

How Do People Walk Side-By-Side?

- Using A Computational Model Of Human Behavior For A Social Robot

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ABSTRACT

This paper presents a computational model for side-by-side walking for human-robot interaction (HRI). In this work we address the importance of future motion utility (motion anticipation) of the two walking partners.

Previous studies only considered a robot moving alongside a person without collisions with simple velocity-based predictions. In contrast, our proposed model includes two major considerations. First, it considers the current goal, modeling side-by-side walking, as a process of moving towards a goal while maintaining a relative position with the partner. Second, it takes the partner's utility into consideration; it models side-by-side walking as a phenomenon where two agents maximize mutual utilities rather than only considering a single agent utility. The model is constructed and validated with a set of trajectories from pairs of people recorded in side-by-side walking. Finally, our proposed model was tested in an autonomous robot walking side-by-side with participants and demonstrated to be effective.

Categories and Subject Descriptors

H.5.2 [Information Interfaces and Presentation]: User Interfaces - *Interaction styles*; I.2.9 [Artificial Intelligence]: Robotics

General Terms

Design, Experimentation, Human Factors.

Keywords

Human-robot interaction, side-by-side walking, path planning.

1. INTRODUCTION

Previous studies revealed a number of scenarios where mobile robots can serve walking people. For example, they have been used to guide people walking together while talking [7, 20]. Robots have also escorted groups of people as in [4]. When walking together, it is known that people tend to walk on a side-by-side formation [3], however, this knowledge was not used in the above studies. The importance of side-by-side walking for HRI is discussed in [19].

How can we enable a robot to walk with a person in a side-by-side formation? On the surface, it seems quite simple to produce a side-by-side walking situation; all that is needed is to let the robot go along the target person. But is this really so simple?

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HRI'12, March 5–8, 2012, Boston, Massachusetts, USA.

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We found that it was not that simple. Figure 1 (b) shows a scene from one of our experiments illustrating the difficulty with such a simple assumption. In this situation, the person was stuck between the robot and an obstacle. This awkward situation happened because the robot simply tried to be aside her but was not aware of the situation that her front was blocked; from the person's perspective, she kept distance with the robot for safety or social reasons, and she did not try to go close to the robot until her path was blocked. On the other hand, when the robot walks in a cooperative way, the robot is aware of the obstacle in front of the person and opens space while keeping distance (Figure 1 (a)), and they successfully walk in side-by-side formation.



(a) Side-by-side walking model (b) A simple model to stay aside

Figure 1. People walking side-by-side with a mobile robot.

To create this model, we first observed how people walk with other people in a narrow environment that includes corners and obstacles. From these data we formulated a model for computing the utilities of future positions and used it to project the expected utility into the future for motion planning. The model was then implemented into a robot and experimentally evaluated.

2. RELATED WORKS

2.1 Human Science for Spatial Formation

Many studies have been conducted related to personal space and social distance. Hall considered the concept of proximity [9]. Spatial formation during conversation has been studied in [12]. In contrast, relatively only few studies have been conducted for spatial formation while walking. When there are only two people walking together, it is observed that people mostly walked side-by-side formation unless it is severely crowded; when three or more people are walking, they start to form more complex formations, such as "V" shapes and side-by-side formations [3].

In pedestrian modeling research, computational models of human walking behaviors have been developed. A social force model [10] simplifies people's computation as a combination of attractive force toward the goal and repulsive force toward nearby

pedestrians. Moreover, recent studies have started to explore a model for group behavior, adding attraction force toward either the group's gravity center [17] or the positions of other members [28]. Predictions of future states are considered crucial for reproducing human walking behaviors [29].

2.2 Walking with a Robot

Spatial formation has been a focused topic in HRI for the last decade. Social distances with robots were observed and analyzed [8, 26] and reproduced in HRI [22]. Spatial formation during conversations have been replicated in HRI, too, including Kendon's concept of F-formation [14].

However, the above works mainly address static situations where people and robots interact while standing, and a few address human-robot spatial interaction for dynamic situations. Gockley et al. is one exception whose work describes a human-like way for a robot to follow a person [6]. There is a simulation study about a formation for shepherding a group of people [4]. Different from these engineering works, since side-by-side walk is very dynamic, we replicate a human computational model, which is the unique point of our study.

Kobayashi et al. took an engineering approach to implement side-by-side walking for a wheelchair robot. In addition to letting the robot go to the side position as a default, their robot wheelchair followed a caregiver when an obstacle was detected and made it stop when a caregiver stopped so that he can support tasks such as opening a door [13]. Prassler et al. proposed an approach to coordinate the motion of a robotic wheelchair in a railway station moving side by side with the person [21] where they extrapolate the partner's velocity based on the past discrete trajectories. In these two works, contrary to our model, the prediction model only considers the linear extrapolation of velocity and does not use environmental characteristics.

