# A Framework with a Pedestrian Simulator for Deploying Robots into a Real Environment

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**Abstract.** We describe a simulation framework aimed to develop and test robots before deploying them in a real environment crowded with pedestrians. In order to use mobile robots in the real world, it is necessary to test whether they are able to navigate well, i.e. without causing safety risks to humans. This task is particular difficult due to the complex behavior pedestrians have towards each other and also towards the robot, that can be perceived either as an obstacle to avoid or as an object of interest to approach for curiosity. To overcome this difficulty, our framework involves a pedestrian simulator, based on a collision avoidance model developed to describe low density conditions as those occurring in shopping malls, to test the robot's navigation capability among pedestrians. Furthermore, we analyzed the behavior of pedestrians towards a robot in a shopping mall to build a human-to-robot interaction model that was introduced in the simulator. Our simulator works as a tool to test the level of safety of robot navigation before deploying it in a real environment. We demonstrate our approach showing how we used the simulator, and how the robot finally navigated in a real environment.

**Keywords:** Pedestrian simulation, Safe navigation, Mobile robot, Field trial

## 1 Introduction

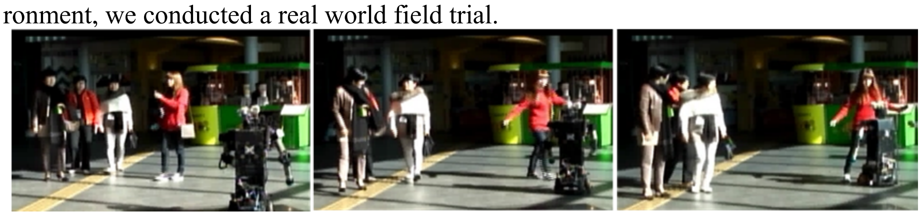
Deploying a robot in a real environment with ordinary people is one of the major targets and challenges in robotics. Due to the improvement of robots' sensing abilities such as human tracking, robots can now assist people working in a real world environment, and lately research works have been performed to deploy robots in environments such as malls [1], science museums [2], or hospitals [3].

adfa, p. 1, 2011.

One of the most serious problems to face when using robots in a real environment is to ensure that they can be operated safely between humans. When operating our robots in the real world we have experienced difficulties in securing the robot's safety due to unexpected behaviors of pedestrians who may, for example, be strongly interested in the robot and surround it or even explicitly obstruct its motion by continuously standing on its front (Fig. 1-(a)). Moreover, the density in a real environment may change strongly with time (for example, the density in a shopping mall at lunch time is higher than in usual situations (Fig. 1-(b)), making difficult to develop and test in the laboratory a navigation system that may be safe in any setting.

Simulations have been already used to test robots before using them in real environments [4, 5], but these works dealt with a "static" environment, i.e. they needed only to simulate the robot behavior and not to cope with complex human behaviors and reactions. When the robot has to interact with humans, and even operate in a human crowd, the necessity to model the complex and diversified behavior of humans makes more difficult to close the gap between simulations and the real world [6].

In this paper, we report the effectiveness of our approach (Fig. 2) that uses a realistic pedestrian simulator in order to test the safety of robot navigation. To this end, we first gathered position data of pedestrians in a shopping mall by using a human tracking system [7], to analyze their behavior in that environment. Then, we used a pedestrian model explicitly developed to describe the relatively low-density situations occurring in shopping malls [8], to simulate the walking behavior of pedestrians and control robot locomotion. Finally, after testing the robot safety in the simulated environment, we conducted a real world field trial.



