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Towards a Socially Acceptable Collision Avoidance for a Mobile Robot Navigating Among Pedestrians Using a Pedestrian Model

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Abstract Safe navigation is a fundamental capability for robots that move among pedestrians. The traditional approach in robotics to attain such a capability has treated pedestrians as moving obstacles and provides algorithms that assure collision-free motion in the presence of such moving obstacles. In contrast, recent studies have focused on providing the robot not only collision-free motion but also a socially acceptable behavior by planning the robot's path to maintain a "social distance" from pedestrians and respect their personal space. Such a social behavior is perceived as natural by the pedestrians and thus provides them a comfortable feeling, even if it may be considered a decorative element from a strictly safety oriented perspective. In this work we develop a system that realizes human-like collision avoidance in a mobile robot. In order to achieve this goal, we use a pedestrian model from human science literature, a version of the popular Social Force Model that was specifically designed to reproduce conditions similar to those found in shopping malls and other pedestrians facilities. Our findings show that the proposed system, which we tested in 2-h field trials in a real world environment, not only is perceived as comfortable by pedestrians but also yields safer navigation than traditional collision-free methods, since it better fits the behavior of the other pedestrians in the crowd.

Keywords Safe navigation · Collision avoidance · Pedestrian modeling · Field experiments

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1 Introduction

Safe navigation for mobile robots remains a major research topic in robotics. Due to recent progress in fields such as localization techniques, robots are now much more capable of moving in real-world environments, enabling applications such as guiding people in museums [1,2] and supermarkets [3], or delivery to offices [4].

Collision avoidance with respect to humans is an essential element for safe navigation in human environments. The traditional approach to robot collision avoidance considers people as moving obstacles and applies collision-avoidance techniques. Various planning [5–8] and prediction [9–12] techniques have been developed, and robots are capable of planning their trajectories to avoid undesired physical contact with pedestrians.

However, we have experienced some difficulties when using traditional collision-avoidance methods in real-world environments. Figure 1 shows one of these troublesome circumstances, in which a pedestrian initially did not notice the robot, and, when he eventually saw it, was surprised and jumped aside to avoid it. In this setting the robot was correctly following a collision free trajectory, but its behavior was not perceived as safe by the pedestrian. This and similar potentially unsafe conditions, or better, conditions that convey a feeling of being unsafe to people, usually arose when pedestrians perceived the robot only when it was quite close to them. Even if they did not lead to any collision, they cause abrupt motions in pedestrians, that may be potentially dangerous.

In this paper we are going to pose, and test, the hypothesis that human-like collision-avoidance is indispensable to avoid these situations that are perceived as dangerous by pedestrians, and that, by causing sudden reactions, may be potentially unsafe. We will thus claim that human-like collision avoid-

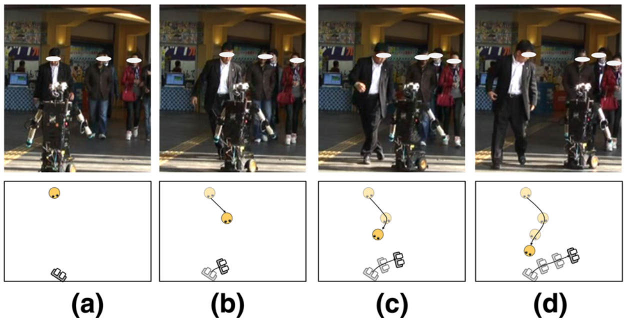

Fig. 1 The video frames and the illustrations show a real world situation in which using a traditional collision-avoidance method generated a possibly unsafe situation. **a** Initially, the pedestrian did not notice the robot. **b** then he unexpectedly found the robot in front of him and felt unsafe although the robot had already started to avoid him; **c** as a consequence the pedestrian quickly moved aside and **d** looked at the robot with surprise

ance is indispensable for robots to safely navigate among pedestrians, who expect other moving agents (pedestrians or robots) to follow given "social norms". An agent that does not respect such social norms, despite having a good planning capability for collision-free motion, would be perceived to behave unexpectedly and generate possibly unsafe behavior. While human behavior can involve complex cognitive processes, human science studies show that the resulting collision avoidance trajectories can be reproduced to a good extent using simple models in which each agent (i.e., pedestrian) only reactively avoids local collisions [13].

In this paper, we apply the pedestrian model introduced by [13], and briefly described in appendix, which was explicitly developed for relatively low-density situations like those occurring in a shopping mall, to achieve collision avoidance in a differential drive wheeled robot with a humanoid torso, navigating through a human environment. The merits of using the pedestrian model are twofold: first, since it is a model of human social behavior, it is likely to produce human-like motion in a robot and thus provide comfortable feelings to pedestrians in collision avoidance, as previous studies [14,15] have shown. Second, since the pedestrian model was developed to describe many-person settings, it can be easily applied to such situations, that were not tackled or resulted in expensive path planning computations in the previous attempts to develop socially acceptable navigation systems. On the other hand, the implementation of the pedestrian model on the robot is not straightforward due to the limited perception and locomotion capabilities of the machine with respect to the human ones.

After determining which parameters values should be used in the robot version of the model in order to obtain trajectories as similar as possible to the pedestrian ones, we explicitly verify that our system is perceived as safer than traditional avoidance methods. We first test it in single-person settings and ask to participants to rate its performance compared to a traditional avoidance method, and then operate it in a real world environment to test that it does not cause any potentially unsafe situation.

2 Related Work

2.1 Collision-Free Navigation

Collision-free navigation techniques have been extensively studied in robotics. A basic method is the dynamic window approach [5], whose extension and development have been widely researched. Stachniss and Burgard [6] integrated path-planning into collision avoidance, and Seder and Petrovic developed the time varying dynamic window (TVDW) method by considering moving obstacles [7]. While the dynamic window approach mainly takes into account a small neighboring area around the robot (usually a "stop distance" within which the robot can stop), other approaches, such as collision cones [8] and velocity obstacle [16], consider the motion of objects far from this neighboring area. Many techniques have also been developed to make planning computationally feasible, including the D-Lite algorithm [17].

