Will I bother here? – A robot anticipating its influence on pedestrian walking comfort

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Abstract—A robot working among pedestrians can attract crowds of people around it, and consequentially become a bothersome entity causing congestion in narrow spaces. To address this problem, our idea is to endow the robot with capability to understand humans’ crowding phenomena. The proposed mechanism consists of three underlying models: a model of pedestrian flow, a model of pedestrian interaction, and a model of walking comfort. Combining these models a robot is able to simulate hypothetical situations where it navigates between pedestrians, and anticipate the degree to which this would affect the pedestrians’ walking comfort. This idea is implemented in a friendly-patrolling scenario. During planning, the robot simulates the interaction with pedestrian crowd and determines the best path to roam. The result of a field experiment demonstrated that with the proposed method the pedestrians around the robot perceived better walking comfort than pedestrians around the robot that only maximized its exposure.

Index Terms—Navigating in a crowd, Perspective-taking, Simulation

I. INTRODUCTION

We believe that in a near future there will be a number of robots moving among people in a city. Already field trials have revealed people’s positive responses to robots like shopping assistants [1], city explorers [2], and garbage collectors [3].

While such applications are promising, robots still lack common sense knowledge and thus often fail to detect problematic situations. Fig. 1 shows an example. Because the robot is novel to them, there are persons who want to stop to look at it; however, people surrounding the robot become obstacles for other pedestrians who wish to go through the environment. The robot is not able to recognize this situation, and therefore keeps causing the congestion until human personnel stops it. We commonly observed such scenes while conducting field studies.

To prevent these situations from happening, we believe it is important that the robot anticipates the consequences of its actions, such as in this case the discomfort of persons around it, and uses this information to plan its actions beforehand. However, as the crowding situation emerges from the interaction of multiple pedestrians, the prediction is not straightforward. Therefore our approach is to use simulation of pedestrian behavior, which enables the robot to find the influence of its actions on the pedestrians.

II. RELATED WORKS

A. Navigation in HRI

Safe navigating among people is often studied from the perspective of constructing a collision free path. Beyond planning to avoid collision with dynamic entities [4], recent studies started to model humans’ cognition and behavior. Trautman et al., have developed a collision-avoidance method based on estimation of people’s future motion with an idea of computationally emulating human’s motion planning [5]. Such local safety is already addressed in previous studies, and in our study we use the method developed in [6].

B. Simulation and Perspective-Taking

Simulation is widely used in robotics, often to reproduce physical laws, etc. A few pioneering studies started to address also the phenomena in human-robot interaction. For instance, as reinforcement learning needs many repeated trials and is thus difficult to do in a real world, Henry et al. [7] applied it on simulated pedestrians to acquire effective behavior in collision avoiding. Garrell and Sanfeliu [8] used simulated pedestrians with social force model, and tested multi-robot coordination mechanism when guiding groups of persons. However, in these studies, simulated people only engaged in collision avoidance.

The study of spatial relationships in interactions dates back to Hall’s work on social comfort zone framework [9]. A series of studies revealed the importance of (spatial) perspective-taking [10-12], in which a robot considers a human user’s viewpoint for efficient cooperation. In our study, we deal with
the perspective of pedestrian regarding to walking comfort. Some studies [13] conceptually addressed walking (dis)comfort, but did not validate/calibrate with reality.

Besides, Hoffman and Breazeal [14] conducted a pioneer study revealing anticipatory computation enables fluent human-robot interaction, and further considered that such similarity in perception would work as a perceptual simulation. Anticipatory computation is also used in walking-together setting [15]. While these studies only deal with a single user, our work addresses a very novel challenge of dealing with anticipation of pedestrian crowd, which are the result of complex emergent phenomena caused by the interaction among multiple persons inside a crowd.

III. OUR APPROACH

Fig. 2 shows the architecture. The central component is the simulator. It receives a candidate plan of the robot’s motion and simulates pedestrian behavior. In each simulation, the simulated pedestrians are generated based on the statistical model obtained from observations of real pedestrians, named the model of pedestrian flow (section IV). The simulated pedestrians are treated as active agents, albeit simplified. They move toward their goal while avoiding collision with other entities. The model of pedestrian interaction (section V) reproduces interaction between pedestrians and the robot.

