


Fig. 2: Margins around the agent body as a function of density

3.3 A Revised Social Force

The reference SFM produces very straight trajectories while in real life dense crowds pedestrians adapt very quickly and slalom to follow the fastest path [9]. Indeed, pedestrians change their behaviour according to the density of others around them [3]. If the density increases, pedestrians walk faster and change their direction at a greater degree than with low flow. The social force factor is tuned to reflect the presence of the attention zone described in 3.1 and the hypothesis that in an open environment, pedestrians are more dynamic and likely to turn if there is space. When computing the social force with the perceived neighbours, the velocity factor is divided by 10 because the original velocity factor slows down pedestrians too much. To compensate, with the neighbours in the attention zone the angular factor is multiplied by 2 and the velocity factor is reduced by 2. This reflects the observations made in [3]. The force parameters were tuned by hand in the simulator over three scenarios and these values yielded the more realistic results. In future work they can be refined using real data.

4 Simulation and Experimentation

All experiments were run using Pedsim_ros [23], an open source crowd simulator that implements Helbing's SFM [13]. Some features were added to compare the SFM model in section 2.2 with the proposed approach in section 3. Except the adaptations presented above, all parameters used for the interaction law are the ones from [13]. The simulation time step is 0.04s and the desired velocity follows a normal distribution with $\mu = 1.34$ m/s and $\sigma^2 = 0.26$ m/s, which is the observed average walking speed [7]. The differences between the two compared models are summarized as follows. In the SFM, the agent size is simply the body size of the agent without any personal space. To compute social forces, a pedestrian considers all the other agents. In the proposed approach, the physical size of the agent plus its personal space, which varies according to the perceived density, are taken into account. Furthermore, to compute social forces, a pedestrian considers only its perceived neighbours and distinguishes between neighbours in the attention zone from more distant ones in order to adapt its avoidance behaviour. Algorithm 1 present an overview of the refined approach.

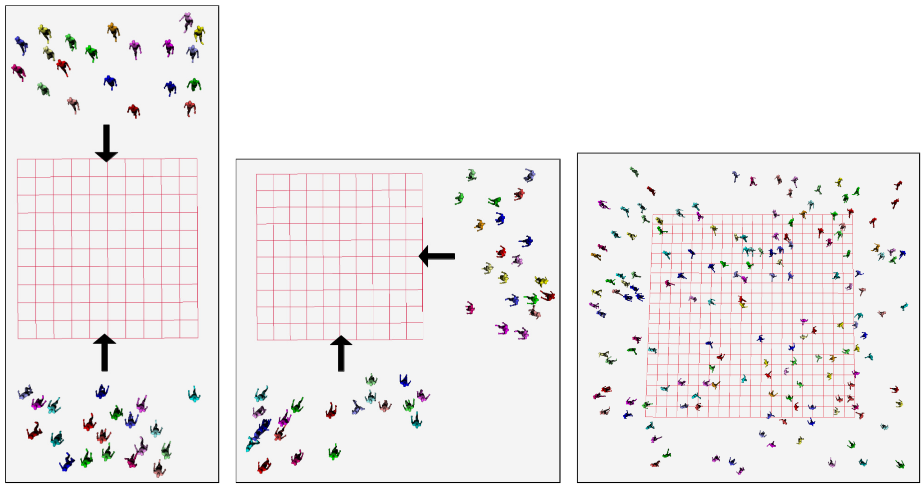
Algorithm 1: Overview algorithm

```
input  : agents: all agents in the simulation
begin
    for a in agents do
        Perceive neighbours in perception zone
        Compute perceived_density in perception zone
        Compute personal space p_space according to perceived_density
    end
    for a in agents do
        a.F_soc = null
        for n in a.neighbours do
            force = null
            Compute distance between a.p_space and n.p_space
            force = social force exerted by n on a
            if n in attention zone of a then
                force = force ×2
            end
            if a and n bodies overlap then
                force + = body force + sliding friction force
            end
            a.F_soc += force
        end
    end
end
```

Three scenarios are considered that occur in an open urban place (see Fig. 3): two crowd flows in a frontal crossing, two crowd flows in a perpendicular crossing and a more disorganized and realistic crowd with pedestrians crossing a big square place from different directions. For each scenario, we studied three densities which are common in public places or large pedestrian streets: very low density (LoS A), low density (LoS B) and moderate density (LoS C). For very low density, 10 pedestrians cross 10 others in the frontal and perpendicular scenarios and 80 pedestrians are present in the big crowd. For low density, 20 pedestrians cross 20 others in the frontal and perpendicular scenarios and 160 pedestrians form the big crowd. For moderate density, 30 pedestrians cross 30 others in the frontal and perpendicular scenarios and 240 pedestrians compose the big crowd. Each simulation case has been replicated 100 times in order to obtain the median results.

Experiments are conducted for a central zone of 10 m x 10 m for the first two scenarios and a zone of 20 m x 20 m for the third scenario. Thus only the interacting pedestrians are considered during crossing.