Research efforts have also improved the prediction accuracy of people's future behavior. A basic method to predict future behavior is to perform a velocity-based linear projection [7,9] while other researchers have used a pedestrian model to predict people's future behavior more accurately in tracking [10]. These methods provide reasonable approximations for short-term behavior, but they are not reliable for long-term prediction; to overcome this limitation, some researchers have used statistical knowledge from a large amount of previously observed trajectories in the environment [11,12].

Another approach is to refer to a model of people's behavior for planning or prediction. Henry et al. [18] proposed a method to learn an effective planning of robot navigation in a crowded environment using a pedestrian crowd simulator, while Tamura et al. [19] used a pedestrian model to predict people's collision avoidance toward the robot, allowing the latter to better avoid pedestrians. Ratsamee et al. [20] realized a collision avoidance behavior that uses a pedestrian model taking also in consideration the body pose and face orientation of pedestrians.

Such planning and prediction techniques can provide collision-free trajectories to robots, but they do not necessarily generate a behavior that resembles people's collision-avoiding strategies and norms. On the contrary, the purpose of this study is not to use the pedestrian model as a prediction tool, but to explicitly introduce a human like collision avoidance behavior in the robot in order to make its navigation perceived as more natural and thus to avoid potentially unsafe situations.

2.2 Human-Like Social Behavior in Navigation

Following the seminal work of Hall [21] on human interactions, a few recent studies in robotics have reproduced human-like social behavior in human-robot interaction. Some of these works focused on the importance of proximity and reported, for example, that people try to maintain a 0.45–1.2 m distance when interacting with a robot [22,23], and a motion planning technique considering such psychological constraints has been developed [14]. Pacchierotti et al. [15] developed a robot that avoids intruding into the personal space of a walking person by starting to deviate from its path 6 m from the on-coming person to create space. Kirby et al. [24] proposed a constraint-optimizing method for person-acceptable navigation for a mobile robot, which considers personal space as a social convention. Pandey and Alami [25] have developed a framework towards a socially aware mobile robot by considering social conventions such as human proximity guidelines and clearance constraints. Qian et al. [26] have developed a framework for human-compliant robot navigation which considers a set of safety strategies to gurantee human physical safety and mental comfort.

From a different perspective, Lichtenthaler et al. [27] have focused on legibility and perceived safety in crossing situations and show the effectiveness of legible motion in providing impressions of safety. Rios-Martinez et al. [28] have developed a navigation method considering human comfort, by using a stochastic and adaptive optimization algorithm. Moreover, several learning approaches are proposed; Henry et al. have used inverse reinforcement learning to learn navigation behavior from a huge amount of example paths. They confirmed the effectiveness of the approach by using a realistic crowd flow simulator [18]. Also Luber et al. [29] take a learning approach by using paths of people in public space to realize socially-aware robot navigation.

However, these previous approaches suffer of two limitations. First, they address only single-person situations and are difficult to apply to interactions with many people, which are clearly the case in real-world settings. Second, it has not been investigated whether these human-like behaviors are indispensable for safe navigation, or if they are just decorative elements not required to safely deploying mobile robots in daily environments.

The present study addresses these two issues by using a pedestrian model that allows reproducing human-like behavior even in many-person settings, and by testing the proposed system in a real world environment to reveal whether such human-like behavior is indispensable for safe navigation, checking if its more natural behavior avoids generating sudden and potentially unsafe motions in pedestrians.

3 Using the Pedestrian Model for Socially Acceptable Collision Avoidance

3.1 Problem Definition

The purpose of this paper is: *To investigate the effect of the introduction of a human-like collision avoiding system for the deployment of a robot in a real world human pedestrian environment.* The proposed collision avoidance system has thus to be able to avoid the pedestrians in a way that is perceived as natural and safe by them. Furthermore, the system has to be stable enough to be deployed in safety in a real world environment, and the presence of the robot in such an environment has not to generate sudden and potentially dangerous motions in the surrounding pedestrians.

In order to accomplish this goal we need to:

1. *Calibrate a human-like collision avoidance model for our robot* based on the results of [13] we assume that the CP-SFM model (specified by Eqs. (1) and (3), see appendix) gives a good enough approximation of the pedestrians' avoidance strategy, at least for navigation in a shopping mall or similar environment. To account for specific interaction patterns with our robot, we perform experiments in which human subjects interact (avoid a collision) with our robot, and use the method of [13], as described in Sect. 1, to find the values of parameters A_r and B_r that, substituted in Eq. (3), better describe how pedestrians avoid our robot (Sect. 3.3). Our hypothesis for the implementation of an avoidance system considered as natural and safe by the pedestrians is to reproduce in the robot the same avoidance behavior that pedestrians had with respect to it in the calibration experiment. In order to do that, we will correct the parameters A_r and B_r to values A_{rc} and B_{rc} that account for limitations in the robot's motion (Sect. 3.4).
2. *Provide a safety system* we use the CP-SFM model to provide a collision avoidance felt as natural and safe by the pedestrians, but this method has not been developed to provide a safe navigation for a robot system in the sense discussed by [30]. For this reason we provide our method with a backup safety system using the well-known traditional planning method for safety of [7] (Sect. 3.5).
3. *Evaluate the perception that pedestrians have about the collision avoidance behavior of the robot* we perform controlled experiments with subjects to confirm that our system, which has been developed to behave *naturally*, i.e. in a human like manner, is well perceived by pedestrians. During the experiments we compare our method with an efficiency oriented one, and ask to the subjects to rate how *comfortable* their interaction with the robot was (more specifically, if they could walk keeping their preferred velocity, if they felt their path to be collision

free, and what was the overall evaluation of the robot's behavior; Sect. 4.1).
4. *Test that the robot can be safely deployed in a real environment* we conduct a field test to confirm that our robot may safely navigate a pedestrian environment; furthermore we compare it to a traditional avoidance method to test that it produces less sudden motions in the surrounding pedestrians (and thus less possibly unsafe situations; Sect. 4.2).

