Walking Together: Side-by-Side Walking Model for an Interacting Robot

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This paper presents a computational model for side-by-side walking within human-robot interaction (HRI). In this work we address the importance of future motion utility (motion anticipation) of two walking partners. Previous studies only considered a robot moving alongside a person without collisions and 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 toward 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 based in a set of trajectories from pairs of people recorded in side-by-side walking; then, parameters of the model were calibrated for a mobile robot and tested in an autonomous robot walking side-by-side with participants. Finally, two evaluations were performed. The first evaluation shows that the proposed model considering mutual utilities performs better than a single utility method and a method that keeps distance from the walking partner. In the second evaluation the proposed method was used for a robot deployed in a shopping mall environment where it demonstrated to be effective.

Keywords: human-robot interaction, side-by-side walking, path planning.

1. Introduction

Previous studies presented a number of scenarios where mobile robots can serve walking people. For example, they have been used to guide people walking together while talking (Gross et al., 2008; Pineau, Montemerlo, Pollack, Roy, & Thrun, 2003). Robots have also escorted groups of people (Garrell & Sanfeliu, 2010). When walking together, it is known that people tend to walk in a side-by-side formation (Costa, 2010), however, this knowledge was not used in the above studies. The importance of side-by-side walking for HRI is discussed in Kahn et al. (2008).

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 alongside the target person. But is this really so simple?

We found that producing a side-by-side walking situation was not so simple. Fig. 1b 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

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happened because the robot simply tried to stay beside her but was not aware of the situation that her forward-going path was blocked; from the person's perspective, she kept distance from 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 (Fig. 1a), and they successfully walk in a side-by-side formation.

(a) Side-by-side walking model

(b) A simple model of staying beside

Figure 1. Different approaches for computing side-by-side walking for a person walking side by side with a mobile robot. In the image on the left (a) the robot uses an anticipation model to predict the person's and its own next position, weighing human and environmental factors that result in a natural side-by-side walking. In the image on the right (b), the robot tries to stay next to the person using a simple model based on human-robot relative information where it can not anticipate the woman's movement, resulting in unnatural movement.

To create this model, we first observed how people walk with other people in a narrow environment that included corners and obstacles. From these data we formulated a model for computing the goodness of motion of future positions and used it to project the expected walking position 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 relating to personal space and social distance. Hall (1966) considered the concept of proximity. Spatial formation during conversation has been studied (Kendon, 1990). In contrast, relatively 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 in a side-by-side formation unless their environment was 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 (Costa, 2010).

In pedestrian modeling research, computational models of human walking behaviors have been developed. A social force model (Helbing & Molnár, 1995) simplifies people's computation as a combination of attractive force toward the goal and repulsive force away from nearby pedestrians. Moreover, recent studies have started to explore a model for group behavior, adding

attraction force toward either the group's center of gravity (Moussaïd, Perozo, Garnier, Helbing, & Theraulaz, 2010) or the positions of other members (Xu & Duh, 2010). Predictions of future states are considered crucial for reproducing human walking behaviors (Zanlungo, Ikeda, & Kanda, 2011).

2.2 Walking With a Robot

Spatial formation has been a topic of focus in HRI for the last decade. Social distances with robots were observed and analyzed (Hüttenrauch, Severinson, Eklundh, Green, & Topp, 2006; Walters et al., 2005) and reproduced in HRI (Sisbot, Marin-Urias, Alami, & Simeon, 2007). Spatial formation during conversations has been replicated in HRI, including Kendon's concept of F-formation (Kuzuoka, Suzuki, Yamashita, & Yamazaki, 2010).

However, the above works mainly address static situations where people and robots interact while standing, and few address human-robot spatial interaction for dynamic situations. Gockley, Forlizzi, and Simmons (2007) provided one exception with work that described a human-like way for a robot to follow a person. A simulation study also discussed a formation for shepherding a group of people (Garrell & Sanfeliu, 2010). Different from pure engineering approaches and since side-by-side walking is such a complex and dynamic behavior, we propose a unique computational model developed from human behavior observation.