In each case, the number of collisions that happen in the central zone are counted for 10s, from 5s to 15s to let the agents reach the zone. A collision happens when the physical bodies of two agents touch each other. The density and the velocity in the central zone are averaged for 3s, between 5s and 8s, to let the agents reach the zone. Longer times are not measured because the fastest agents have already left the area and only the slow ones remain, which biases the measurement. In the case of the frontal crossing, the lateral spreading is also measured to check if the agents take up more space.



(a) Frontal crossing (b) Perpendicular crossing (c) Big crowd

Fig. 3: The three scenarios with low density at simulation time t = 0 s

5 Results and Discussion

Fig.4 shows the measured density for each scenario for both models at the same initial density, i.e. same number of pedestrians. For the frontal scenario (triangle markers) and the perpendicular scenario (square markers), the proposed model, represented by the lines in orange-red tones, produces less dense crowds than the SFM, shown in blue lines, regardless of the initial density.

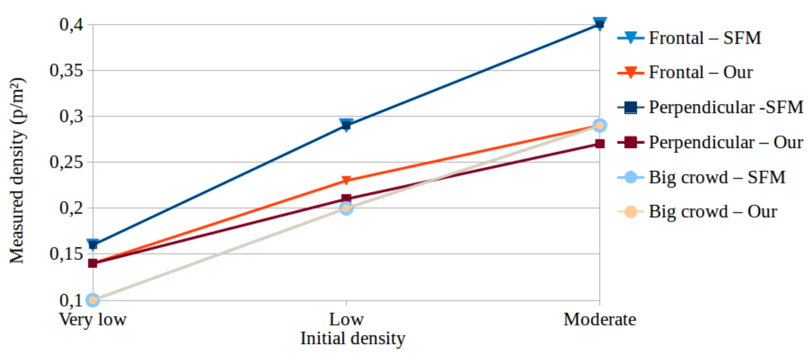


Fig. 4: Measured density depending on initial density, scenario and model

For the big crowd scenario, both models produce the same measured density, regardless of the initial density. The lower density produced by the proposed model can be explained by a better use of the available space. For the frontal scenario, for instance, the lateral spread is slightly larger with the proposed model than with the SFM. The lowest density obtained with the proposed model is realistic because pedestrians tend to spread out in a wide and open space [4].

We then studied how the number of collisions evolves with the measured density in the three scenarios for both models (see Fig.5). From the figure in the frontal and the big crowd scenarios, no collisions occur at very low density with both models. For low density, some collisions happen with SFM (median 5 collisions in 10s for frontal scenario and 3 collisions in 10s for big crowd scenario) while very few or no collisions happen with the proposed model. At moderate density, the number of collisions in the SFM becomes significant while in the proposed model it is low (5 collisions instead of 13 in the big crowd scenario and 4 collisions instead of 15 in the frontal scenario). In the frontal scenario, the proposed model gives a lower density than the SFM, which explains why with the same number of pedestrians the density does not exceed 0.3 p/m^2.

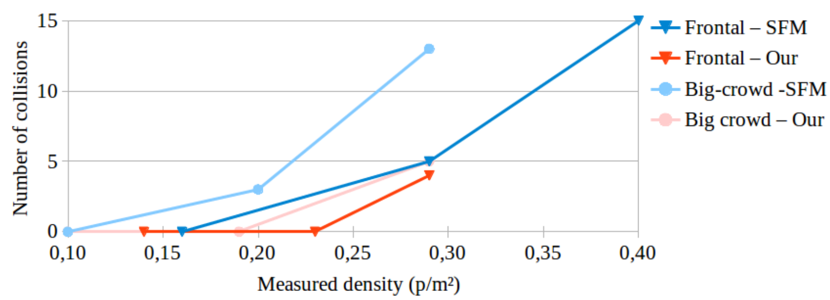


Fig. 5: Number of collisions in 10s depending on density, scenario and model

The perpendicular scenario is not presented because in both models and for all measured densities, no collisions appear in the median result. Nevertheless the proposed model introduces some rare collisions at moderate density of 0.27 p/m^2: on average, 2 collisions for 10s. Collisions are very rare in the perpendicular crossing scenario for two main reasons. Firstly, there is less body surface for a possible collision with a perpendicular crossing than with a frontal crossing. At a frontal crossing, pedestrians are facing each other and must avoid collisions by taking into account their, and the oncoming pedestrian's, shoulder width. At perpendicular crossings, some pedestrians are rotated 90 degrees and must avoid collisions by taking into account their shoulder width and the body depth of the arriving pedestrian. The width of the shoulders is greater than the depth of the body, which is a reason why collisions are easier to avoid in perpendicular crossing. The second reason is due to the way the social force is calculated between two pedestrians. If two pedestrians arrive perfectly ahead, they will slow down but continue to move forward and sometimes the social force to avoid the collision is triggered too late and the shoulders of the pedestrians touch. If two pedestrians cross perpendicularly, this model limit does not apply. This reflects what is observed in reality: it is more common and socially accepted that two pedestrians touch each other shoulder to shoulder during frontal crossing, rather than a perpendicular crossing collision (which would mean that a pedestrian touches the chest or back of another pedestrian with his shoulder). Indeed,"pedestrians hesitate to a greater extent to come into contact with other pedestrians at their chest than at their shoulders" [16].