2.3 Perspective Taking and Anticipation

The literature reported the importance of considering the partner's perspective for a robot that interacts with a human partner. A robot must understand the partner's perspective and act based on an estimate of the partner's view. For instance, in deictic interaction, a scene perceived by one agent does not necessarily resemble the partner's due to different viewpoints. Thus, implementing a perspective-taking capability in a robot improves efficiency [1, 25]. Further, beyond perception, anticipatory action was found to be effective in a joint work scenario [11]. We consider important to develop a robot that perceives situations in a similar way as humans and produces actions to improve the partner's future utility. In this work we study a side-by-side walking phenomenon built on the success of previous works that stressed the importance of perspective taking and anticipation.

3. SIDE BY SIDE WALKING MODEL

We propose a computational model that reproduces two-person side-by-side walking even when there are corners and obstacles in a narrow corridor. We took an analytical approach to find a computational model that explains human side-by-side walking. We collected trajectory data of people walking side-by-side and created a utility model that describes a walking motion that fits the data. Finally, we projected this utility model to predict people's walking behavior in the near future, which is a necessary step for planning robot motion. The proposed model uses a utility function to approximate the trajectory of a walking partner and outputs a trajectory similar to the one followed by a human when walking with a partner, we do not imply that humans use this exact model when walking together.

3.1 Data Collection

3.1.1 Tracking infrastructure

Human's trajectories while walking were measured using a laser-based human tracker. We used a network of 9 Hokuyo Top-URG laser range finders with a nominal detection range of 30 m. Each sensor was mounted at the top of a pole at a height of 83 cm. For this configuration, the sensors were set to scan an angular area of 180° at a resolution of 0.25°, at 40 Hz. The sensor poles were placed around the perimeter of the environment to track the positions of people. Range data was stored and analyzed offline to compute participant trajectories using the particle filter tracking algorithm presented in [5].

3.1.2 Procedure

We collected side-by-side walking trajectories of two people in a hallway environment. Fifteen pairs of participants without any knowledge of our research were paid for their participation. We asked each pair of participants to walk together from a start to a goal. For each pair, we collected 34 walking sessions by changing the obstacle positions (see Figure 2.). In total, 510 sets of side-by-side walking trajectories were collected. Each walking experiment lasted approximately 18 seconds. The participants walked in a side-by-side formation, except when avoiding obstacles or passing through narrow spaces. Since the trajectories were measured every 30 ms, we collected 238000 time frames of data. The first and last two seconds of each log were discarded to avoid frames where participants started or stopped walking.

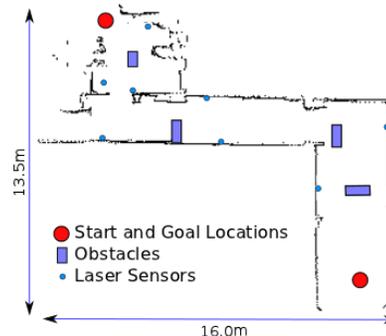


Figure 2. Map of the hallway (16m x 13.5m) where two people walked together from a start to a goal locations.

3.2 Modeling

3.2.1 Assumption

We believe that humans walk together while taking mutual decisions about their next motion. In this case, a person anticipates the partner's next motion and incorporates it in the planning of his own. Our assumption is that when people walk, they share information about their destination considering that subgoal-based path planning is common in human navigation [16]. Hence, we propose a model for side-by-side walking based on utility function and planning with anticipation.

3.2.2 Utility function for Walking Side by Side

We considered several parameters to compute the goodness of people's next motion. We included these parameters in a utility function and are briefly detailed below and illustrated in Figure 3.

Social relative distance (f_{R_d}): According to proxemics studies [9], people stay within a certain relative distance to the partner.

Relative angle (f_{R_a}): When walking together, people tend to walk in the same direction. This utility refers to the relative angle between the trajectories of the walking partners.

Relative velocity (f_{R_v}): Pairs of people coordinate their relative velocity, which is zero or close to zero. Hence, this utility contributes for having people walking at similar velocities.

Distance to obstacle (f_o): People prefer to walk away from obstacles. Positions far away from obstacles have more utility than positions close to obstacles (Eq. 1).

Sub-goal (f_s): While coordinating the position and motion toward the partner, the purpose of the walk is to arrive at the destination. Thus, one prefers to keep facing to the destination. This is computed as an angle between the next point and the subgoal.

Velocity (f_{M_v}): People have their own individual preference concerning walking velocity, referred to as their preferred velocity [10]. Thus, walking at a different speed than their preferred velocity is less comfortable. This utility differs from relative velocity in that it does not take into consideration the partner.

Angular velocity (f_{M_w}): People generally walk in straight lines or paths. This utility represents such a characteristic in which straight trajectories have more utility than non-straight trajectories.

Acceleration (f_{M_a}): When walking one minimizes energy consumption, thus, one minimizes the changes of speed.

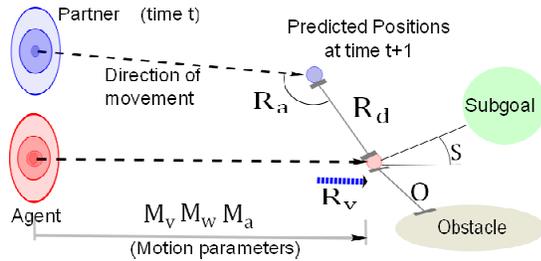


Figure 3. Utility function parameters. Illustrated parameters correspond to the agent's point of view.