Kobayashi et al. (2011) 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 robotic wheelchair followed a caregiver and when an obstacle was detected the robotic wheelchair stopped when the caregiver stopped so that the caretaker could support tasks such as opening a door. Prassler, Bank, and Kluge (2002) proposed an approach to coordinate the motion of a robotic wheelchair in a railway station moving side by side with the person where the researchers extrapolated the partner's velocity based on past discreet trajectories. In these two works, contrary to our model, the prediction model only considered the linear extrapolation of velocity and did not use environmental characteristics.

2.3 Perspective Taking and Anticipation

The literature reported the importance of considering a 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 perspective due to different viewpoints. Thus, implementing a perspective-taking capability in a robot improves efficiency (Berlin, Gray, Thomaz, & Breazeal, 2006; Trafton et al., 2005). Furthermore and beyond perception, anticipatory action was found to be effective in a joint work scenario (Hoffman & Breazeal, 2007). We consider it 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 in corridors with corners and obstacles. The model considers both walking agents' relative information together with environmental and motion factors. We took an analytical approach to find a model that explains human side-by-side walking. First, we collected trajectory data of people walking side-by-side and created a utility model (utility-based techniques are standards in high level decision-making) that describes walking motion fitting the data. Finally, we projected this utility model to predict people's walking behavior, which is a necessary step for planning robot motion. The proposed model uses a utility function to approximate and predict the trajectory of a walking partner; we do not imply that humans use this exact model when walking together.

3.1 Human Data Collection for Trajectory Analysis

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 degrees at a resolution of 0.25 degrees 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 Glas, Miyashita, Ishiguro, and Hagita, (2009).

Figure 2. The experimental environment is 16 m x 13.5 m in size and the participants walked approximately 23 m per experiment. In the experiment there were several objects (desks) in the hallway to analyze different human walking behaviors during obstacle avoidance while walking side by side.

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 Fig. 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 at every 30 ms, we collected 238,000 time frames of data. The first and last two seconds of each log were discarded to avoid frames where participants started or stopped walking.

3.2 Modeling

We believe that ‘humans walking together’ is one form of collaborative interaction. In collaborative interaction, it is found that anticipatory motion is important: A person anticipates the partner’s next motion and incorporates it in planning of following motion (Hoffman & Breazeal, 2007). Similarly, we hypothesized that when people walk together, the following cognitive processes occur:

- They plan their future motion together with reactive walking
- In planning, they anticipate the partner’s future utility and plan mutual future motion
- They share environmental knowledge such as the location of obstacles and destination locations (subgoal-based path planning has been used for human navigation, see Morales, Satake, Kanda, & Hagita, 2011)

Hence, in order to model two people walking in side-by-side formation, our model extrapolates future possible locations of the walking agent, and using a utility function, it evaluates them while anticipating the next location.

To build a computational model that can explain humans' side-by-side walking we took the following approach:

- (1) Collected a data set of two persons walking side-by-side
- (2) Analyzed the data and extract factors involved in this interaction
- (3) Established a utility function (commonly used for high level decision making) and calibrated the parameters
- (4) Using the utility function, tested for the idea of single or mutual planning (i.e., whether people would plan for mutual future motion)

For our experimental analysis, we observed the collected side-by-side walking trajectory data sets (as shown in Section 3.1.2) and extracted eight different factors involved when people walk side by side (as explained in Section 3.2). These factors were then classified into three groups: motion factors, relative factors, and environmental factors.

We computed the observed distributions (histograms) of each factor, which provided information about preferences of people walking together (peaks in histograms as shown in Fig. 4). To model the walking factor functions, our approach was to use initial parameters taken from histogram distributions and then calibrate them reducing the error between the real trajectories of a walking agent toward a simulated one when walking next to the trajectory of the partner. The set of parameters offering smaller error was used for the modeling function (Table 1 and Fig. 6). Calibration was performed because some factor distributions could have been the consequence of other parameters. For example, in the case of distance to obstacles, it was observed that the distance peaked at 0.6 m; however, it is intuitive to treat this distance as the consequence of other interaction (e.g., trying to keep social distance with the partner, and as a consequence, one would often be around the same such distance from the wall).