(a) An adult approaches and explicitly obstructs the robot

(b) Relatively high density situation in a mall

**Fig. 1.** Example of difficult situations for the deployment of a robot in real environments

## 2 Related works

It is quite common to use simulators in robotics, in particular to reproduce physical phenomena. For example, León et al. developed a simulator to reproduce grasping behavior [4], while Tsai et al. used a simulator to investigate the safety of motion planning in a dual arm robot [9], and Boedecker et al. used a simulator to test the walking behavior of a two-legged humanoid robot [10]. A few research works consider also the behavior of robots around people [11,12]. For instance, Sisbot et al. used a simulator to investigate socially appropriate path planning around humans [12]. However, none of these studies addresses the influence of diverse, dynamical and reactive human behavior, focusing on static posture or fixed motion patterns.

On the other hand, pedestrian behavior has been relatively well studied in human science. Helbing proposed a “social force” model to simulate people's motion in escape situations [13], which has been used by Pelechano et al. to simulate high-density crowds [14]. These studies addressed pedestrian behavior in high-density situations, which is different from the one exhibited at lower densities of interest for normal social interactions. In our study, we use a pedestrian model specifically prepared for low-density settings as those occurring in shopping malls [8]. Also some previous works used pedestrian models to simulate robot navigation in a crowd [15, 16], but their approach was limited to simulation and did not address real world situations. Thus, we consider that the novelty of our study resides in addressing a method to use a pedestrian simulator in the deployment process of a robot toward real world use.

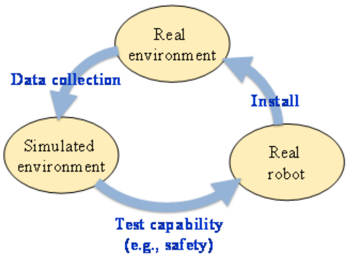



**Fig. 2.** The interaction of simulated and real environment enables testing robot capabilities

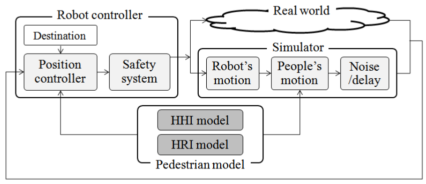



**Fig. 3.** Overview of our framework

## 3 System

Our framework (Fig. 3) consists of three main components: a pedestrian model, a robot controller, and a simulator. In the pedestrian model, the social forces among people were computed using the model as described in [8] (HHI model), while the force toward the robot was computed using specific parameters (HRI model), [17]. The robot controller navigates the robot by using the HRI model.

### 3.1 Robot and sensors

We used a 120-cm-high 60-cm-wide humanoid robot, Robovie-II. Its mobile base is a Pioneer 3-DX (Active Media). We used it at a maximum velocity of 750 mm/sec and preferred velocity of 700 mm/sec. Its maximum acceleration is 600 mm/sec$^2$. It has bumpers and laser range finders (Hokuyo, UTM-30LX) for ensuring safety.

The pedestrian model needs information about people's positions far from the robot, which is not easy to collect using only on-board sensors. We thus used 8 environmental laser range sensors and a tracking system with shape matching at torso-level and a particle filter method [7], whose position error was in average 0.06 m.

### 3.2 HHI model

Models of pedestrian collision-avoidance have been developed since the 50s to deepen understanding of crowd dynamics and design better facilities. The Social Force model (SFM) [13] is a popular pedestrian model that describes the behavior of pedestrians in a crowd through reaction forces inspired by physics.

However, the original social force model is designed to describe well high-density settings such as panic and escape situations [13], and it is not suitable to reproduce low-density many-people environments such as shopping malls. To solve this problem, we use a SFM specification which can reproduce such low-density settings [8]. This work proposes a new SFM specification called "collision prediction" (CP-SFM) in which relative velocity is used to compute the relative distance among pedestrians at the moment of maximum approach in future, a computation performed by assuming current velocities to remain constant. The acceleration of pedestrian i is given by

$$\boldsymbol{f}_{i,j} = A\frac{v_i}{t_i}e^{-d_{i,j}/B}\frac{\boldsymbol{d}'_{i,j}(t_i)}{d'_{i,j}(t_i)} \qquad (1)$$

where $\boldsymbol{v}_i$ is the velocity of pedestrian $i$, $t_i$ is the time of maximum approach and $\boldsymbol{d'}_{ij}$ is the (predicted) relative distance to pedestrian $j$ at $t_i$. The parameters of the model, A= 1.13, B=0.71, were calibrated on real pedestrian trajectories (see [8] for details).