Regarding the functions used in the utility computation, we modeled the **distance to obstacle** utility function as a step function (Eq. 1). People feel comfortable if they are far from obstacles (walls), but when they approach them, their desire to avoid obstacles rapidly increases:

$$f_o = - \left| \left(\frac{x}{a} \right)^{-2b} \right| \quad (1)$$

All other utility functions are modeled as a generalized bell function in the expression (Eq. 2), because their distribution has a clear peak and is roughly symmetrical. For example, Fig. 4 shows the histogram of the relative distance between the humans resulting from the trajectory analysis of the experiments in Section 3.1. This indicates that people's average distance during walking alongside was 0.75 m.

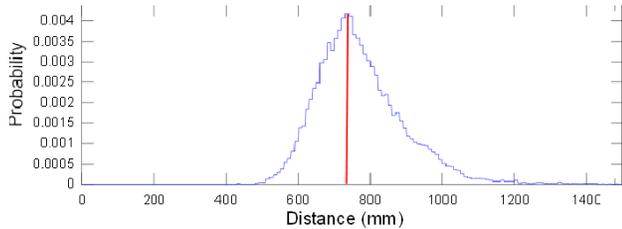


Figure 4. Probability corresponding to the relative distance between center of mass of two people walking together.

$$f_x = \frac{1}{1 + \left| \left(\frac{x-c}{a} \right)^{2b} \right|} - 1 \quad (2)$$

This power function expression, which evaluates variable x , has three parameters. Parameter “ a ” is related to the tolerance of the function, parameter “ b ” corresponds to the curve steepness factor, and parameter “ c ” is the curve’s center. The values of each variable are shown in Table 1.

In our model, we propose to compute the overall walking utility as a combination of individual utilities. We propose a utility function U_t for agent i positioned at point p_i toward its partner's position p_j as follows:

$$U(p^i, p^j) = k_o \cdot f_o + k_s \cdot f_s + k_{R_d} \cdot f_{R_d} + k_{R_a} \cdot f_{R_a} + k_{R_v} \cdot f_{R_v} + k_{M_a} \cdot f_{M_a} + k_{M_v} \cdot f_{M_v} + k_{M_w} \cdot f_{M_w} \quad (3)$$

In this expression variables f_x correspond to the utility functions of each variable x which are weighted by weighting constants k_x . Expression (3) outputs a higher utility when a walking agent and a partner are moving side by side towards a goal location.

3.2.3 Planning

We propose the following three models for the planning process:

Standard Prediction:

This is based on a commonly used method [13, 21] of side-by-side walking that uses linear extrapolation of the velocity to predict the position of the partner at the next moment and moves the robot to a position that is next to the partner (figure 5a). It predicts the partner's position at the next moment as a projection of the previous position with previous velocity, i.e.

$$\hat{p}_{t+1}^j = p_t^j + v_t^j \cdot \Delta t \quad (4)$$

where \hat{p}_{t+1}^j is the predicted position of partner j at next time step $t+1$ and p_t^j and v_t^j are the observed position and velocity at time step t . This model does not fully use the developed utilities (Eq. 3). Instead, it uses the following equation:

$$U_{St}(p_i, p_j) = k_o \cdot f_o + k_{R_v} \cdot f_{R_v} + k_{R_d} \cdot f_{R_d} + k_{R_a} \cdot f_{R_a} \quad (5)$$

Among all possible positions P , the next position is selected to maximize utility $U_{St}(p_i, p_j)$ in (Eq. 5):

$$\hat{p}_{t+1}^i = \operatorname{argmax}_{\{p^i | p^i\}} U_{St}(p^i, \hat{p}_{t+1}^j) \quad (6)$$

Self anticipation:

In this model an agent anticipates its future utility. Thus, it plans a motion to maximize its own utility (Eq. 3) in the next time step. It only anticipates its utility, not the partner's utility. Instead, it uses the linear extrapolation of velocity to predict the position of the partner at the next moment (Eq. 4). Fig. 5b illustrates how this model plans its next motion. This model's planning can be described with the following equation:

$$\hat{p}_{t+1}^i = \operatorname{argmax}_{\{p^i | p^i\}} U(p^i, \hat{p}_{t+1}^j) \quad (7)$$

The main difference in the implementation between standard prediction and self anticipation is the additional knowledge of subgoals in the environment together with the preferred linear velocity, angular velocity and acceleration.