3.2.1 Side-by-Side Walking Modeling Factors

We considered eight factors to compute the goodness of people's next motion. We included these factors in a utility function to predict and compute the position that provides a higher value of utility. There are three types of factors (illustrated in Fig. 3):

- a) Motion (**M**). Motion factors have to do with the mobility of each agent: velocity, angular velocity, and acceleration.
- b) Relative (**R**). Relative factors are related to the walking partner: social relative distance, relative angle, and relative velocity.
- c) Environmental (**E**). Environmental factors are related to the physical world in which the agents walk together: angle toward the next subgoal and distance to static obstacles.

At a present time t we define the position of a walking agent i as p_t^i and the position of the partner j as p_t^j ; in the same way, the predicted positions after a sampling time Δt are defined as $\hat{p}_{t+1}^i$ and $\hat{p}_{t+1}^j$ respectively. Each walking modeling factor is detailed below taking p_t^i as reference and illustrated in Fig. 3.

3.2.1.1 Motion Factors

Velocity (f_{M_v}): People have their own individual preference concerning walking velocity, referred to as their preferred velocity (Helbing & Molnár, 1995). Thus, walking at a different speed than their preferred velocity is less comfortable. This utility represents this preference of velocity:

$$M_v = \left| \frac{dis(p_t, \hat{p}_{t+1})}{\Delta t} \right| \quad (1)$$

where $dis(p_1, p_2)$ is a function to compute the distance between points p_1 and p_2 .

Angular velocity (f_{M_w}): People generally walk in straight line trajectories feeling strong aversion to moving opposite to the desired walking direction (Helbing, Farkas, Molnár, & Vicsek, 2002):

$$M_w = \frac{ang(\hat{p}_{t+1}) - ang(p_t)}{\Delta t} \quad (2)$$

where $ang(p)$ is a function that computes the walking angle of an agent at point p .

Figure 3. The utility of the side-by-side goodness of motion is computed according to relative (R), environmental (E), and motion (M) factors. The illustrated factors correspond to the agent's point of view (i).

Acceleration (f_{M_a}): When walking one minimizes energy consumption, thus, one minimizes the changes of speed walking at a preferred natural velocity (Helbing et al., 2002; Ralston, 1958). The acceleration M_a histogram values are shown in Fig. 4, it is evident that people tend to walk at regular velocities. High acceleration values are low in Fig. 4c because the histogram was created using data when people had started walking and before they had fully stopped.

$$M_a = \frac{\hat{M}_{v_{t+1}} - M_{v_t}}{\Delta t} \quad (3)$$

3.2.1.2 Relative Factors

Social relative distance (f_{R_d}): According to proxemics studies (Hall, 1966), people stay within a certain relative distance to their partner. In our work, we computed this parameter as the distance between the center of mass of the two walking partners.

$$R_d = dis(\hat{p}_{t+1}^i, \hat{p}_{t+1}^j) \quad (4)$$

Relative angle (f_{R_α}): This utility refers to the relative angle between the trajectories of the walking partners. When people walk together, they tend to walk in the same direction (Zanlungo & Kanda, 2013).

$$R_\alpha = ang(\hat{p}_{t+1}^j) - ang_b(\hat{p}_{t+1}^i, \hat{p}_{t+1}^j) \quad (5)$$

where $ang_b(p_1, p_2) = atan2(p_{1y} - p_{2y}, p_{1x} - p_{2x})$. Angle R_α was computed as the angle normal to the direction of partner j to avoid walking in line or cross-over. From Fig. 4e it can be seen that R_α had a peak close to $\frac{\pi}{2}$.