To accomplish tasks 1 and 2 we rely on previous contributions [7,13], that have nevertheless to be adapted to our system. Task 3 resembles the investigation performed by [15], while task 4 may be considered the main original contribution of our work. As described in Sect. 4.2, our main criterion for evaluating the safety of the robot system is to test that it may be deployed in the environment without disrupting the normal flow and behavior of surrounding pedestrians; see our discussion in Sect. 4.2 for a comparison with the usual meaning given to the term safety in robot navigation, as defined for example by [30].

Obviously this paper does not completely fulfill all the requirements for a safe and socially acceptable navigation system that may be used in a real world environment for practical applications, and in Sect. 5 we discuss the problems that have to be coped with before achieving such a goal.

3.2 Hardware

We used a 120-cm-tall, 60-cm-wide humanoid torso robot whose mobile base is a Pioneer 3-DX (Active Media), at a maximum velocity of 750 mm/s and a preferred velocity of 700 mm/s (the maximum acceleration is 600 mm/s^2). The pedestrian model needs information about people's positions far from the robot, which is not easy to collect using only the robot's on-board sensors. Thus, we used eight laser range finders and applied the human-tracking system described in [31].

3.3 Calibrating the Social Force toward the robot: H–R (Human–robot) Model

We specifically calibrated the pedestrian model on human-robot interaction with our robot to account for the potential differences in the collision-avoiding behavior between a pedestrian and the robot with respect to the inter-pedestrian interaction.

In the data collection experiments, performed in a shopping mall corridor, the robot moved straight toward a participant at 700 mm/s, and the participant walked toward the robot starting from a distance of 18 m. Participants were instructed to walk freely toward a goal located behind the robot, but were informed that the robot would not change its course to avoid collisions. Fourteen subjects participated to the experiments, each participant repeating the trial nine times. We used the genetic algorithm described in Sect. 1 to select the parameter values that maximize the similarity among the trajectories generated from the pedestrian model and those obtained in the data collection.

Calibration yielded parameter values $A_r = 0.62$, $B_r = 1.07$, which generate a collision avoidance behavior that does not qualitatively differ from the inter-human values of [13] ($A_h = 1.13$, $B_h = 0.71$), at least for the head-on encounter experiments that we performed to calibrate the robot. More in detail, since $A_h > A_r$, the maximum interaction intensity is lower towards robots, but since $B_r > B_h$ the interaction range with robots is wider. It is nevertheless important to notice that for the head-on experiments, the interaction distance d'_{ij} of Eq. (3) is typically in the order of $\approx$ 1 meter, for which the (A_h, B_h) and (A_r, B_r) parameters yield very similar values. We may thus assume that the behavior of pedestrians with respect to our robot is basically equivalent to the inter-pedestrian one, even if we refer to Sect. 5 for a discussion of the limitations concerning the use of only head-on encounters for calibration.

3.4 Calibrating the Force Taking into Account Locomotion Capabilities

In our study, position information is provided by the environmental human-tracking system [31], while the robot controller (Fig. 2) converts the output of Eq. (3) into velocity commands to navigate the robot. Namely, the pedestrian model outputs the effect of the social forces as an update in the Cartesian velocity (v_x, v_y), and the controller translates it into a polar coordinates velocity command (v_p, ω_p) to be implemented in the wheeled locomotion used in our robot. To compute the target velocity, the system should ideally use the H–R parameter values in Eq. (3) However, the robot's motion capability is limited by its hardware (e.g., slow acceleration and inability to move aside by being a differential drive robot), while limitations and delays in the perception system may affect the computation of the interac-

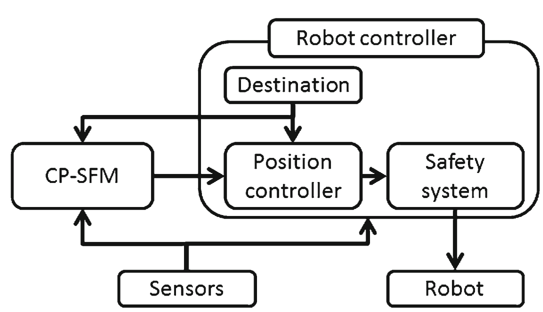

Fig. 2 Overview of our framework

tion forces. For these reasons a straightforward application of Eq. (3) with the H–R parameters $(A_r,\ B_r)$ by the robot controller may result in real robot trajectories quite different from those that would result from a numerical integration of the equation using $A_r,\ B_r$ (we will refer to this latter trajectory as the "ideal trajectory", meaning the trajectory that the robot should ideally follow in order to resemble the behavior of pedestrians in the experiment of Sect. 3.3).

To compensate this difference, we further calibrated the values of the pedestrian model parameters to obtain in the real robot system a trajectory as similar as possible to the "ideal" one. In order to do that, we numerically computed a few trajectories in different settings using the "ideal" H–R model (Eq. 3) and fixed the parameter values used by the robot controller so that the motion of the real robot was as close as possible to the ideal one. As a result, we found that both the intensity and range of the social force for the real robot should increase to $A_{rc} = 0.93$, $B_{rc} = 1.61$ (robot controller parameters), which are 1.5 times larger than the original H–R model parameters, in order to reproduce as faithfully as possible the ideal trajectories in the real robot system.

3.5 Safety System

The collision avoidance system described by Eqs. (1) and (3) has not been designed to be safe in the sense discussed in [30]. While the system described by the equations is arguably collision free in the pedestrian density of interest for the scope of this work, this is true for the noiseless "ideal" trajectories, and could fail when implemented in a robot with specific motion and sensor limitations. Furthermore, the model has not been designed to deal with pedestrians whose behavior is very far from the norm (for example, very low attention levels, or possibly dangerous curiosity driven approaches to the robot). For these reasons we introduced in our system a backup safety check.