### 3.3 HRI model

We extended the pedestrian model to also include, besides collision avoidance, the behavior around the robot. While some people only interact with the robot to avoid collisions, others slow down or stop to observe it, while some of them approach it to initiate a conversation. Modeling these people is important; if we rely on a pure collision avoidance model the robot may collide with people who behave differently.

#### 3.3.1 Data collection and coding to establish HRI-behavior categories

We used a field trial in which a robot provided information about shops to people that approached it and stopped to talk [18]. In the field trial, in which the robot roamed a 144 $m^2$ wide area in a shopping mall corridor, we recorded (using tracking system [7]) 266 pedestrians' trajectories during an hour of data collection. We have analyzed these trajectories based on how the pedestrians change their walking course in relation with the robot, and found four major patterns:

**Approach to stop:** People approached the robot and stopped to talk at social distance zone (approx. 1.2m)

**Stop to observe:** People stopped to observe the robot at a distance larger than the social zone one.

**Slow down:** People did not change their walking course toward the robot but slowed down to observe it and passed by without stopping.

**Collision avoidance only:** People avoided the robot but did not change their walking course toward it nor slowed down their walking speed.

To confirm these patterns, we coded the data using a standard human science procedure. Two independent persons (coders) classified the trajectories using these four categories, and the coding process resulted in Cohen's kappa coefficient 0.709, showing a reasonable concordance between the coders. No trajectory was classified out of these four categories, while the number of trajectories in each category was: 70 approach to stop, 69 stop to observe, 11 slow down, and 116 collision avoidance only.

### 3.3.2 Development of the models

We developed equations to model people's walking behavior around the robot according to the four patterns (HRI type models):

**Approach to stop:** In the "approach to stop" category (Fig. 4), 90.1% of the people approached the robot from the front and their motion was straight toward the robot. We assumed that people in this category approach the robot only when it falls within their sight, and the following equation represents this idea. Note that it is used in combination with (1), so that the motion is also affected by the social force from other pedestrians.

$$\boldsymbol{v}_i^0 = \begin{cases} 0 & (d_{i,r} \le D_{stop}) \\ \boldsymbol{v}_i^{robot} & (D_{stop} < d_{i,r} \le D_{notice}\ and\ |\theta_{i,r}| < 90) \\ \boldsymbol{v}_i^{goal} & (otherwise) \end{cases} \tag{2}$$

Here $v_i^0$ is the preferred velocity of pedestrian $i$, $v_i^{goal}$ is the preferred velocity directed to the goal, $v_i^{robot}$ is the vector directed to the robot with the same scalar size as $v_i^{goal}$ (i.e. the pedestrian aims to move toward the robot with her own preferred velocity), $d_{i,r}$ is the distance between the pedestrian and the robot, and $\theta_{i,r}$ is the angle between her frontal direction and the direction to the robot . We computed $D_{stop}$ from observed trajectories (in average people in this category stopped at a distance of 0.893m, S.D. 0.229 m from the robot), and set $D_{notice}$ to 10 m (the SFM visibility range).

**Stop to observe:** As people in the "approach to stop" category (Fig. 5), people in this category come close to the robot as soon as it falls within their sight, but they stop at a larger distance. Thus, we approximate their behavior as:

$$\boldsymbol{v}_i^0 = \begin{cases} 0 & (d_{i,r} \le D_{observe}) \\ \boldsymbol{v}_i^{robot} & (D_{observe} < d_{i,r} \le D_{notice}\ and\ |\theta_{i,r}| < 90) \\ \boldsymbol{v}_i^{goal} & (otherwise) \end{cases} \tag{2}$$

where $D_{observe}$ is 2.38 m (average stopping distance from the robot, S.D. 1.19 m).