Relative velocity (f_{R_v}): Pairs of people walking together constantly keep monitoring their mutual positions and velocities relative to each other uniformly coordinating their movements (Hoogendoorn and Bovy, 2003); this results in walking with a relative velocity close to zero (Fig. 4f); hence, this utility contributes for having people walking at similar velocities.

$$R_v = M_{v_{t+1}}^i - M_{v_{t+1}}^j \quad (6)$$

3.2.1.3 Environmental Factors

Moving toward subgoals ($f_{E_{S_n}}$): While coordinating position and motion toward the partner, the purpose of the walk is to perform a subgoal-oriented movement to arrive at a final destination (Montello, 2005; Morales et al., 2011); thus, one prefers to keep facing toward the next subgoal_n until arriving at the destination (passing sequentially through all the f subgoals). The subgoals of the environment were extracted using the subgoal extraction algorithm proposed in Morales et al., (2011). Angle E_{S_n} toward n^{th} subgoal_n is illustrated in Fig. 3 and computed as:

$$E_{S_n} = \text{ang}_b(\text{subgoal}_n, p_t) - \text{ang}_b(\hat{p}_{t+1}, p_t) \quad (7)$$

Distance to obstacle (f_{E_o}): People prefer to walk at a certain distance from other pedestrians and obstacles (Helbing et al., 2002). This is a common assumption across pedestrian modeling where $c_{obst}(p)$ is a function that returns the position of the closest obstacle to position p .

$$E_o = \text{dist}(\hat{p}_{t+1}, c_{obst}(\hat{p}_{t+1})) \quad (8)$$

3.2.2 Walking Factor Histograms

To understand people's preference when walking together toward each walking factor, we applied expressions in Eq. 1–8 to the data set of Section 3.1 and computed their observed distributions (histograms). These histograms provided an insight of the behavior of pairs of people walking together in indoor corridor environments by providing the shape of the distribution of each parameter and the preferences of people visible in the peaks of the distributions. Fig. 4 shows the normalized histogram of each walking factor where values close to 1 (distribution peaks) represent people's preferred walking tendencies.

3.2.3 Function Modeling

All utility functions except the **distance to obstacle** function are modeled as a generalized bell function in the expression (Eq. 1), because their distribution has a peak and is symmetrical.

$$f_x = \frac{1}{1 + \left| \left(\frac{x-c}{a} \right)^{2b} \right|} - 1 \quad (9)$$

This power function expression, which evaluates variable “ x ” corresponding to each utility, 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 peak. The values of each variable are shown in Table 1.

We modeled the distance to obstacle utility function as a step function (Eq. 2). People feel comfortable if they are far from obstacles (walls), but when they approach them, their desire to avoid obstacles rapidly increases:

$$f_o = - \left| \left(\frac{x}{a} \right)^{-2b} \right| \quad (10)$$

Utility Function. 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:

$$U(p^i, p^j) = k_o f_o + k_s f_s + k_{R_d} f_{R_d} + k_{R_\alpha} f_{R_\alpha} + k_{R_v} f_{R_v} + k_{M_a} f_{M_a} + k_{M_v} f_{M_v} + k_{M_w} f_{M_w} \quad (11)$$

Figure 4. Normalized histograms for walking modeling factors. The histograms were extracted from pairs of people walking together. The peak in each graph shows people’s preference when walking together.

The utility function of expression (11) adds the utilities f_x of each variable x multiplied by weighted constants k_x . The function outputs a higher utility when a walking agent and a partner are moving side-by-side toward a goal location. In this function, only first order terms were included as a result of balance between simplicity and accuracy where there was no necessity to build a more complex model (i.e., using higher order terms). Calibration parameters of the utility function are shown in Table 1 (Section 3.4), and simulated and real world experimentation show the performance of the utility function.