Furthermore, in this work we introduce the concept of “walking comfort”, which we describe as subjective impression of one’s easiness of traversing an environment. The walking comfort of a pedestrian is estimated using the model of walking comfort (section VI).

The robot controller uses the simulator as a tool for planning by predicting the influence of its presence on situations such as the occurrence of corridor congestion. We illustrate the use in a friendly roaming scenario (section VII).

IV. MODEL OF PEDESTRIAN FLOW

We model the flow of pedestrians inside our target environment based on observation of real pedestrians, and use this model in simulation.

A. Data Collection for Pedestrian Flow Modeling

We conducted our study in a shopping mall (Fig. 3) in the Osaka bay area, Japan. The area includes a corridor of around 70 m with 3-6 m width and 4 shops alongside, and one big hall of approximately 300 m². The corridor connects the hall to a train station, and it is relatively more crowded with pedestrians than the hall.

Both the corridor and the hall were covered with our people-tracking infrastructure using 49 3-D range sensors attached on the ceiling (combination of Panasonic D-Imager, ASUS Xtion, and Velodyne HDL-32E), providing an estimate of persons locations every 33 ms. Due to the page limit we omit further details, which will be reported elsewhere.

The data collection was conducted from 8 am to 8 pm for two days, one weekday and one weekend day. In total, we collected 66,035 trajectories.

B. Modeling

Figure 4 illustrates the elements included in the pedestrian flow model. From collected trajectories we retrieved the following:

- Rate of arrival: We divided the environment into 1 m² square cells, and measured the rate at which persons enter each cell.
- Preferred velocity: We measured the walking velocities of pedestrians: the average was 1.12 m/sec with SD 0.16.
- Subgoal-transition: Subgoals are points and landmarks of the environment toward which pedestrians walk or where they take directional choices before reaching the final destination. The location of subgoals as well as the transition probability model are retrieved based on the technique reported in [16].

- Group membership: People walking in groups have an effect on the crowd dynamics [17]. We extracted groups (family or friends) using a relationship analysis technique [18], and obtained their distributions. There were 46.4% single persons, 41.0% groups with two persons, etc.

We also modeled the environment:

- Wall: Using robot localization and mapping, we obtained a grid-based map of static objects like walls.

The above elements are used for the simulation. Simulated pedestrians move toward subgoals in a sequence defined by the
above subgoal-transition model until they exit. The ratio of arrival and preferred velocity are used to define the number and speed of simulated pedestrians. All members in the same group have the same subgoals and preferred velocity.

V. MODEL OF PEDESTRIAN INTERACTION

A. Model of Robot Influence

Many pedestrians change their walking behavior when they encounter a robot, thus it is also important to model such local behavior. The behaviors can be classified into four categories that we briefly summarize here (refer to [6] for details).

1) Stop to interact: There are people who approach the robot and stop to interact at social distance (Fig. 5 (a)), and stay there for a while. This is modeled as follows: when a person finds the robot within the $D_{\text{notice}}$ distance in frontal direction, he/she changes the course and approaches the robot until it reaches the $D_{\text{interact}}$ distance. After stopping for $T_{\text{stop}}$ time, he/she leaves the robot and continues moving toward his/her original goal.

2) Stop to observe: There are people who stop to observe the robot outside of the social zone (Fig. 5 (a)). Similar to the stop and interact behavior, the persons in this category approach the robot and stop; however, the stopping distance $D_{\text{observe}}$ is larger so they are apparently not involved in social interaction, but only observe the robot from distance.

3) Slow down to look: There are people who slow down to look at the robot, though they do not change their course and pass by without stopping (Fig. 5 (b)). They slow down by a factor $\alpha$ when their distance to the robot is less than $D_{\text{slowdown}}$.

4) Uninterested: Finally, a considerable number of persons do not show interest toward the robot. They avoid the robot in a similar manner as they avoid other pedestrians. Except for such collision-avoiding behavior, their walking course and velocity are not affected.