In detail, the polar coordinate $(v_p,\ \omega_p)$ velocity command computed by the robot controller is examined using a safety-check mechanism. We implemented this safety system using the TVDW method [7], whose window time was set to 1.5 s, a time interval long enough to stop our robot. For the safety implementation, the pedestrian future positions were projected using their average velocity from the previous 0.5 s. These parameters were chosen on the basis of the maximum acceleration and velocity of the robot, along with the precision of the tracking system. In detail, since the maximum velocity of the robot is 750 mm/s, and the acceleration is 600 mm/s^2, the robot can stop in 1.5 s even if a 200 ms delay occurs. We also empirically verified that a 500 ms average over the velocity output of the tracking system provides the best information about the pedestrian velocity, by filtering out noise.

The TVDW method uses the robot's and pedestrians current velocities to project their positions in the future and computes a safe but maximally efficient path for the robot. It does not include notions of "socially acceptable distance" like those investigated by [15], so in a head-on approach like those of Sects. 3.3 and 4.1 it will have a tendency to deviate later and less than our method (or not to deviate at all, if the pedestrian avoids the robot in advance). As a result we may expect, in normal conditions, the safety system to have very little or no effect on the robot's motion.

4 Evaluation

We conducted two different evaluation tests, in which we compared the proposed method with the efficiency oriented one of [7], which was implemented using the same parameters of the safety system described in 3.5.

1. *Evaluate the perception that pedestrians have about the collision avoidance behavior of the robot*: we use a controlled experiment with head-on collision setting, in which the subjects are asked to rate the collision avoidance behavior of the robot. The purpose of this experiment is to test and evaluate our system in a simple scenario before deploying the robot in an uncontrolled real world environment, and also to reproduce the results found by [15] while using a rule-based model under a similar single person controlled setting (the main difference between our scenario and theirs is that in our work also the controlled experiments with subjects were performed in a real world environment, and not in the laboratory).
2. *Test that the robot can be safely deployed in an uncontrolled real environment*: we conduct a field test to confirm that our robot may be operated in a real world environment without disturbing the natural flow of pedestrians. In the scope of this experiment, our definition of safety diverges from the one of [30]; we are interested to check the occurrence of situations in which the robot causes sudden and possibly dangerous movements in the surrounding pedestrians.

4.1 Evaluation of Comfortable Feeling

4.1.1 Method

The evaluation was conducted in the same shopping mall corridor used for data collection. Participants freely walked toward a goal, while a robot moved from that goal toward the point from which the participant started walking, i.e. the robot and pedestrian had to avoid each other to reach their target. Participants started walking at a 18 m distance from the robot.

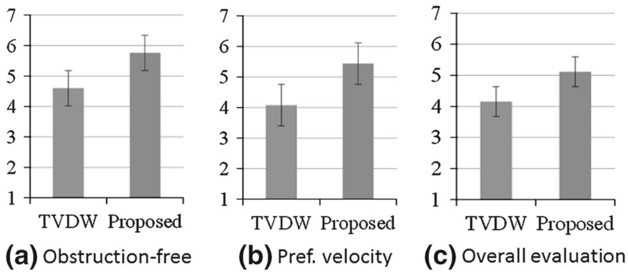

Fig. 3 Impressions from participants

The experiment was conducted as a within-subjects design, and the order of the sessions was counter-balanced. 25 Japanese subjects participated in the experiment (14 females and 11 males, average age 23.1 years with S.D. 5.6 years) and filled out a questionnaire for each session after reaching the goal. In the questionnaire participants graded their impressions of the behavior of the robot towards them on a 1-to-7 point scale, where 7 stands for the most positive, 4 is neutral, and 1 is the most negative impression, based on the following criteria: 1) obstruction-free, 2) their own ability to maintain their preferred velocity, and 3) overall evaluation.

4.1.2 Result

Under the TVDW condition, the average speed of the robot was 0.65 m/s and the one of the pedestrians was 1.17 m/s. The average minimum distance between the robot and pedestrians was 0.76 m. Under the proposed condition, the average speed of the robot was 0.65 m/s and the pedestrian velocity was 1.16 m/s, while the average minimum distance between the robot and pedestrians increased to 0.87 m.

Figure 3 shows the questionnaire results. We conducted a pair-wise t-test for each item of the questionnaire. There were significant differences between the impression of the pedestrians when interacting with the robot using the proposed method or with TVDW; in detail, for obstruction-free we have ($t(25) = 3.231$, $p = .004$, $r = 0.54$), regarding whether they were able to walk at their preferred velocity we have ($t(25) = 3.180$, $p = .004$, $r = 0.54$), and for overall evaluation ($t(25) = 2.964$, $p = .007$, $r = 0.51$). The results suggest that the pedestrian model was fit to the participants' natural way of walking and allowed them to walk at their preferred velocity, and for these reasons they perceived the robot as obstruction-free.

Figures 4 and 5 show the average robot and participant trajectories during the collision-avoiding experiment. The robot started moving from the left side, and the participant started from the right side. Under the proposed method condition, the robot started deviating from its straight trajectory after four seconds, i.e., at a distance of approx. 8 m from the pedestrian, a value in agreement with the one reported in [15]. On the

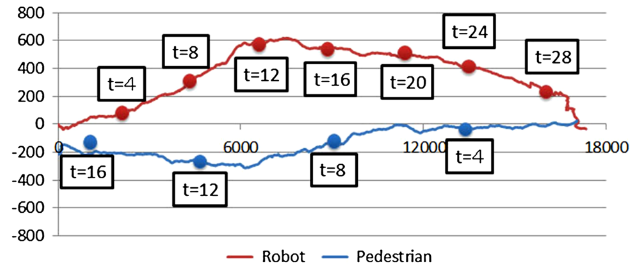

Fig. 4 Average trajectories under the proposed method

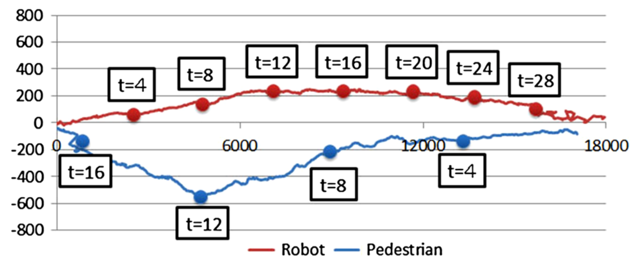

Fig. 5 Average trajectories under the TVDW method

other hand, under the TVDW condition, the robot's collision-avoiding behavior occurred much later: after $t = 8$ s, neither the robot nor the pedestrian had deviated from their straight path. Under this condition the pedestrian deviated more strongly from the straight path (at $t = 12$ s), and the robot's collision-avoiding behavior was reduced.