Partner and self anticipation:

In this model an agent anticipates its future utility as well as its partner's future utility. It plans to output a motion to maximize its own utility as well as its partner's utility, both denoted with (Eq. 3), in the next time step. Fig. 5c illustrates how this model plans its next motion. This model's planning can be described with the following equation:

$$\hat{p}_{t+1}^i = \operatorname{argmax}_{\{p^i|p^i\}, \{p^j|p^j\}} \{U(p^i, p^j) + U(p^j, p^i)\} \quad (8)$$

All models are implemented as a planner that searches for the next position among possible positions in the next step. The possible positions are implemented as a grid which we call the *anticipation grid* (P^i in Eqs. 6-8). The center of the grid is the linear extrapolation of the current velocity, i.e., \hat{p}_{t+1}^i . The grid is composed of a 7×7 matrix of cells of $0.20 \text{ m} \times 0.20 \text{ m}$ in size. We set the time for prediction/anticipation (Δt) to be 1 second.

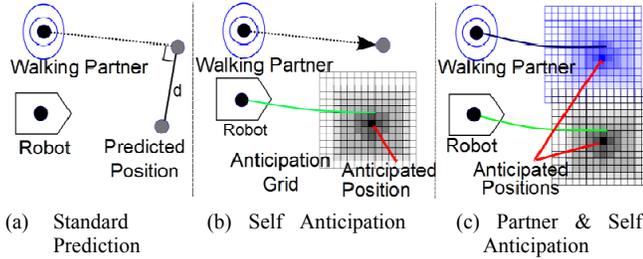


Figure 5. Different approaches for side by side walking.

3.3 Analysis

3.3.1 Calibration of parameters

We manually calibrated the parameters for utility in Eqs. 3 and 5 from the observed data. The same set of data was used for calibration and testing. The same set of parameters is used for each of the three different planning methods: *standard prediction*, *self anticipation*, and *partner and self anticipation*. We took the following steps for parameter calibration:

1. Set initial parameters

It is highly possible that the probability distribution (e.g., Fig. 4) for each characteristic is a consequence of each utility. Thus, we determined the initial parameters from the probability distribution. We set the utility function to output 0 when $x = x_{\text{peak}}$ and -1 when $x = x_{\text{peak}} \pm x_{\text{sd}}$, where x_{peak} is the peak and x_{sd} is the standard deviation for this probability distribution for variable x . We set c to be x_{peak} , a to be x_{sd} , and b to be 1. Each k was set to be 1.

2. Calibrate parameters for each utility function

We used the human collected data to run a simulator and adjust the value of parameters a , b , and c . In this simulator an agent receives the initial position and the orientation of one of the persons, and then at step (p_t^i, p_t^j) , the next position at (\hat{p}_{t+1}^i) is predicted, and prediction error $(|\hat{p}_{t+1}^i - p_t^i|)$ is computed. This process was done for different pairs of people and different obstacle configurations for each of the three planning methods.

3. Calibrate the integration parameter

Finally, the best set of parameters k was adjusted. These constants determine the dominant factors in the utility functions.

The table 1 shows the calibrated parameters for *partner and self anticipation* method. The k parameter represents the balance among each utilities. It indicates that mainly the utility is affected by relative distance, angle, and distance to the object, all of which are also used in the equation (5) too. In addition, one fundamental difference is the considerable influence from the subgoal utility. The c parameter represents the peak of utilities.

3.3.2 Comparison of planning model

To evaluate our proposed utility function and planning method, we ran the simulator using the collected data. For each set of collected trajectories (we dropped non-useful trajectory sets which

Table 1. Parameters determined for utility function

Parameter	a	b	c	k
f_{R_d} : Social relative distance (m)	0.45	2.00	0.75	0.25
f_{R_a} : Relative angle (rad)	0.08	3.00	$\pi/2$	0.32
f_{R_v} : Relative velocity (m/s)	0.20	1.20	0.0	0.01
f_O : Distance to Obstacles (m)	20.0	0.20	----	0.11
f_S : Angle to Subgoal (rad)	0.75	1.00	0.0	0.20
f_{M_v} : Velocity (m/s)	0.90	1.6	1.10	0.05
f_{M_w} : Angular velocity (rad/s)	0.7	4.4	0.0	0.01
f_{M_a} : Acceleration (m/s^2)	1.50	1.0	0.0	0.01

contained noise in the human trajectories, hence, 395 trajectories were processed in total), we used the utility function and planning method to simulate the person's motion (referred as *simulated agent* and *simulated trajectory*), while the partner's motion was read from actual collected trajectories. In the simulation, the initial position and orientation as well as the destination were given to the *simulated agent*, which were read from real trajectories. Then, for each sampling rate of 30ms, the *simulated agent* computes its next position from its previous position and the partner's real position. Finally, the goodness of fit is computed as the error in the distance of each time step of the *simulated trajectory* and its real trajectory.

The figure 6 shows the average and standard error of the error in distance from each planning method. A one-way repeated-measure analysis of variance (ANOVA) was conducted for the error. A significant main effect was revealed ($F(2, 788)=17.519$, $p<.001$, $\eta_p^2=.043$). A multiple comparison with Bonferroni method was conducted, which revealed that the error for *standard prediction* is significantly higher than that for *partner and self anticipation* and *self anticipation* ($p<.001$). No significance was found between *self anticipation* and *partner and self anticipation* ($p=1.0$). Thus, from this simulation, we confirmed that the anticipation is effective, but the effect of *partner and self anticipation* towards a simple *self anticipation* is not revealed. However, in the simulation, the partner agent moved based on the recorded trajectory and not reacted to the agent's motion. We wondered whether this would be due to a lack of reactivity in the simulation, and thus decided to test the methods with a real robot.