B. Model of Collision Avoiding Behavior

The motion of pedestrians is influenced by the surrounding persons and objects. Such collision avoidance behavior is described using a social force model. Several models for calculating the social force exist, however most of them are for high density situations such as panic and escape. Instead, we use a model specifically developed for low-density situations occurring in public spaces, in which simulated agents predict future collision and change their course in advance [19].

In concrete, the "force" $f^i$ a pedestrian $i$ would receive at an instant $t$ is described as:

$$f^i(t) = k(v^i_{\text{intend}}(t) - v_i(t)) + \sum_{j \neq i} f_{ij}(t)$$  \hspace{1cm} (1)$$

where $v_i$ is the velocity of pedestrian $i$, $v^i_{\text{intend}}$ is the intended velocity obtained from the models of pedestrian flow and robot influence, and $k$ is a feedback gain for acceleration. $f_{ij}$ is the social force between pedestrian $i$ and $j$ (Fig. 6) given by:

$$f_{ij} = A \frac{v_i - d_{ij}/u}{d_{ij}(t)}$$  \hspace{1cm} (2)$$

where $t_i$ is the predicted future time when pedestrian $i$ and $j$ will be closest, and $d_{ij}(t)$ is the vector of predicted relative distance to pedestrian $j$ at $t_i$. The parameters $k=1.52$, $A=1.13$, $B=0.71$, were calibrated using real pedestrians data (see [18]).

The equation for the overall velocity of a person $i$ is then:

$$v_i(t + \Delta t) = v_i(t) + f^i(t)\Delta t$$  \hspace{1cm} (3)$$

C. Calibrating Parameters

1) Data collection: To calibrate the robot influence model, i.e. determine the ratio of persons belonging to each behavior category and the parameters of each behavior, we collected pedestrian data in the same target environment as in the section IV. This time we also let the robot Robovie-II (Fig. 1, 120 cm high and 40 cm in diameter, maximum velocity 750 mm/s) roam back and forth on predefined paths in the corridor and hallway and observed people’s responses. When a pedestrian stopped in front of the robot, a human operator halted the robot and waited until the pedestrian left. We collected trajectories and videos of pedestrians and the robot.

2) Analysis: We collected 1115 trajectories. A human coder first classified all trajectories into the four behavior categories by looking at videos and trajectories. Table I shows the obtained result. A second coder conducted a validation coding for 10% randomly chosen cases. Their classifications were very consistent (Cohen's kappa coefficient was 0.991).

After the coding process, we computed $D_{\text{interact}}$ and $D_{\text{observe}}$ from trajectories in "stop to interact" and "stop to observe" categories; in average people in these categories stopped at a distance of 0.92 m (S.D. is 0.25) and 1.51 m (S.D. is 1.18) from the robot, respectively. For "slow down to look" category, we analyzed the change of the velocity and found that their velocity around the robot was 76% of the average within 3.0 m from the robot; therefore we set $D_{\text{slowdown}}$ to be 3.0 m and $\alpha$ to be 0.76. Finally, we set $D_{\text{notice}}$ to be 10 m, as an upper limit on the distance where significant interactions can occur.

The obtained behavior ratios and parameters were used in simulation. When a simulated pedestrian is generated, one behavior category is randomly assigned based on the corresponding ratio. For members of the same group, the same behavior category is assigned.
TABLE I. RATIO OF PERSONS IN EACH CATEGORY

<table>
<thead>
<tr>
<th></th>
<th>Stop to interact</th>
<th>Stop to observe</th>
<th>Slow down to look</th>
<th>Uninterested</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratio (Number)</td>
<td>11.39% (127/1115)</td>
<td>11.48% (128/1115)</td>
<td>8.07% (90/1115)</td>
<td>69.06% (770/1115)</td>
</tr>
</tbody>
</table>

VI. MODEL OF WALKING COMFORT

A. Collection of Walking Comfort Data

The data collection was conducted in an indoor arena (Fig. 7). 16 Japanese persons participated (8 males and 8 females, 21.2 years old), for which they were paid. They were instructed to walk in a natural way with their preferred velocity. There were 20 measurement sessions for each participant. We varied the number of people in the space, their starting location and destination, the time to start walking (at once or with 2 s delay), environment (open-space or 1.5 m crossing corridor made using low partitions), and the presence of a stopping person.