An analysis of these average trajectories suggests that while under the TVDW condition the collision avoiding load was mainly on the pedestrian, that clearly felt the robot's avoiding behavior to be too reduced or too delayed, under the proposed method the collision avoidance load was mainly on the robot. As a result, as shown by the results of Fig. 3, the pedestrians felt obstruction-free and could walk with their own preferred velocity. The method of [13] is intended to take in account the reciprocity in collision avoiding when calibrated on pedestrian-pedestrian interactions (see also [32] about the importance of reciprocity). Nevertheless, our calibration process on single person human-robot interaction seems to have led to an anticipation of the collision avoidance behavior on the robot's part, which is well perceived by the pedestrians. The evaluation of Sect. 4.2 will show that our robot does not "over-avoid" the pedestrians and can be stably deployed in a multi-person real world environment.

4.2 Field Test of Safety in Navigation

4.2.1 Method

This evaluation was conducted as a field trial in a shopping mall, and thus the robot did not interact with instructed subject, but with uninstructed pedestrians of a real world crowd.

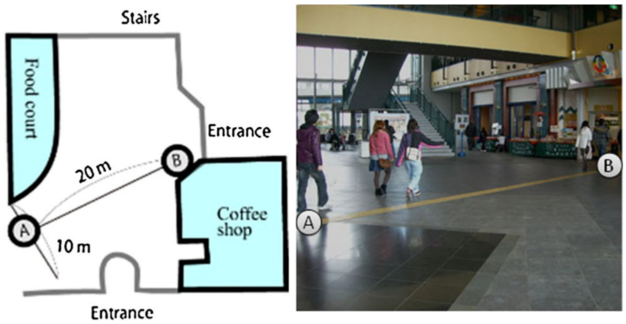

Fig. 6 Map and image of the field trial site

Fig. 7 Safe behavior under the proposed method

The robot was placed in a 10×20 m area of a large corridor (Fig. 6) bordered on both sides by restaurants and a variety of shops. The visitors were mainly families, couples, and sightseers, all of whom could freely walk down the corridor. The robot was autonomous in the experiments except for the start signal sent by an operator to trigger it to move. After sending the signal, the robot started to move from points A/B to B/A fully autonomously. We defined a single movement from these points as one trial.

Our aim was to reveal whether the robot could navigate in a socially acceptable way in a real-world environment, without disrupting the normal flow of the crowd by causing abrupt motions in the surrounding pedestrians. For simplicity sake's we name such situations as "unsafe", even if this is not the usual meaning assigned to this term in robot navigation [30]. We video recorded the scene of the field trial, and we relied on two coders to understand if the robot was causing any "unsafe situation". In detail, for each human robot "encounter", i.e. for each person who passed within 5 m from the robot, we determined whether the robot's behavior was safe for the pedestrian using the following criterion:

– The robot behavior was judged $unsafe$ if the pedestrians appeared to feel themselves to be in an unsafe situation, e.g., about to collide with the robot, and quickly changed their walking speed and/or moving direction (e.g., jumped aside) to avoid the robot;
– Otherwise, the robot's behavior was coded as $safe$.

Figure 8 shows an example of unsafe behavior.

4.2.2 Result

In the evaluation, we conducted a 2-h test for each condition, each test consisting of 27 trials. Under the TVDW condition, there were 168 encounters, i.e. 168 visitors walked within 5 m from the robot, while under the proposed method condition, there were 160 such encounters. Two coders classified the interactions between all 328 visitors and the robot as safe or unsafe by observing the recorded videos. Cohen's kappa coefficient was 0.89, indicating that their observations were highly consistent. Moreover, for consistent analysis, they discussed and reached a consensus on all the observed situations.

As a result, six behaviors over 168, i.e., 3.6% of the encounters, were coded as unsafe under the TVDW condition, but no unsafe behavior was found when using the proposed method. A χ^2 test revealed significant differences in the ratio of the occurrence of unsafe behaviors ($\chi^2(1) = 5.821,\ p = .030$).

The experiment results revealed that the robot using the proposed method is perceived as safer than the alternative method, suggesting that when using the pedestrian model the robot moves similar to humans and gives the impression of performing socially acceptable collision-avoiding. As a result the proposed method does not disrupt the normal flow of the crowd by causing sudden motions in the surrounding pedestrians. This consideration is supported by the observation of some scenes in which pedestrians and the robot collaboratively avoided collisions (Fig. 7). In this scene, the robot approaching two pedestrians starts to change its moving direction a few seconds before reaching the contact distance; at the same time the robot does not deviate very strongly from its trajectory, but does it in such a way that the collision is smoothly avoided through the collaboration of the two pedestrians, who deviate from their trajectories in a similar way. Such a behavior (anticipating the collision-avoiding behavior in order not to surprise the opponent, and enhancing collaboration from other pedestrians) is an example of socially acceptable avoidance behavior. This "social norm" was not explicitly introduced in the pedestrian model, but was implicitly coded in the parameter values through the learning process based on human trajectories.