For the frontal and the big crowd cases, the proposed model produces less collisions than the SFM for the same initial conditions and the same density. This confirms that the SFM is suitable for congested panic situations, where collisions frequently occur. Note that experimental data concerning the number of collisions in crowds was not found. However, it is reasonable to assume that pedestrians do not collide with each other in normal conditions at very low or low density crowds. Thus, the proposed model appears to perform better than the SFM. The rare collisions with the perpendicular scenario at moderate density could be verified if more collision data were available. A number of collisions greater than zero is acceptable because in dense conditions, some pedestrians may pass very close to each other or even touch. In reality, many collisions will be avoided by a slight rotation of the shoulders [16, 17].

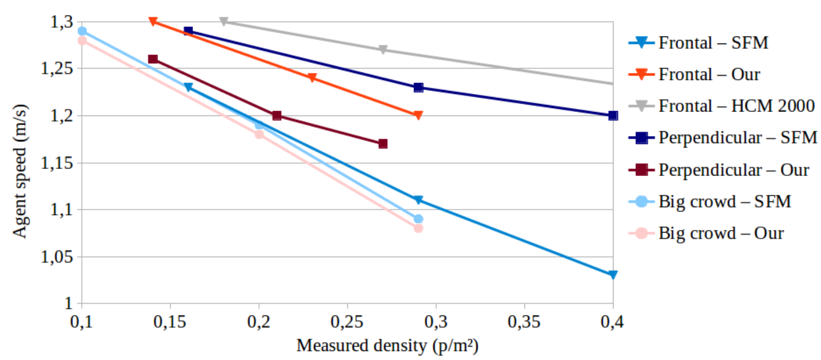


Fig. 6: Agents speed depending on measured density, scenario and model

The median speed of agents according to the measured density and the scenario was compared for the two models (see Fig.6). For the frontal scenario, the agents in the proposed model are faster than those using the SFM. Their speed better fits the pedestrian speed in the HCM 2000 [6] for walkways and sidewalks, where the interactions are frontal. For the perpendicular scenario, the proposed model produces slower pedestrians than with the SFM. This result requires further validation but is conceivable as it is harder to cross perpendicular flow than a parallel one, where the formed lines are easy to follow. In the big crowd scenario, the SFM and the proposed model show very similar speeds in all densities. This speed complies with the average walking speed in pedestrian zones [7].

A video showing the differences between the SFM and the proposed adaptation on the three scenarios is available [4]. At moderate density, lane formation is observed in the two models. In medium situations, some impatient pedestrians try to overtake others if they find a gap [5]. This phenomenon appears in the proposed model. It is important to notice that in the video the pedestrians sizes are not realistic since they all have the same size. This is why some collisions are not seen or collisions appear in the video and do not really happen in simulation.

Finally, a very positive point about the proposed model is that it results in faster simulations. The computational performance of both approaches were assessed on standard PC hardware (Intel Core i7-7920HQ, 4.10GHz). The big crowd scenario was simulated with 100, 200 and 500 pedestrians during 15 s. For 100 pedestrians, both models run in 15.02 s (i.e. close to real time). For 200 pedestrians, the SFM approach runs in 20.30 s while the proposed approach runs in 15.02 s. For 500 pedestrians, the SFM runs in 126.97 s while the proposed model runs in 66.51 s. This confirms that the SFM slows down quickly as the number of agents increases. The adapted model is faster since only the close neighbours are considered for the social forces. In the new model, the density has more influence on performance than the total number of agents.

6 Conclusion

This paper introduced a modified social force model to simulate a low density crowd (< 0.3 p/m^2) in an open environment under normal conditions, such as pedestrians moving in an urban public square. The modified model considers the pedestrians' perception, with a large zone and a restricted frontal zone to which they pay more attention. Through their perception, pedestrians estimate the crowd density and dynamically adapt their personal space. Finally, the social force is tuned to reflect pedestrians preference to avoid dense areas by turning rather than slowing down. Simulations were performed with scenarios with densities ranging from 0.1 p/m^2 to 0.4 p/m^2 in order to compare the number of collisions, the density, the velocity and the lateral spreading with the reference SFM and the proposed model. Simulation results show that the proposed model produces less dense crowds of more dynamic pedestrians with less collisions. This better fits the experimental observations for a crowd in open area with density under 0.3 p/m^2 [3–8]. Moreover, the proposed model is faster and provides a simple way to vary sizes, perception and attention levels among agents.

Although many works have analyzed people movements in corridors, pedestrian trajectories in open urban environment are needed to further calibrate the model parameters. The quantification of collisions will be complemented by other metrics, such as the evaluation of the simulation realism by human observers or a quantitative comparison with video sequences. Usually the simulated pedestrian flows go from a large place to a narrower street to study bottlenecks. The proposed model can be used to study the spreading of pedestrian flows from a street to a wider place.

[4] https://youtu.be/Rk2R76VFId8

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