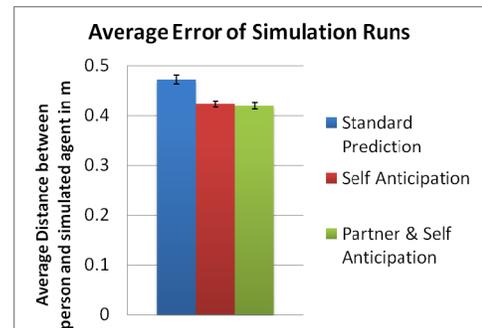


Figure 6. Error distance estimation from the simulation results.

4. IMPLEMENTATION

A robot walking together with a human requires that several functionalities be operating simultaneously. Fig. 7 shows the framework of our system. The environmental map and the positions of the robot and the human partner are fed to the path

planner; the output of the system is the next position of the robot where the best utility is anticipated.

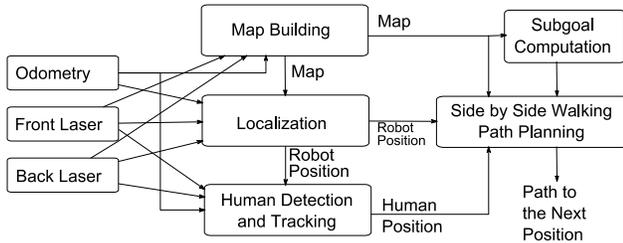


Figure 7. **System framework.** The map building and subgoal computation are performed beforehand. Then the robot performs localization, human tracking, and Side-by-Side planning simultaneously. The output is the robot's next anticipated position.

4.1 Hardware

We used Robovie, a communication robot characterized by its human-like physical expressions to interact with people through utterances and gestures. It is 1.20 m high and 0.40 m in diameter. For perception, it has motor encoders for proprioceptive sensing (Pioneer 3 mobile platform from Adept MobileRobots), and two 30 m range laser sensors (UTM-30LX from Hokuyo) covering 360° around the robot.

4.2 Human Detection and Tracking

For human detection and tracking we used range information from the robot's on-board laser sensors [15, 27]. The robot segments data into clusters to identify leg candidates and identify human candidates (leg pairs). The system initializes a human position at the center of two successive leg clusters and employs a particle filter (PF) per human for tracking the human position in successive cycles. The tracking is performed in an odometry based coordinate system and then transformed to global coordinates to avoid data jumps when the global position is corrected from the robot localization.

4.3 Map building and subgoal computation

We modeled the environment based on our previous study [16]. The model involves two tiers of representation. The first tier corresponds to a *survey view* of the environment. For this, we followed established procedures and state of the art algorithms for map building. To build a grid map, we applied ICP [2] for aligning consecutive laser scans. We used libraries provided in the slam6d framework [18, 23] for the final implementation in the map alignment. The resulting points were voted in a grid. We set the resolution of the grid as 0.05 x 0.05 m. The second tier of representation corresponds to a *route view*. Morales et al. proposed a path segmentation algorithm for retrieving a *route* [16]. In the algorithm, the Voronoi diagram of the grid map of the environment is computed, then, from the topological representation, redundant nodes are erased and remaining nodes are the *subgoals* humans walk in the environment. The obtained *subgoals* were used in the side-by-side walking path planner.

4.4 Robot Localization

We used a particle filter based method for localization with the grid map we built. Each particle contains a pose given by the state vector $\bar{x} = \{x, y, \theta\}$ which is the position x and y and the orientation θ of the robot. The particle filter estimates the posterior using two laser sensors scanning the environment taking into consideration the measurement likelihood. The laser likelihood model used in this work computes $p(z|x, m)$ based on a laser scan z at a position x compared to the grid map m [24].

The map update depends on the state of the particle dispersion and the matching of the laser scans. The particles which are more likely to be correct after the map matching have a higher likelihood, then particle re-sampling is performed and the robot's pose is given by the average weight of the particles.

4.5 Side-by-side Walking Path Planner

The outputs from other modules is combined at this planner for side-by-side walking. The planner is implemented with the model described in Section 3. The position of the robot and the surrounding obstacles are fed from the localization module and the map. The position of the target human is fed from the human detection and tracking module. A moving average filter with a 1 second time window is applied for the positions when we compute velocities (for f_{M_v} and f_{M_w}) and acceleration (for f_{M_a}).

For planning, we used a 7x7 matrix of 0.20 m grids whose center is the linear extrapolation of the current velocity, i.e. \hat{p}_{t+1}^i . We set the time for prediction/anticipation (Δt) to be 1 second. With Eqs. 3 and 8, we computed the grid so that it can anticipate the best utility. The robot's forward and rotation velocities are computed to arrive at the center of the computed grid, which is sent to the mobile base.