3.3 Planning

We propose the following three models for the planning process:

3.3.1 Standard Prediction

This is based on a commonly used method (Kobayashi et al., 2011; Prassler et al., 2002) 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 agent to a position that is next to the partner (Fig. 5a). This method predicts the partner’s position at the next moment as a projection of the previous position with previous velocity, i.e., $\hat{p}_{t+1}^j = p_t^j + M_{v_t}^j \cdot \Delta t$ where $M_{v_t}^j$ is the velocity at time t . This model

does not fully use the developed utilities (Eq. 11). Instead, it uses the following equation:

$$U_{St}(p_i, p_j) = k_O \cdot f_O + k_{R_v} \cdot f_{R_v} + k_{R_d} \cdot f_{R_d} + k_{R_a} \cdot f_{R_a} \quad (12)$$

Among all possible positions P , the next position is selected to maximize utility $U_{St}(p_i, p_j)$ in Eq. 13:

$$\hat{p}_{t+1}^i = \operatorname{argmax}_{\{p^i | p^i\}} U_{St}(p^i, \hat{p}_{t+1}^j) \quad (13)$$

3.3.2 Self-anticipation

In this model, an agent anticipates its future utility. Thus, it plans a motion to maximize its own utility (Eq. 11) 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 in the next moment (Eq. 12). Fig. 5b illustrates how this model plans its next motion. This model's planning can be described with the following equation:

$$\hat{p}_{t+1}^i = \operatorname{argmax}_{\{p^i | p^i\}} U(p^i, \hat{p}_{t+1}^j) \quad (14)$$

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.

Figure 5. Different planning approaches for computing side-by-side walking.

3.3.3 Partner- and Self-Anticipation

In this model, an agent anticipates its own and its partner's future utility by planning to output each motion for maximizing utility (both denoted with Eq. 11) in the next time step. Fig. 5c illustrates how this model plans its next motion, which can be described with the following equation:

$$\hat{p}_{t+1}^i = \operatorname{argmax}_{\{p^i | p^i\}, \{p^j | p^j\}} \{U(p^i, p^j) + U(p^j, p^i)\} \quad (15)$$

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. 14, 15, and 16). The center of the grid is the linear extrapolation of the current velocity, that is, $\hat{p}_{t+1}^i$. 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.

3.4 Parameter Analysis and Tuning

3.4.1 Calibration of Parameters

We calibrated the parameters for utility in Eqs. 11 and 13 from the observed data. The same set of data was used for calibration and testing. The same set of parameters was 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. For utilities modeled by Eq. 9 we set the utility function to output 1 when $x=x_{\text{peak}}$ and 0 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. For the case of distance to obstacle, the utility is modeled as a step function (Eq. 10), the initial parameter for variable b was x_{peak} , and a was set to 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 determined the dominant factors in the utility functions.

Table 1 shows the calibrated parameters for the *partner- and self-anticipation* method. Utility function parameters f_x have been illustrated in graphs (Fig. 6). These graphs show that the shape and values of the functions differ from the histograms of Fig. 4 after parameter calibration. For instance, we modeled the function for relative angle (f_{R_a}) not to be tolerant against values away from $\pi/2$ in order to avoid crossovers by the walking agent and the partner, as this behavior was not observed in our data set. The utility function for angular velocity (f_{M_w}) was modeled to allow angular velocities up to 1.0 rad/sec, which allows a walking agent to turn, avoid obstacles, and adapt to the partner.

Table 1. Parameters determined for computing the utility functions.

Parameter	a	b	c	k
f_{R_d} : Social relative distance (m)	0.25	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_{E_s} : Angle to Subgoal (rad)	0.45	1.00	0.0	0.20
f_{E_o} : Distance to obstacles (m)	20.0	0.40	----	0.11
f_{M_v} : Velocity (m/s)	0.30	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)	0.20	1.0	0.0	0.01

The major change was on the function for distance to obstacle. As people tend to stay away from obstacles we modeled the function f_{E_o} as a step function where no utility was given for distances under 0.4 m and full utility was given for any other location.

The k parameter represents the balance among each utility. It indicates that the utility mainly is affected by relative distance, angle, and actual distance to the object, all of which were also used in Eq. 13. In addition, one fundamental difference was the considerable influence from the subgoal utility.

3.3.2 Comparison of Planning Mode

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 that contained noise in the human trajectories; hence, 395 trajectories were processed in total), we used

Figure 6. Side-by-side walking utility factor functions. The functions were evaluated with parameters in Table 1.