**Slow down:** People's motion direction did not change toward the robot, but their speed decreased as they were close to it. We analyzed the change of the speed and found that their speed around the robot was 62% of the average in other areas. Thus, we modeled slow down behavior using the following equation:

$$\boldsymbol{v}_i^0 = \begin{cases} \alpha \boldsymbol{v}_i^{goal} & (d_{i,r} \le D_{slowdown}) \\ \boldsymbol{v}_i^{goal} & (otherwise) \end{cases} \tag{3}$$

where $\alpha$=0.62. We set $D_{slowdown}$ =4 m on the basis of the observed pedestrian behavior.

**Collision avoidance only:** This behavior was modeled using eq. (1), as for inter-pedestrian interactions. However, since we expected a difference in the amount of force perceived from the robot (e.g. keep a larger distance), we re-calibrated the social force toward the robot (see Section 3.3.3).

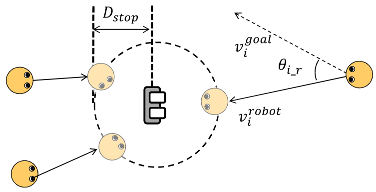



**Fig. 4.** Illustration of "approach to stop" trajectories

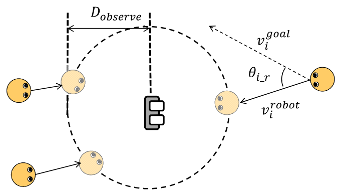



**Fig. 5.** Illustration of "stop to observe" trajectories

### 3.3.3 Calibration of the social force toward the robot

We conducted a data collection to investigate how people behave when avoiding a robot. Fourteen Japanese people (six men and eight women whose average age was 25.1 years, S.D. 8.7) participated in this experiment. Each subject repeated the trial nine times. In each trial the robot moved straight toward a participant at 700 mm/sec, and the participants moved toward the robot, starting at a distance of 18 m. Subjects were instructed to walk freely toward a goal located behind the robot, and informed that the robot would not change its course to avoid collision.

For calibration we used a genetic algorithm to select the parameters maximizing similarity between simulated trajectories and real ones while minimizing collisions in simulation [8]. The algorithm provides parameters values for the interaction force (Ar=0.62, Br =1.07) that, from the point of view of collision-avoiding intensity, do not qualitatively differ from the inter-human values of [8] (Ah= 1.13, Bh =0.71). We expected the pedestrians to avoid the robot more strongly than they avoid other humans, but this behavior was not clearly observed in the experiment performed for data collection. We note that the parameters for the robot are eventually re-adjusted taking into account noise, delay, and robot motion capabilities (Section 4.1).

## 3.4 Robot controller (Position controller and Safety system)

We assume that while global path-planning providing the destination is conducted at an upper layer, this robot controller is responsible of local navigation, i.e. of safely avoiding collision with static and dynamic entities around the robot.

We could use our framework to test various navigation strategies to reveal the most appropriate navigation mechanism; in fact, we explored the navigation strategy of the robot using this same simulator, and the results of our analysis will be reported elsewhere [17]. In this paper we report only the most suitable strategy we found.

The idea underlying the navigation mechanism is to use a strategy similar to that used by pedestrians, to obtain human-like collision avoidance in the robot. To this end we used the social force model [8] with the human-robot parameter values. In concrete, given the local destination to obtain the preferred velocity, the system computes the robot's desired next position on x-y coordinates using the "collision prediction" (CP-SFM) social force model of eq. (1), and converts it into a polar coordinates velocity command ($vp$, $\omega p$). However, we needed to consider the discrepancies between the "ideal" simulation world and the real one as, for example, slow acceleration, the inability of our differential drive robot to move aside, the noise in the human tracking system and the computation delays; discrepancies that cause the robot's trajectory to diverge from that determined by the "ideal" model. To compensate this difference, we further calibrated the pedestrian model parameters to fit the real world behavior (see section 4.1). The polar coordinates ($vp$, $\omega p$) velocity command is finally examined through a safety-check mechanism, a time varying dynamic window method [19] using a 1.5 sec window time by considering maximum speed and acceleration of our robot, which is long enough to stop the robot.