In contrast, the unsafe behaviors generated by the TVDW method appear to reflect the lack of any attempt to reproduce such a socially acceptable behavior. This method plans a trajectory that is assured not to collide with pedestrians by assuming them to be moving obstacles with constant velocity, an assumption that results to be strong enough to provide collision-free navigation. As expected, this method never caused collisions and was coded as "safe" (accord-

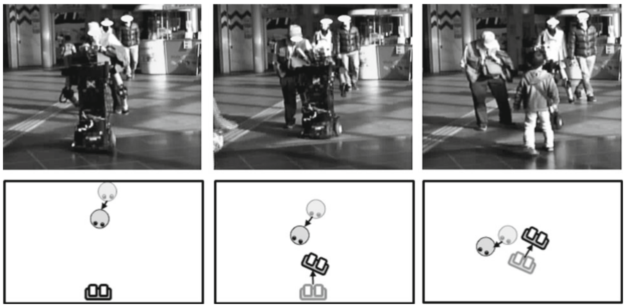

Fig. 8 Unsafe behavior under the TVDW method

ing to the meaning given to this term in this section) in the large majority of the encounters (96.4 %) during the experiment. However, despite being collision free, the robot was sometimes perceived as unsafe by the pedestrians, since it might not correspond to the expected "social norm". Figure 8 shows a scene coded as unsafe. Here the pedestrian started to slightly deviate from his course before getting close to the robot (Fig. 8-left). The robot waited to avoid the pedestrian until reaching a close distance, where it stopped and started to turn right (Fig. 8-middle). This behavior was felt as unsafe by the pedestrian, who probably expected the robot to start to deviate much earlier and more smoothly. The pedestrian eventually almost jumped aside to avoid the robot (Fig. 8-right). The occurrence of such a possibly unsafe situation suggests that the robot's behavior was not socially acceptable.

We further analyzed how the robot behaved in more crowded situations. Figure 9 shows a scene in which the proposed method successfully navigated the robot in a many-people setting. The robot was initially heading toward a group of people, which yielded a social force strong enough to make the robot turn right to avoid all of them. After avoiding the first group, the robot again changed its moving direction to successfully avoid a second group. This example illustrates that the proposed method reproduces human-like collision avoidance even in many-people settings.

In contrast, the TVDW method generated awkward situations in multi-people settings. Figure 10 shows a situation in which the robot controlled by the TVDW method headed toward a group of pedestrians. It passed through the group, since the pedestrians yielded before the robot started to change its motion to avoid them. The members of the group had to part to allow the robot to pass, a situation that is seldom observed in inter-pedestrian interaction. The collision-free computation of the TVDW method was performed correctly in this situation, since at the moment the pedestrians parted to avoid the robot, the latter had still plenty of time to modify its trajectory to avoid the collision. Nevertheless this collision-avoiding behavior occurred too late to be perceived as acceptable by the pedestrians.

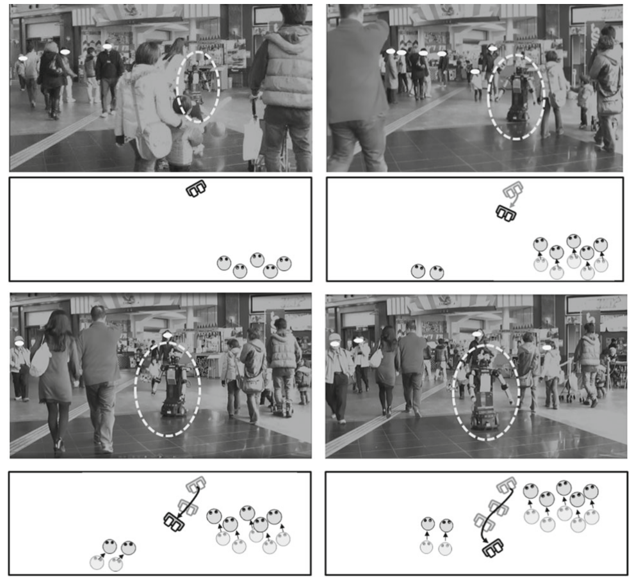

Fig. 9 Video frames and illustration of a situation in which the robot safely navigated through a crowd using the proposed method

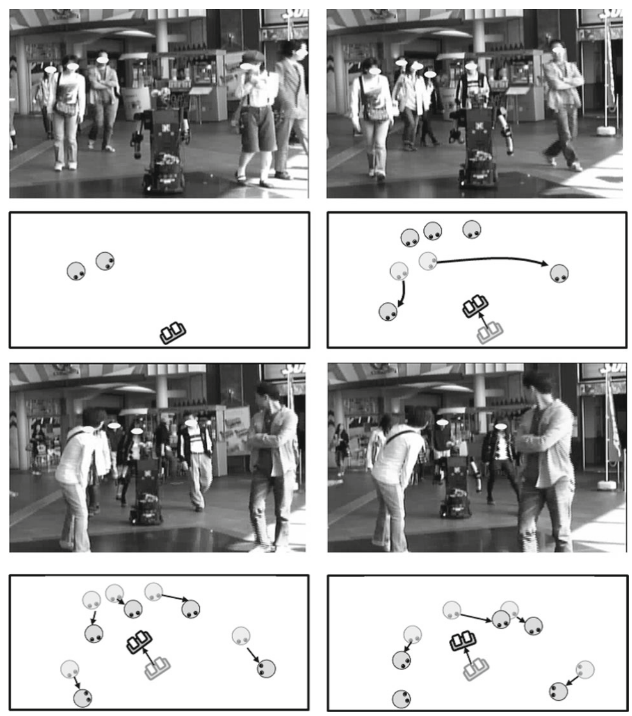

Fig. 10 Video frames and illustration of a situation in which some pedestrians had to part to avoid the robot using the TVDW method

5 Discussion

5.1 Alternative Methods for Safe Navigation

In this research work, in order to attain a safe collision-avoidance movement for the robot, we used a pedestrian model as a compact method to reproduce human-like and thus socially acceptable collision avoidance behavior for a robot deployed in a pedestrian crowd. A similar result could probably be reproduced using different methods as, for example, a motion planning method with constraints about social distance or personal space. We nevertheless stress that introducing the concept of social space in a motion planner, even if done in accordance with social studies, does not imply necessarily realistic behavior in a multi-person setting. Concepts as social distance are usually introduced for two people situations and very often for static settings. Thus the introduction of these concepts in a motion planner has to be performed with a calibration on real pedestrian trajectories, which may be a non-trivial process.