Regarding the parameters for a robot, we found it necessary to adjust them. For instance, a person in the data collection might closely approach an obstacle, but this is not safe enough for a robot. Due to its locomotion constraints, when it approaches too close to a wall, it might have a collision. Similarly, due to the sensory noise in the human tracking module, the reading of the velocities is not as stable as the velocities measured with a human tracker with multiple laser-range finders used in the data collection. Thus, we manually adjusted the parameters to be feasible for real robots. For the comparison to be as fair as possible, in each planning method the same parameters were used.

5. Evaluation

5.1 Hypotheses and Prediction

While the anticipation model was found to be more effective than the standard prediction in the simulation, it does not necessarily ensure the usefulness of the proposed method with a real robot. There are two possible problems in the real world. First the dynamics of the real robot and second the behavior of real people towards the robot, both of which were not considered in the simulation. Further, in the simulation, the difference between the two anticipation methods was not revealed.

Hence, we conducted an evaluation experiment to confirm that the method works as designed and produces good side-by-side walking with real people. For that purpose, we primarily compared the proposed method (*partner and self anticipation method*) with the *standard prediction method* because the latter represents a traditional approach. Previous studies only proposed a method with linear extrapolation of velocity (which the *standard prediction method* performs) without proposing a way to anticipate either the robot or its partner's position. In addition, we expect to reproduce the improvement from *self anticipation to partner and self anticipation* in the evaluation.

With good side-by-side walking, a person's walking would probably be less hindered, so he/she could walk smoothly and consider the robot good. Based on this idea, we made this prediction:

Prediction: since the robot with the *partner and self anticipation method* provides a **smoother** and **more natural** impression, it will be perceived as better in its **overall**

evaluation than either the one with the *standard prediction method* or with the *self anticipation method*.

5.2 Method

5.2.1 Participants

Fifteen Japanese people (nine males and six females whose average age was 21.9) were paid for their participation in the evaluation experiments.

5.2.2 Conditions

The experiment was a within-subject design with one factor, *control method*. Three conditions were prepared:

Standard prediction: the robot navigated with the *standard prediction method* (Eqs. 5 and 6) described in Section 3.2.

Self anticipation: the robot navigated with the *self anticipation method* (Eqs. 3 and 7) described in Section 3.2.

Partner and self anticipation: the robot navigated with the *partner and self anticipation method* (Eqs. 3 and 8) described in Section 3.2.

5.2.3 Procedure

Participants evaluated three methods of side-by-side walking. They walked in a side-by-side formation with the robot toward their destination along a given course. The side-by-side situation was explained as a situation where people talk during the walk and typically see their face each other.

Two courses were prepared: **with obstacles** (Fig. 8) and **without obstacles** (the same start positions and goal with the course shown in Fig. 8). This was to confirm the effect in situations with or without obstacles. Each participant walked each course three times with each condition presented in Section 5.2.2. The orders of the conditions were counterbalanced.

For each walk, participants stood at the start position (Fig. 8). After the experimenter confirmed that he/she was ready, the robot's program was initiated. The robot autonomously navigated based on the program reported in Section 4 until it arrived at the goal. Participants answered questionnaires after they arrived at the goal.

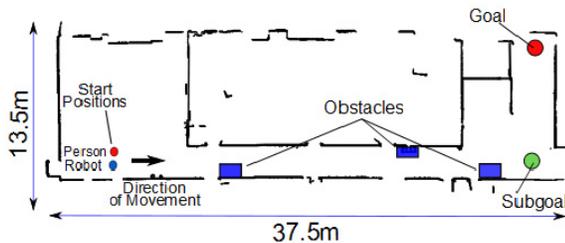


Figure 8. Experimental Environment

5.3 Measurement

After each session, participants filled out questionnaires with the following single item scales on a 1-to-7 point Likert scale for the following impressions:

- **Smoothness**
- **Naturalness**
- **Overall evaluation.**

5.4 Result

Fig. 9 shows the without-obstacle situation result. A one-way repeated-measure analysis of variance (ANOVA) was conducted. A significant main effect was revealed in *smoothness* ($F(2, 28)=13.485, p<.000, \eta_p^2=.491$), *naturalness* ($F(2, 28)=13.000,$

$p=.007, \eta_p^2=.539$), and *overall evaluation* ($F(2, 28)=15.697, p<.001, \eta_p^2=.529$).

A multiple comparison with the Bonferroni method revealed that the ratings for *partner and self anticipation* are significantly higher than that for *standard prediction* (For *smoothness*: $p=.001, naturalness$: $p=.005$, and *overall evaluation*: $p=.001$). The difference between *standard prediction* and *self anticipation* are almost significant in all ratings (For *naturalness*: $p=.065, smoothness$: $p=.084, overall evaluation$: $p=.069$). The difference between *self anticipation* and *partner and self anticipation* are almost significant for *smoothness* ($p=.051$), not significant for *naturalness* ($p=1.0$), and significant in *overall evaluation* ($p=.009$).