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, orientation, and destination were given to the *simulated agent*, which were read from real trajectories. Then, each sampling rate of the *simulated agent* computed its next position from its previous position and the partner's real position. Finally, the goodness of fit was computed as the error in the distance in each step of the *simulated trajectory* and its real trajectory.

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 showed 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* toward a simple *self-anticipation* was not revealed. However, in the simulation, the partner agent moved based on the recorded trajectory and not out of reaction to the agent's motion. We wondered whether this would be due to a lack of reactivity in the simulation, and thus we decided to test the methods with a real robot. Fig. 7 shows the average and standard error of the error in distance from each planning method.

4. Implementation

A robot walking together with a human requires that several functionalities be operating simultaneously. Fig. 8 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.

4.1 Hardware

We used Robovie, a communication robot that has motor encoders for proprioceptive sensing perception (Pioneer 3 mobile platform from Adept MobileRobots), and two 30 m range laser sensors (UTM-30LX from Hokuyo) covering 360 degrees around the robot. The robot framework is the same for the robots used in Sections 5 and 6.

Figure 7. Error distance estimation from the simulation results.

Figure 8. System framework. The map building and subgoal computation are performed off-line. Then, the robot performs localization, human tracking, and side-by-side planning simultaneously. The output is the robot’s next anticipated position.

4.2 Human Detection and Tracking

For human detection and tracking we used range information from the robot’s on-board laser sensors (Montemerlo, Thrun, & Whittaker, 2002; Wang & Thorpe, 2002). The robot segments data into clusters to identify leg candidates and human candidates (leg pairs). The system initializes a human position at the center of two successive leg clusters and employs a particle filter 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’s localization.

4.3 Map Building and Subgoal Computation

We modeled the environment based on our previous study (Morales et al., 2011). 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 iterated closest point “ICP” (Besl & McKay, 1992) for aligning consecutive laser scans. We used libraries provided in the slam6d framework (Nüchter, Lingemann, Hertzberg, & Surmann, 2007; Nüchter et al., 2011) for the final implementation in the map alignment. The resulting points were down-sampled into a grid with a resolution of 0.05 m x 0.05 m. The second type of representation corresponds to a *route view*. Morales et al. (2011) proposed a path segmentation algorithm for retrieving a *route*. In the algorithm, the Voronoi diagram of the environment’s grid map 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 that we built. Each particle contained a pose given by the state vector $\bar{\mathbf{x}} = \{\mathbf{x}, \mathbf{y}, \boldsymbol{\theta}\}$ that is the position $\mathbf{x}$ and $\mathbf{y}$ and the orientation $\boldsymbol{\theta}$ 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 $p(\mathbf{z}|\mathbf{x}, \mathbf{m})$ based on a laser scan $\mathbf{z}$ at a position $\mathbf{x}$ compared to the grid map $\mathbf{m}$ (Thrun, Burgard, & Fox, 2005). The map update depends on the state of the particle dispersion and the matching of the laser scans. The particles that 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 are combined on this planner for side-by-side walking. The planner is implemented with the model described in Section 3. The position of the robot and 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 computed velocities (for $\mathbf{f}_{M_v}$ and $\mathbf{f}_{M_w}$) and acceleration (for $\mathbf{f}_{M_a}$).

For planning, we used a 7 x 7 matrix of 0.20 m grids, of which the center is the linear extrapolation of the current velocity, that is, $\hat{\mathbf{p}}_{t+1}^i$. 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 then sent to the mobile base.

5. Evaluation

5.1 Hypotheses and Prediction

While the anticipation model was found to be more effective than the standard prediction in simulation, it does not necessarily ensure 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. Furthermore, 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 this purpose, we primarily compared the proposed method (*partner- and self-anticipation*) 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’s or its partner’s position. In addition, we expect to reproduce the improvement from *self-anticipation* to *partner- and self-anticipation* in the evaluation.