We believe that using a pedestrian model calibrated on actual pedestrian behavior is a relatively easy way to effectively reproduce human-like collision-avoidance in the robot. Since the pedestrian model uses simple equations to calculate the social forces to represent human-like collision-avoidance movements, it is not only simple to implement and efficient from a computational point of view but also more stable to environmental changes than traditional approaches that use relatively complex equations. As written above, the pedestrian model calculates the social force based on collision predictions (CP) with regards to people. Therefore, it is robust to changes of the density in the environment, while a traditional approach for safe navigation might need fine tuning of many parameters to be used at different densities. Some previous studies required explicit learning about the environment to be able to predict people's future behavior, e.g., where people would go and how they would walk [33–35]. Since our method only performs a simple velocity-based prediction, it does not require previous knowledge or learning of the environment properties. Based these considerations, we think that using a pedestrian model as the one proposed in this work is an appropriate way to attain human like collision avoidance for a robot moving in pedestrian facilities.

5.2 Future Work

This work deals with socially acceptable collision avoidance with respect to pedestrians in a possibly dense but open environment. In order to safely navigate the robot in a pedestrian facility, all the aspects of navigation have to be developed, such as global path planning, and collision avoidance with respect to non-human obstacles of different size and velocity. Others issues could be investigated and represent possible future research topics:

1. *Pedestrian social norms* In this paper we coped with the development of a socially acceptable navigation system for a mobile robot, but our approach was based on the analysis of dynamical features of pedestrian trajectories, under the assumption that in a collision avoidance maneuver the behavior of the involved pedestrians is completely symmetrical. Nevertheless human behavior is more complex, due to the presence of a few social norms. For example pedestrians are known to have a culturally dependent tendency to walk on the left or right side of a corridor [36], which seems to be connected to a bias in collision avoidance [37]; there are usually some social priorities involved in deciding who has to give the way [38]; furthermore social groups are an important component of pedestrian crowds [39], and the correct behavior with respect to this groups has to be taken in consideration, and introduced in the pedestrian model. Recently, Zanlungo et al. [40] have reported that Japanese pedestrians have a tendency to avoid on the left and overtake on the right, with effects on the density and velocity distributions, and extended the CP model in such a way to cope with this social norm. The same authors introduced also a SFM based description of the behavior of small social pedestrian groups [41].
2. *HRI model* The pedestrian model used in this paper only considers people's goal-directed and collision-avoiding behaviors, while ignoring other social activities that humans may perform in pedestrian facilities. Thus, any pedestrian behavior that goes beyond the model would break the assumptions under which our system works. A case of particular interest for robot studies regards those pedestrians that actively approach the robot to interact with it. Such human-robot interaction behavior is not modeled in this study. We consider that, for safe navigation, developing such a model is not mandatory, since people who intentionally approach the robot are obviously aware of its presence, and thus we may expect that they do not behave dangerously from a navigation point of view. Nevertheless the development of a model of these people's behavior will be indispensable when actually deploying a robot to provide services in a pedestrian environment.
3. *Evaluation* The current paper bases its evaluation criteria entirely on subjective metrics (questionnaires, coders). Other works ([42,43]) use more quantitative criteria to evaluate the easiness of walking of pedestrians, criteria that could be introduced in the evaluation of a "socially acceptable" pedestrian system as the one proposed in this work.

5.3 Limitations

Finally, we may discuss some limitations of our approach, whose solution may also be the subject of future research work

1. *The learning set* Even if we assume that Eq. (3) correctly describes human-like behavior, we need a good learning

set of pedestrian trajectories around the robot in order to use the method of [13], or an equivalent learning algorithm, to extract the correct interaction force function (i.e., parameters A_r, B_r). The trajectories of our controlled experiments in Sect. 3.3 are far from fulfilling the definition of a large enough learning set (the robot was interacting with a single pedestrian, the pedestrian was always coming from an head-on direction, and the robot was moving straight, i.e. it was not interacting). Designing multi-person setting experiments as those used for inter-pedestrian model calibration in [13] is not trivial, due to the robot motion limitation with respect to the pedestrians, and to the problem of defining the robot's avoidance behavior during the experiments (since in principle such a behavior has to be determined by the same experiments). One solution could be to deploy the robot using the collision avoidance parameters obtained in this work in a shopping mall, and use the trajectories of the pedestrians around the robot as a learning set, even if this approach implies the use of a very high quality tracker in a real world setting.

2. *Calibration to different robots* The parameters for the robot collision avoiding system that we obtained in this work were determined through experiments involving a particular robot model interacting with Japanese people. Since evidence suggests that people maintain different distances depending on the robot's appearance [44] and cultural factors [36], the method might need to be recalibrated before being applied to different robots and cultures. For example, in our experiments of Sect. 3.3, pedestrians avoided the robot in a way similar to the one with which they avoid other pedestrians; such a behavior is surely influenced by the fact that our robot's size is similar to the human size, and probably also by the robot's reduced velocity.
3. *Environmental sensors* For this work we relied on environmental sensors for tracking the pedestrians around the robot. We believe that our system can be used also with only on-board sensors, but it has to be expected that the capability of tracking surrounding pedestrians would be reduced. It is not easy, using just theoretical arguments, to predict the range of usage, in terms of pedestrian densities, of the on-board system, and how it compares to the environmental sensors one, but it has to be expected that the former one will be more limited. Such a question has to be assessed in order to develop a completely autonomous navigation system.