### 3.5 Simulator

The simulator is used to test the robot navigation, reproducing people's walking behavior around the robot. The simulator has three sub-modules: pedestrian simulator, noise/delay simulator, and the robot's motion simulator.

The pedestrian simulator computes pedestrians' positions every 100ms, on the basis of the pedestrian model [8]. The noise/delay simulator simulates the noise in sensing, modeled as a Gaussian noise, and delay in observation and computation. The parameters of the noise simulator were decided on the basis of data collected in the target environment (section 4.1). The robot's motion simulator simulates the movements of the robot by using the robot controller taking also in account the dynamics of its two-wheeled mobile base.

Fig. 6 shows the trajectories of the robot (red ellipse) and of a pedestrian (black ellipse) that got closer and stopped around the robot before directing to his goal. As the pedestrian approached the robot, the latter deviated to the right and was able to avoid him, even if the pedestrian approached and stopped around the robot.

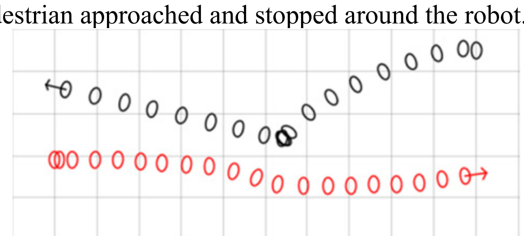


**Fig. 6.** Trajectories in simulation

# 4 Simulation

## 4.1 Overview

The simulation was conducted in a 10 x 20 m virtual corridor. The simulator sets people's initial positions and goals to opposite sides of the corridor, along with their arrival time to the environment and preferred velocity (average and S.D are 1.4m/sec and 1.33, based on the data collection in Section 3.3.1). The ratio of HRI type behaviors is set as the same as the one observed in data collection (section 3.3.1). We also measured the delay of the system in the laboratory, which resulted to be 350msec, and defined the noise of the sensing system as 0.06m, as reported in [7]. The initial position and goal of the robot are set as for the pedestrians.

By using delay and noise information, we further calibrated the values of the pedestrian model parameters to obtain in the real robot system trajectories as similar as possible to the "ideal" ones (i.e. obtained using the HRI model with no noise or delay). As a result, the parameters for the real robot were increased to Ar= 0.93, Br =1.61, showing that the collision-avoiding interaction has to be strengthened to cope with the robot's motion limitations.

## 4.2 Measurement

We propose two performance measures:

**Ratio of collision:** we defined a collision initiated by the robot as a situation in which the distance between a center of person and the center of robot gets smaller than 30cm, and the ratio of collision was computed as the number of collisions per the number of people who entered within a 5m distance from the robot. In this evaluation, we did not count collisions caused by a pedestrian, defined as either a) a pedestrian collided with the robot while it was stopped, or b) a pedestrian collided with the robot from behind. Note that in the real world collisions might not happen even if this distance is attained, as humans may rotate their body to avoid the collision; nevertheless this is a valid measure of the safety of the robot's behavior.

**Efficiency**: defined as: "time to reach the goal" over "time to reach the goal going straight at preferred speed". Deviations due to collision avoiding reduce efficiency.

## 4.3 Results

To confirm the safety capability of robot navigation in various situations, we conducted simulations by increasing density from 0.01 to 0.05 people/$m^2$ with 0.01 intervals. In each density setting, we conducted 1000 simulations.