We used the human tracking system [20] with 10 Hokuyo UTM to record pedestrian trajectories. For each session, a participant rated the following items in 1-to-7 point Likert scales where 7 was positive (comfort): “When you walked did you perceive disturbance?”, “Was your walk interfered by someone?”, and “Would you have walked more comfortably if you were not disturbed?” The walking comfort (denoted comfort(i, T)) was calculated as average of the three answers and converted to the range [0, 1] for later computation. Their answers were consistent, with Cronbach’s α = 0.96.

B. Analysis and Modeling

Our objective was to predict the walking comfort from trajectories. We proposed a number of factors which we assumed could have a significant influence and tested them using regression analysis, where comfort(i, T) was the target variable.

Distance: Pedestrian models typically use (the inverse of) distance to compute the influence of other pedestrians [21]. We speculated that it would be more comfortable for a pedestrian if distances to nearby persons are larger. Based on this idea, person j’s comfort at time t is defined as:

\[ c_{dist}(i, S, t) = \min_{j \in S} \frac{a/d(i,j,t) + b}{j} \]

where \(d(i,j,t)\) is the distance between pedestrian i and j’s body center, S represents set of people walking around i, and a and b are regression parameters.

Velocity: People prefer to walk with constant velocity when possible [15], so the change of velocity forced by congestion would decrease the walking comfort. We therefore considered the amount of change of velocity.

C. Using the Walking Comfort Model in Simulation

Fig. 8 shows an example scene from the simulation. The robot (red circle) is surrounded with three persons whose behavior is stop to interact (bold black circle). People with blue circles are in the uninterested behavior category, whose momentary comfort values \(c_{dist}(i, S', t)\) are illustrated with the intensity of the color (dark blue is low comfort, light blue is high comfort). Only uninterested people’s comfort is displayed, as they are the ones affected by the crowding around the robot.

The comfort values are relatively high at t=1 (Fig. 8 (a)). At t=2, one pedestrian came close to the crowd around the robot from bottom-right (comfort value = 0.61), and finally at t=3 he became blocked by the crowd and his comfort dropped significantly (comfort value = 0.38).

VII. APPLICATION TO FRIENDLY ROAMING

A. Friendly Roaming

In order to test the walking comfort estimation in a real robot application we applied it to “friendly roaming”. Friendly roaming is a scenario where a robot roams around the environment to show it is available for providing services [22]. The aim is that people can easily find the robot when needed. The robot should therefore be exposed to as many visitors as possible. Therefore, when given a number of possible roaming paths, in the basic method in [22] the following utility function is used to determine the most appropriate path:
where $encounter(p_k)$ is the ratio of persons who pass nearby the robot that roams around on the path $p_k$. This means that it is usually better if a robot chooses a path in which there is a large flow of pedestrians.

**B. Planning with Anticipation of Walking Comfort**

While Eq. 6 gives a simple solution for choosing the roaming path, as explained previously this could also lead to crowding situations and discomfort of persons trying to pass by. We therefore extend the utility function Eq. 6 with a factor describing the walking comfort to consider a balance of both exposure and disturbance to pedestrians:

$$U_{\text{anticipation}}(p_k) = encounter(p_k) + \beta \cdot \text{comfort}(p_k)$$ (7)

where $\text{comfort}(p_k)$ is an average of walking comfort of all persons who meet the robot during the time the robot roams around on the path $p_k$. To compute this, we run the simulation where a simulated robot moves on the path $p_k$. As the pedestrian behavior is unpredictable and statistical in nature, we run 5 minute simulations for 20 times for each path. After the simulation, we compute the walking comfort of a simulated person $i$ influenced by the robot using Eq. 5, where we only consider the parts of persons’ trajectories within distance $d_{th}$ from the robot ($T'$ denotes the duration in which they stay within $d_{th}$).