6 Conclusion

This paper reports a system for safe and comfortable collision avoidance toward people by a mobile robot using a pedestrian model. We used a particular specification of the Social Force model, CP-SFM, which has been explicitly developed for such low-density settings as those normally found in a shopping mall corridor, to reproduce human-like collision-avoidance behavior in robots. We first tested the developed robot in a single-person setting to confirm that it provides a comfortable feeling to pedestrians. The results suggest that a robot using the proposed method is significantly more socially acceptable than one using an alternative traditional method. Second, we conducted a field experiment in a shopping mall corridor to investigate whether the robot could navigate safely among pedestrians. The results revealed that our method enables safer navigation without causing any possibly unsafe abrupt movements in the surrounding pedestrians during a 2-h trial.

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Appendix: Background Work: Collision Prediction Social Force Model

Model Definition

Models of pedestrian collision-avoidance have been developed since the 50 s to deepen understanding of crowd dynamics and design better facilities. The Social Force Model (SFM) [45] is a popular pedestrian model that describes the behavior of pedestrians in a crowd through reaction forces inspired by physics. More than a single model, SFM may be considered as a framework in which the acceleration of a pedestrian i is given by

$$\frac{d\boldsymbol{v}_i(t)}{dt} = \frac{\boldsymbol{v}_i^0 - \boldsymbol{v}_i(t)}{\tau} + \sum_{j \neq i} \boldsymbol{f}_{i,j}(t). \tag{1}$$

Here $\boldsymbol{v}_i(t)$ is the pedestrian velocity at time t, $\boldsymbol{v}_i^0$ is the pedestrian's preferred velocity, a vector directed towards the current pedestrian sub-goal and whose magnitude corresponds to the velocity the pedestrian is more comfortable walking at, while τ is the relaxation time to recover the preferred velocity (0.66 s^{-1} in [13]). The actual avoidance behavior is determined by the interaction term with the other pedestrians j in the environment, $\boldsymbol{f}_{i,j}$, whose precise form determines the *SFM specification*. The original Circular Specification (CS) of the model was determined by symmetrical repulsive forces as

$$\boldsymbol{f}_{i,j}(t) = A e^{-d_{i,j}(t)/B} \frac{\boldsymbol{d}_{i,j}(t)}{d_{i,j}(t)}, \tag{2}$$

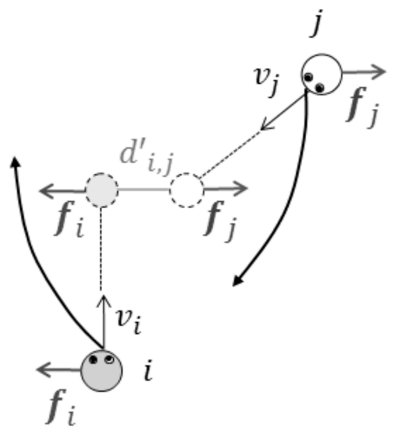

Fig. 11 Collision prediction among pedestrians with CP-SFM. d'_{ij} is the distance between pedestrians at the time of maximum approach t_i

where $\boldsymbol{d}_{i,j}$ is the distance between the pedestrians, A is the maximum interaction intensity and B determines how the intensity changes with d. The model is popular for its simplicity, and it works well at the high densities that describe the egress conditions it has been developed for [46], but it fails in describing lower density regimes and for this reason a few improved specifications, taking in account relative velocities in the computation of $\boldsymbol{f}_{i,j}$, have been proposed [47].

Zanlungo et al. [13] compare a few of these specifications to the CP specification that they propose. This model, that develops on ideas originating from Reynold's boid model [48], uses the relative velocity between the pedestrians to compute how their "future" distance $\boldsymbol{d}'_{i,j}$ will vary with time according to the hypothesis that the pedestrians will keep a constant velocity. The time at which the projected distance $d'_{i,j}$ assumes a minimum value is called the "interaction time" t_i for pedestrian i and the value of the corresponding future distance $\boldsymbol{d}'_{i,j}(t_i)$ (see Fig. 11) replaces the current distance in the equation for the CS specification force (2) in order to obtain the CP specification equation

$$\boldsymbol{f}_{i,j}(\boldsymbol{d}_{i,j}, \boldsymbol{v}_{i,j}, \boldsymbol{v}_i) = A \frac{v_i}{t_i} e^{-d'_{i,j}/B} \frac{\boldsymbol{d}'_{i,j}(t_i)}{d'_{i,j}(t_i)}. \quad (3)$$

Here the term v_i/t_i is introduced to modulate the force in such a way that the pedestrian is able to stop in time t_i. According to the analysis of [13], the CP-SFM model outperforms the previous SFM specifications in simulating pedestrian collision avoidance in low and average density multi-person settings, a characteristics that makes this model suitable to robot applications.

[49] compares the performance of CP to other popular pedestrian methods for egress oriented applications.

Model Calibration

To calibrate and evaluate the CP-SFM model, [13] uses a set of pedestrian trajectories obtained in a controlled experiment to which eight subjects took part. Each subject was given a start and goal point, and was prescribed to walk as naturally as possible towards the goal. The trajectories of pedestrians were tracked in a square area with an 8 meters side. The start and goal points were decided in such a way that the trajectories of all pedestrians will converge, if walking straight to the goal, at the center of the experimental area, creating a potentially complex collision avoiding problem; but the density of the environment was low enough to allow the pedestrians to freely choose their avoidance strategy. The calibration process used a genetic algorithm to minimize a fitness function that consisted in the average distance between the simulated and actual trajectories of pedestrians plus a penalty term assigned to those trajectories that "collided" between them (more exactly, trajectories that reached a minimum distance smaller than the distance between any pair of actual pedestrians during the experiment). The genetic algorithm used 500 genomes per generation, over 1,000 different generations; tournament selection over a pool of five solutions, crossover and random Gaussian mutation with probability 0.1. The solution was determined through 50 independent runs of the algorithm. The CP-SFM method outperformed all the other specifications with an average position error of 30 ± 1 centimeters (55 ± 1 for CS-SFM).

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