Fig. 7 shows *efficiency* and *ratio of collision* in each density setting. We had *ratio of collision* 0% until density 0.03, while the robot caused 0.01% and 0.02% collisions at density 0.04 and 0.05, respectively. The *efficiency* at density 0.01 was 79%, and it decreases with increased density (65% at density 0.05).

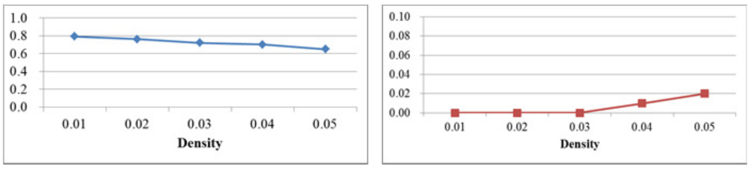



**Fig. 7.** Efficiency (left) and ratio of collision (right) in simulations

# 5 Field Trial

## 5.1 Overview

According to the results of simulations, our robot has enough safe capability in real environments provided that the density is not higher than 0.03. To confirm this prediction, we conducted a field trial in a real environment with characteristics similar to the simulated one. Fig. 8 shows the corridor of a shopping mall in which we performed the field trial, an area of size 10 x 20 m, in which people walk with an average speed of 1.32m/sec (s.d. 1.33) at a density up to 0.03 people/ $m^2$. The purpose of the field trial is to test (a) whether the robot safely navigates as predicted by simulations, and (b) whether the efficiency trend is reproduced as predicted.

The robot was fully autonomously operated, except for the start signal sent by an operator to trigger it to move. After receiving the signal, the robot moved from points A/B to B/A (we defined a single movement between these points as one trial).

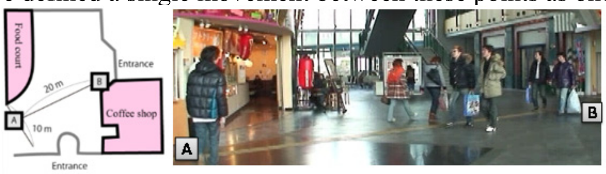



**Fig. 8.** Map and image of the field trial site

## 5.2 Measurements

To confirm whether the robot could navigate safely in a real environment, we measured *efficiency* and coded whether the robot's behavior caused any problems in terms of safety, i.e., for each person who walked within 5 m from the robot, we asked *coders* to determine whether the situation was safe, using the following criteria:

**Unsafe:** due to the presence or motion of the robot, the pedestrian had to make a quick change in his/her moving direction to avoid colliding with the robot.

Otherwise, the person's situation was coded as **safe**.

## 5.3 Results

In the field trial, we conducted a two-hour test consisting of 27 trials. Two coders classified the interactions between the robot and the 160 pedestrians that walked within a 5 m distance from it as safe or unsafe by observing the recorded videos. Cohen's kappa coefficient was 0.89, indicating high consistence. Moreover, for consistent analysis, the coders discussed and reached a consensus on all the observed situations.

Fig. 9 shows *efficiency* and *unsafe situation* in the field trial. As shown in the figure, no *unsafe situation* was found, confirming that our system safely navigates the robot in both simulated and real environments. The *efficiency* was 59%, 58% and 51 % for density 0.01, 0.02 and 0.03, respectively. These values are lower than the simulated ones, possibly due to the more complex behavior of actual pedestrians (the models reproduce only average pedestrian behaviors; introducing stochasticity in pedestrian decisions could thus reduce the gap between simulations and the real world). However, the results showed a trend similar to the simulated one (an increase in density caused a decrease of efficiency). These results suggest that our simulation system reproduces properly the interaction between the robot and a pedestrian crowd.

Fig. 10 shows a scene in which the robot successfully navigated in a many-people setting. The robot initially changed its moving direction to avoid a group of people, just to meet another incoming group (Fig. 10-a). As a result the robot slightly deviated to slip through the groups (Fig. 10-b). After avoiding the two groups, the robot tried to reach its goal, but another pedestrian was coming from the goal direction (Fig. 10-c). Therefore, the robot deviated again to avoid the pedestrian and eventually headed toward its goal (Fig. 10-d).