Finally, we define the walking comfort influenced by the robot on the path $p_k$. We take the average of $\text{comfort}(i, T')$ of the set $\text{uninterested}$ of simulated person who meet the robot and whose walking behavior is $\text{uninterested}$ (as defined in section V). We assume that people who are interested in the robot (people in stop to interact, stop to observe, and slow down to look categories) would not consider the robot to be a disturbance. We take an average because we aim to provide better comfort to all other pedestrians in average. That is:

$$\text{comfort}(p_k) = \text{average}_{i \in \text{uninterested}}(\text{comfort}(i, T'))$$ (8)

The robot chooses the roaming path that maximizes the equation (8). That is, $p_{\text{selected}}$ computed as follows is used for the roaming path:

$$p_{\text{selected}} = \arg \max_{p \in p_{\text{candidates}}} U_{\text{anticipation}}(p_k)$$ (9)

where $p_{\text{candidates}}$ is the set of all candidate paths.

We view $\beta$ as an application-dependent parameter. If one cares less about the pedestrians comfort, $\beta$ can be made small or equal to zero, resulting in a utility function similar to the one in Eq. 6. If the pedestrians comfort is the main concern, $\beta$ should be set to a very large value. For this study, we set the parameter $\beta = 1$ as sort of an equal balance of the two factors, meaning that 100% walking comfort has equal utility as exposing the robot to all people in the space. The distance threshold $d_{th}$ was set to $D_{\text{max}}$ to make it large enough.

**C. Planning Result**

We first obtained the environmental information using the technique reported in the section IV. In Fig. 9, the walls are shown in black and calculated subgoals as red circles. There are subgoals along the main corridor (G1, G2, G3, and G4), as well as at important junctions in the hall (G5, G7 and G10), and at important points of the environment, like elevator (G6), stairs (G9 and G12), shop entrances (G11, G13, and G14), a bench (G8), and entrance of a narrow corridor (G15). We used all possible pairs of neighbor subgoals for $p_{\text{candidates}}$ in Eq. 9.

The result of the planning using Eq. 9 is shown in Fig. 9. The blue line (G1-G4) indicates a roaming path that maximizes the utility $U_{\text{anticipation}}$ in Eq. 7. Table III shows the list of paths and their computed utility values. There is a major pedestrian flow in the main corridor, and the robot would meet many pedestrians coming from the main corridor when it moves on the path G4-G7. Also, this area is an open space (see Fig. 10 (a)) so people gathering around the robot will not cause large disturbance to other pedestrians. The second best path is G1-G5, which is in a wide area, but as the pedestrian flow splits around point G4 not many persons take this path. Therefore, the simulation yields higher comfort but a low encounter ratio.

<table>
<thead>
<tr>
<th>Rank</th>
<th>$p_k$</th>
<th>$\text{encounter}(p_k)$</th>
<th>$\text{comfort}(p_k)$</th>
<th>Utility</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>G1G4</td>
<td>0.485</td>
<td>0.646</td>
<td>1.131</td>
</tr>
<tr>
<td>2</td>
<td>G2G3</td>
<td>0.347</td>
<td>0.762</td>
<td>1.109</td>
</tr>
<tr>
<td>3</td>
<td>G3G5</td>
<td>0.460</td>
<td>0.637</td>
<td>1.089</td>
</tr>
<tr>
<td></td>
<td>...</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>G1G5</td>
<td>0.533</td>
<td>0.369</td>
<td>0.902</td>
</tr>
<tr>
<td>27</td>
<td>G1G5</td>
<td>0.086</td>
<td>0.792</td>
<td>0.878</td>
</tr>
</tbody>
</table>

The green dotted line G3-G4 in Fig. 9 indicates a roaming path that gave the highest utility $U_{\text{exposure}}$. Eq. 6. However, this path only ranked 25th in the $U_{\text{anticipation}}$ calculation. As this path is in the main corridor there is large flow of pedestrians expected, it gave the best encounter value. However, since the corridor is fairly narrow (Fig. 10 (b)) the robot can easily cause a bottleneck, which is reflected in the low comfort value.
VIII. FIELD EXPERIMENT

A. Hypothesis and Prediction

When a robot simply tries to meet as many people as possible (i.e. maximize exposure), sometimes congestion occurs around the robot. The proposed method involves anticipation of walking comfort (comfort anticipation) to prevent bringing the robot into congestion and prevent it from causing congestion. If the proposed method is effective it should yield better walking comfort around the robot. That is, Prediction 1: Pedestrians around the robot using the proposed method would perceive better walking comfort than pedestrians around the robot that only maximizes its exposure.