A person's walking would probably be less hindered with good side-by-side walking, effecting smooth motion while perceiving the robot with a positive regard. Based on this idea, we made the following prediction:

Since the robot with the *partner- and self-anticipation method* provides a **smoother** and **more natural** impression, it will be perceived better in its **overall evaluation** than with the *standard prediction method* or with the *self-anticipation method*.

5.2 Method

5.2.1 Participants

Fifteen Japanese people from the general public, without knowledge of the purpose of the experiment (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-subjects design with single factor, *control method*. Three conditions were prepared (as described in Section 3.2):

Standard prediction: the robot navigated with the *standard prediction method* (Eqs. 13-14).

Self-anticipation: the robot navigated with the *self-anticipation method* (Eqs. 11 and 15).

Partner- and self-anticipation: the robot navigated with the *partner- and self-anticipation method* (Eqs. 11 and 16).

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 each other's face.

Two courses were prepared (Fig. 9a): **with obstacles** and **without obstacles** (having the same start position and goal within the course). An identical route was designed for both conditions to confirm the effect in situations with or without obstacles. Each participant walked each course three times with each condition (as presented in Section 5.2.2). The orders of the conditions were counterbalanced.

For each walk, participants stood at the start position (Fig. 9a). After the experimenter confirmed that everything was ready, the robot's program was initiated. The robot autonomously navigated based on the program (as reported in Section 4) until it arrived at the goal. The robot used for the experiment had a limited velocity of 0.5 m/sec and is shown in Fig. 9b. Participants answered questionnaires after they arrived at the goal.

Figure 9. Experimental environment and the human-like mobile robot. The robot and the person walked together from the start to the goal locations passing through a subgoal (in green). Obstacles in the environment are represented by blue rectangles.

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.

Fig. 10 shows the result for the without-obstacles situation, and Fig. 11 shows the result for the with-obstacle situation. We conducted one-way repeated-measures analyses of variance (ANOVA), and 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 the Bonferroni method was conducted for each rating.

Figure 10. Evaluation results without obstacles

Figure 11. Evaluation results with obstacles showing the better overall performance for the partner- and self-anticipation method

The ratings for *partner- and self-anticipation* were 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 changed the

perception of the *self-anticipation* method. Participants possibly evaluated it differently from the *standard prediction* method in a without-obstacle situation (as there were almost-significant differences), but with obstacles it was evaluated rather similarly to the *standard prediction* method.

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

In the interview, we asked participants about perceived differences 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 Fig. 1a: "I felt that when I was coming close to the trash can the robot moved away and gave me space to pass." This suggested that the *self- and partner-anticipation* method successfully considered the partner's utility, and thus participants perceived a better impression toward the robot.

Fig. 12 shows a scene when the robot opened 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 the obstacle. The partner is represented as the circle at the top (red), and the bottom circle (blue) shows the 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.

A notable moment is shown in the center of Fig. 12 where the robot anticipated the person going to the center of the corridor to avoid the obstacle, and then planned its position toward the right side (bottom in the figure) of the corridor. Thus, in the figure on the right, when they were close to the obstacle, they are already in a course of jointly avoiding the obstacle while still in a side-by-side formation.

Figure 12. Behavior of “self and partner anticipation” while avoiding an obstacle

Such motion was only possible with the partner- and self-anticipation method. In the case when the *self-anticipation method* faced the same situation, the robot did not open space for the partner. Fig. 13 shows a scene of the *self-anticipation* method experiment. It is the same situation as presented in Fig. 12 where the partners were approaching the obstacle. At the moment where there was an obstacle in front of the partner, the robot failed to anticipate the partner's avoiding motion. It only noticed the partner's avoiding motion after the partner started to move toward the center of the corridor.

6. Field Demonstration

Finally, we tested the proposed method in a shopping mall. The purpose of this demonstration was to observe the pragmatic value of the proposed method in a real context. We initially considered

Figure 13. Behavior of self-anticipation while avoiding an obstacle

using the same robot, Robovie, as used for the evaluation experiment; however, we found that people are often frustrated with slow walking speeds, thus we decided to use a mobile robot that could move at a maximum velocity of 1.1 m/sec (Fig. 14b).