Thus, in a situation without obstacles, participants clearly evaluated the *partner and self anticipation method* as smoother, more natural, and better overall than the *standard prediction method*. The difference between the *partner and self anticipation* and *self anticipation* methods was rather subtle, although overall participants preferred the former method.

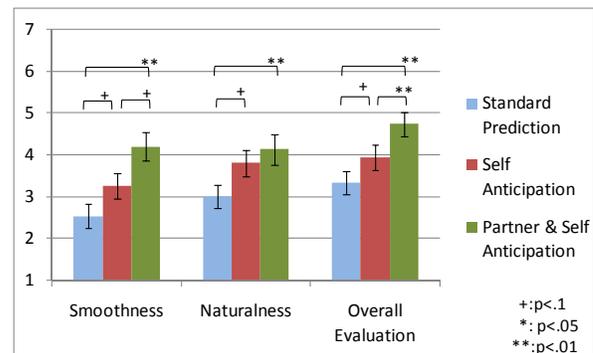


Figure 9. Evaluation result (without obstacle)

Fig. 10 shows the result for with-obstacle situation. A one-way repeated-measure analysis of variance (ANOVA) was conducted. A significant main effect was revealed in *smoothness* ($F(2, 28)=17.982, p<.001, \eta_p^2=.562$), *naturalness* ($F(2, 28)=8.788, p=.001, \eta_p^2=.386$), and *overall evaluation* ($F(2, 28)=6.923, p=.004, \eta_p^2=.331$). A multiple comparison with Bonferroni method was conducted for each ratings.

The ratings for *partner and self anticipation* are significantly higher than that for *standard prediction* for all ratings (*smoothness*: $p=.001, naturalness$: $p=.006$, and *overall evaluation*: $p=.010$), and for *self anticipation* (*smoothness*: $p=.001, naturalness$: $p=.034$, and *overall evaluation*: $p=.016$). The difference between *standard prediction* and *self anticipation* was not significant (*smoothness*: $p=.136, naturalness$: $p=.660$, and *overall evaluation*: $p=1.0$).

Thus, in a situation with obstacles, participants evaluated the *partner and self anticipation method* as the best in all ratings. The difference between the *standard prediction method* and the *self anticipation method* was not significant. It seems that the presence of obstacles change the perception of the *self anticipation method*. Participants possibly evaluated it different from the *standard prediction method* in a without-obstacle situation (as, there are almost significant differences), but with obstacles it is evaluated rather similar to the *standard prediction method*.

Overall, the result follows our prediction. The robot with *partner and self anticipation method* provided more *smooth* and *natural* impression than other methods (in both situation for *standard prediction method*, and in with-obstacle situation for *self anticipation method*). The participants' *overall evaluation* for the

partner and self anticipation method is better than their ratings for standard prediction method.

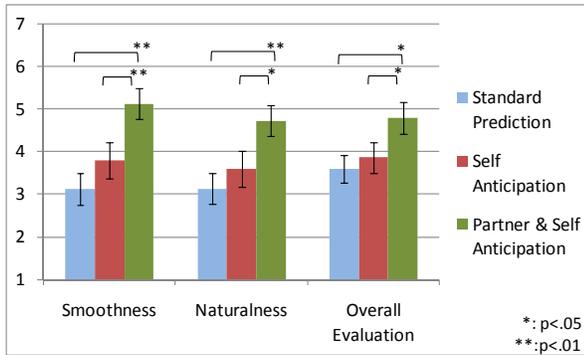


Figure 10. Evaluation result (with obstacle)

In the interview, we asked participants about perceived difference across the conditions. Participants mentioned that the robot kept a constant distance with which they felt comfortable while walking in all three methods; they also realized that the robot was adapting to the relative distance.

In relation with standard prediction, participants mentioned that the robot seemed to be nervous and sensitive to their movements, therefore they did not feel that the walking was smooth and natural. Some participants commented that the robot in the self and partner anticipation method made space for them, as shown in the figure 1 (a): "I felt that when I was coming close to the trash can the robot moved away and gave me space to pass". This suggests that the self and partner anticipation method successfully consider the partner's utility, and thus participants perceived better impression to it.

Figure 11 shows a scene when the robot opens space for the partner to walk while avoiding an obstacle with the self and partner anticipation method. The figure shows a transition of utility when the partner was approaching to the obstacle. The partner is represented as the circle at the top (red), and the bottom circle (blue) shows the current position of the robot. Their anticipated/planned position is shown to their right (yellow and blue circles) respectively. The anticipation grids are shown around the anticipated positions for both, the partner and the robot.

The notable moment is shown in the center of Figure 11 where the robot anticipated the person to go to the center of the corridor to avoid the obstacle, and planned its position towards the right side (bottom in the figure) of the corridor. Thus, in the right figure, when they were close to the obstacle, they are already in a course of jointly avoiding the obstacle still in a side-by-side formation.