B. Method

The experiment was conducted in the shopping mall described in the section IV. There were two conditions: Comfort anticipation (proposed method): The system used \( U_{\text{anticipation}}(\mathbf{p}_k) \) (Eq. 7) as the utility function in the planning of roaming path. Thus, it anticipates walking comfort of pedestrians as well as exposure of the robot.

Maximize exposure: The system used \( U_{\text{exposure}}(\mathbf{p}_k) \) (Eq. 6) as the utility function in the planning of roaming path.

The planning only considers exposing the robot to as many persons as possible.

Following the method described in the section VII, the system computed the best paths for the robot to roam (Fig. 9). In order to run experiments in equivalent situations across conditions, there was a pair of 20 minute slots within an hour for which each condition was randomly assigned. Three pairs of slots were prepared, all during daytime.

In this study, for simplicity, the robot did not engage in conversation when people approached it. Instead, it stopped and resumed the movement only after the person left. Specifically, it stopped its locomotion when there was a person in front of it was within 50 cm from the center and within 30 degrees from the forward direction. We used a semi-autonomous approach [23] where a human operator helped the robot to recover from unexpected situations.

C. Measurement

Two measurements were taken:

Estimated comfort: People’s trajectories were recorded using the tracking system reported in section IV, from which their walking comfort was estimated. Eq. 8 was applied for a set of pedestrian \( O_{\text{uninterested}} \) who passed within \( d_{th} \) distance from the robot and whose walking behavior was uninterested:

\[
\text{estimatedComfort} = \text{average}_{o \in O_{\text{uninterested}}} (\text{comfort}(o))
\]

Subjective comfort: We asked pedestrians to volunteer to answer our questionnaire. We only asked people who passed by the robot within distance \( d_{th} \) and who we evaluated as uninterested. We separately asked about their walking comfort based on the disturbance from the robot (subjective comfort influenced by robot), and disturbance from the people around the robot (subjective comfort influenced by people).

D. Result

1) Scene of interaction

Fig. 10 (a), (b) show observed scenes during the experiment, where (a) shows the path chosen with comfort anticipation condition, and (b) with maximize exposure condition. As can be seen from Fig. 10 (b), using the best path according to maximize exposure the robot is able to closely encounter with almost all persons who went through the corridor (measured encounter(G5G4) = 0.51, similar to what was predicted in the simulation shown in the Table III). However, people would often start gathering around the robot and this significantly reduced the space to pass. In these cases pedestrians wishing to go through had to either slow down considerably or stop and wait for other persons to pass (Fig 10 (b)-right).

On the other hand, on the path chosen using comfort anticipation the robot also has a chance to encounter most of the persons coming from or going towards the corridor (Fig. 10 (a)-left) (measured encounter(G5G4) = 0.47). Moreover, robots presence basically did not cause disturbance or interruption of the flow of pedestrians. Situations where persons gathered around the robot (Fig. 10 (a)-right) were also
frequent, but this did not influence the walking velocity of the persons passing by.

2) Verification of the hypothesis: In total, 5944 people passed (of which 3583 were categorized as uninterested), and 90 persons answered the questionnaire. Fig. 11 shows the results of the measurement (the estimated comfort was converted to range [1, 7] to match the 1-to-7 point Likert scale of the questionnaire). T-test revealed significant difference in all measured items: estimated comfort (p<.001), subjective comfort by robot (p=.022), and subjective comfort by people (p<.001). We therefore conclude that prediction 1 is supported.

Note that there are large differences in values between estimated comfort and subjective comfort, although both support our prediction. While the ratings in the data collection in section IV were with relative evaluation in which participants experienced a range of comfort, the ratings in the field are absolute evaluation without having a baseline comparison. In addition, in the questionnaire about half of people provided positive free-form comments, such as the robot was enjoyable, it made their children happy, etc., which possibly also made them refrain from giving negative ratings. We suspect that these are the sources of such difference.