The robot was equally able to deal with pedestrians that tried to approach it, as predicted by our HRI type behaviors. In Fig. 11 we analyze one of these situations. While heading to its goal, the robot met a group of pedestrians coming from the opposite side (Fig. 11-a). After noticing the robot, a pedestrian deviated suddenly to approach it, and the robot changed its moving direction in order to avoid him (Fig. 11-b). The pedestrian continued to approach the robot despite this avoiding maneuver (Fig. 11-c), but the robot could safely cope with the pedestrian's motion (Fig. 11-d). These examples illustrate that the robot is able to navigate safely in the real environment as well as in the simulated environment.

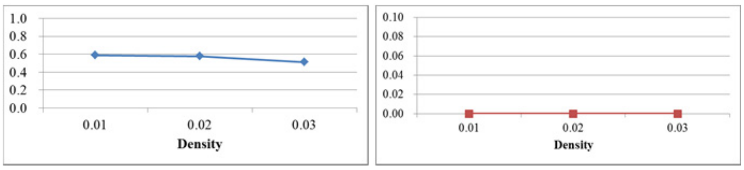
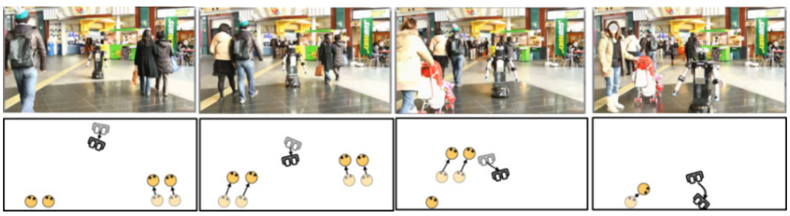
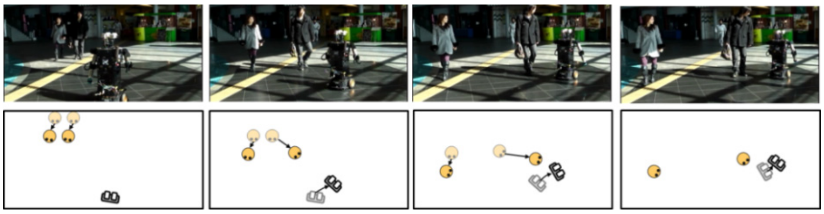



**Fig. 9.** Efficiency (left) and unsafe situations (right) in the field trial



(a) (b) (c) (d)

**Fig. 10.** The robot safely navigates through pedestrians in the mall



(a) (b) (c) (d)

**Fig. 11.** The robot safely avoids an approaching pedestrian

## 6 Conclusion

We report our framework to deploy robots in a real shopping mall environment. We used a pedestrian simulator in order to develop and estimate the safety of the robot navigation system among a human crowd. In the simulator we employed a particular specification of the Social Force pedestrian model that has been developed to describe the relatively low-density settings occurring in shopping malls and the like [8]. We further addressed the diverse behavior of pedestrians toward the robot, i.e. we gathered data from a real environment and built a "HRI behavior model" for people slowing down to look at the robot, or approaching and stopping for curiosity, and included such a model in our simulator.

We first tested the developed robot, which is navigated using the same collision avoidance model used for simulated pedestrians, in a simulation to confirm its safety. The results showed that the robot safely navigated among people with reasonable efficiency. Given that the simulation yielded safe navigation for densities up to 0.03 people/$m^2$, we estimated that we could deploy it in a real world environment with a similar density. To confirm this estimation, we conducted a field trial in a real shopping mall, and the results of this trial demonstrated that the robot can navigate safely among people even when facing complex situations.

## Acknowledgements

This work was supported by JST, CREST. We thank the staff of the Asia & Pacific Trade Center for their cooperation and ATR's Yoshifumi Nakagawa for his help.

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