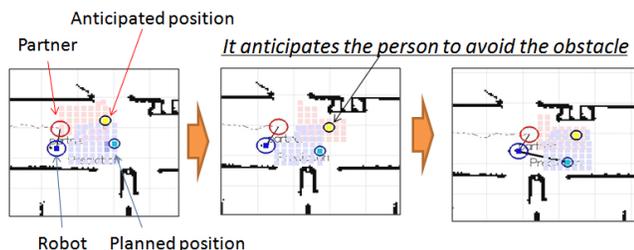


Figure 11. Behavior of "self and partner anticipation" while avoiding an obstacle.

Such motion is only possible with the partner and self anticipation method. In the case when self anticipation method faces the same situation, it does not open space for the partner. Figure 12 shows a scene of the self anticipation method experiment. It is the same

situation as the figure 11 where they were approaching to the obstacle. At the moment where there is the obstacle in front of the partner, it failed to anticipate the partner's avoiding motion. It only noticed the partner avoiding motion after the partner started to move towards the center of the corridor.

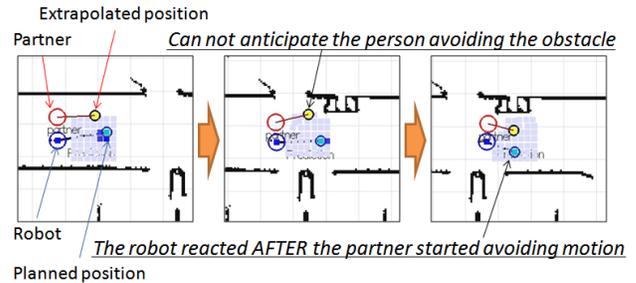


Figure 12. Behavior of "self anticipation" while avoiding an obstacle.

6. DISCUSSION

6.1 Contributions

The capability of side-by-side walking developed here promises to provide substantial pragmatic value. Many possible scenarios exist in daily interactions where a robot might walk side-by-side with a person. For example, consider a guidance application in a shopping mall, where a robot escorts a visitor to his destination. If they engage in conversation while walking, a side-by-side walking formation would be much more natural than a formation where the robot leads or follows.

6.2 Extending the Model

So far, the model is only for side-by-side situations with static obstacles, but we believe we can easily extend the method to more general situations. The basic idea of using utility is very close to the general idea in robotics to use potentials. The potential field method and its extension are widely used in robotics.

Our method requires subgoal information and assumes that when people walk, they share the information about their destination. At the same time, we consider it possible to extend our method to situations where a robot is not informed about the destination. From how people walk, it might be possible to infer the next subgoal of the person walking. For example, when a person is around a corner, a robot could have two hypotheses: going straight toward a subgoal or turning toward a subgoal in the branching direction. Based on how people walk, from the fitting with the assumed utility value, we consider it possible to predict the direction the person will take so that the robot can quickly update its hypothetical subgoal for moving. We consider this interesting future work.

6.3 Limitations

In this study, the parameters were not systematically calibrated, though it would be important to develop a method to calibrate them. Particularly a computational method to translate parameters used for human-human interaction to human-robot interaction would be beneficial. The reported parameters were calibrated for Japanese people, but it would require re-calibration for a different culture or context, as social distance alter along with context [9].

We did not specifically adjust parameters in favor of the proposed method for the experiment with the robot, though one could argue that the result would be due to the specific parameters we used. We believe that there are quantitative difference across the methods. For example, the standard prediction method and the self anticipation method lacks the capacity to quickly make a

space for the partner (see Fig. 1 right and Fig. 12), as it does not predict the partner's motion constraints relate to obstacle (see Fig. 1 left and Fig. 11). The *standard prediction method* further lacks the capacity to move the robot toward the goal. Thus, we consider that the observed difference is due to the nature of the methods, but not due to the specific parameters.

The study only addressed peer-type relationship between people who walk in side-by-side, but leader-follower relationships would considerably change the situation. For example, as reported in [13, 21], in case a caregiver leads and a robotic wheelchair follows, it is clear who is leading, thus the *standard prediction model* would produce side-by-side walking as good as our proposed model. As observed, what is missing in *standard prediction method* is a capacity to take a lead and move toward the goal; the experimental result revealed that this is crucial in side-by-side walking with peer-type relationship.

7. CONCLUSION

We developed a computational model for side-by-side walking. A utility model describing how people prefer to move was built based on recorded trajectories of pairs of people walking side-by-side. Parameters for the model were chosen which best predicted the future walking motion of the people recorded in the trajectory data. This model was then used to generate appropriate walking behavior for an autonomous robot walking alongside a person. Our evaluations showed that the *partner and self anticipation method*, that is, projecting the future position of the partner based on the utility model and then planning an appropriate path for an autonomous mobile robot by using the same utility model to mimic human behavior, provided better results than simpler planning mechanisms.

8. ACKNOWLEDGMENTS

This research was supported by the Ministry of Internal Affairs and Communications of Japan. The authors thank the help and contribution of Thomas Kaczmarek and Trevor Condon.

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