3) Congestion in simulation and real: We further analyzed the situation around the robot, aiming to confirm whether simulation reproduced situations that are similar to reality.

Fig. 10 (c), (d) shows two scenes during simulation, in which a simulated robot is in a location similar to the one in the real scene. In Fig. 10 (c), (d), the red circle represents the robot, while circles with bold black line are the persons whose behavior category is not uninterested. For persons in the uninterested category the circle is painted blue, with the color intensity representing their comfort (darker means less comfort). In the simulation of maximum exposure condition path (Fig. 10 (d)) there are simulated pedestrians who gathered around the robot, making the available space for passing narrow. The uninterested pedestrians tried to go through this narrow space, but this resulted in a small distance to other pedestrians, and thus low estimated comfort. In comparison, in the simulation of comfort anticipation condition path (Fig. 10 (c)) when persons gathered around the robot there was enough space left for uninterested pedestrians to pass and distances to other pedestrians were larger. We believe that our simulation reasonably reproduced the congestion phenomenon.

IX. DISCUSSION

A. Novelty effect?

There are certainly novelty effects. People stop walking because the robot is novel and interesting to them. We expect the ratio of people in the robot influence model to change over time, so the robot will need to observe and update the model parameters in longitudinal deployment. When a robot becomes common to people there might be only a small number of persons stopping around it, and as a result crowding would not occur. Note that in our experience, even after three years of using robots in a shopping mall children still gathered around the robot, so such changes might not happen in near future.

Further, we believe that even in the distant future crowding would happen with some robots. E.g. in amusement parks there are “mascot characters” — costumed persons who imitate characters from animation films, and they usually attract large crowds. We observed that even with costumed persons wearing non-familiar characters (e.g. a nameless rabbit), children crowd around it. In the future, we believe that some robots will be used for such purpose providing friendly impression and enjoyable atmosphere, for which our model should be very useful.

B. Alternative Approaches

The model of walking comfort could also be used to estimate the phenomena around the robot in real time so one could wonder why we did not use it in a reactive way. The reason is that we wanted to prevent causing a problem, rather than fixing the problem after it happened. Another difficulty is that the congestion is caused by the robot itself, so even if a robot reactively moves toward a seemingly less crowded location, new congestion could occur due to its presence.

One could also argue that we can find the optimal threshold value for encounter(\(\bar{\rho}\)) that does not cause discomfort but yields good exposure; however, this is not easy. The problem are the constraints of the environment, e.g. on some locations the corridor is narrow so more congestion occurs there.

C. Limitations and Future Works

Our model involves a number of parameters. There are robot-dependent and environment-dependent parameters, which would apparently need a calibration for different robots and for different environments. The planning was tested in a single environment. As it needs a large environment where robots have a choice of location to roam around, it was difficult to test the method in a number of environments; nevertheless, we expect that the method would work if we recalibrate the environment-dependent parameters. We believe this calibration process could be automated with a simple pattern-recognition technique to classify people’s behavior toward the robot. We consider this as future work.

The number of subjects used for the derivation of the model of walking comfort in section VI was limited, and the circumstances under which the experiments were done are not representative for all possible situations. This could also be one reason for the discrepancy between estimated and obtained comfort values in field trials. For better results in future applications it will be necessary to improve the
modeling using a larger dataset with more varied samples, and possibly also expand the model itself.

In this study we did not consider the influence of the time of the day; however, some environments that are crowded during daytime are less crowded at night, and vice-versa. Such time-to-time trends would need to be modeled, e.g. with a technique to find temporal patterns from trajectories [24].

X. CONCLUSIONS

In a shopping mall where a robot roam around, we faced a problem of crowd and congestion caused by the robot. Some people around the robot appreciate its presence while other pedestrians passing by suffer from decrease of walking comfort. We addressed this problem using simulations where the pedestrians’ flow, their interaction with other pedestrians and robot, and their perception of the walking comfort was modeled. This enabled the robot to consider a balance between pedestrians’ walking comfort and its task (in this study, the task was to try to be seen by many pedestrians). The study demonstrates the usefulness of modeling people behavior, particularly for emerging complex phenomena.

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