6.1 Method

We performed the demonstration in the corridors of a shopping mall environment. The corridors had widths of up to 5.8 m (below *S1* in Fig. 14a) and presented narrow places of 2.0m (left of *S2* in Fig. 14a). Experiments were held in during normal shopping mall operation hours while customers freely walked through the corridors while shopping. The robot was fully automated, and for reasons of security, a person with a remote control followed the participants in each walking experiment. As with any other shopping mall, the places of objects (mainly clothes) changed on a daily basis. The map of the environment with the trajectories of the robot and a walking partner is shown in Fig. 14a and shots of the experiments are shown in Fig. 15.

Twenty Japanese people (twelve females and eight males whose average age was 23.6) were paid for their participation. We asked participants to walk side by side with the robot (Fig. 15) from a start to a goal location, walking as they would usually walk with a friend while being side by side. Before the trial, we showed the participants the route to be followed from start to end as the pre-computed subgoals had to be sequentially followed. Finally, we conducted an interview asking their impression, points to be improved with the robot system, and if they would have any future intention of using the robot system.

For this demonstration, we used a cart robot that was originally developed for shopping assistance in supermarkets (Iwamura, Shiomi, Kanda, Ishiguro, & Hagita, 2011) with the modification that it presented a humanoid-like robot on its top (Fig. 14b). As explained in Section 4.1, the robot has a non-holonomic differential drive configuration that differs from the robot of Section 5 in that it is capable of running at velocities of 1.1 m/sec.

6.2 Result

6.2.1 General Observations

In general, participants were able to walk in a side-by-side formation with the robot through the corridors of the shopping mall (Fig. 15a). There was a difficult location at the left side of *S2* in Fig. 14 as a clothing shop placed a sales announcement that narrowed the already small corridor; this situation is visible in Fig. 15b. The difficulty was that while turning, as there was not much space available, the prediction grids would not find available cells to place the predicted position of the robot, regularly making it slow down until the person had passed.

6.2.2 Interview Result

Table 2 shows the interview result when we asked the participants for their general impression. In general, they expressed positive impressions. For instance, one participant mentioned:

It was the first time that I walked with an autonomous robot; actually I was surprised that it could move in a smooth way.

(a) Example of walking partners trajectories in a shopping mall environment.

(b) Cart robot with a communication robot on top

Figure 14. Shopping mall environment and cart robot. The robot trajectory is shown as a continuous red line; the walking partner is shown as a dotted blue line. The subgoals “S” are shown with circles; the numbers refer to the traverse order through the subgoals.

(a) Walking in a wide corridor.

(b) Turning at a narrow corridor.

Figure 15. Side-by-side walking experiments in a shopping mall environment.

Another participant said:

I noticed that even when I went far from the robot it noticed this and was trying to keep close to me

They experienced that the robot was able to engage in the side-by-side walking, finding that it was able to keep appropriate distance and adjust its speed.

Table 3 shows the interview results about the question related to the points to be improved. Although they started to report a positive impression in the earlier question, when we asked them about possible improvement, they brought up a couple of missing capabilities. Particularly, they found the robot’s turning motion to be insufficient. This was partly due to the fact that the robot was driven by differential drive wheels, so it was not possible to turn as smooth as humans do. It could only move forward or turn but could not move to the side. In relation to the speeding up issue, we noticed a slight time lag in the computation of the velocity of the walking person; this happened because our human tracker provided the position of the person of interest and in order to compute the participant’s velocity, we took a history of smoothed positions. This resulted in the robot being slightly slow for detecting the start of movement of a person; this issue was not

observable when they had started walking.

Table 2. General Impressions about the robot while walking side by side

General Impressions	Number of participants mentioning the impression
Positive comments on side-by-side walking (mostly about walking distance and velocity)	8
Robot cuteness	4
The robot should have been able to talk	4
Could consider the robot as a walking partner	3
Would like to see the robot in a real application	3
Wondered if the robot could adjust to different types of people	3
Robots should be able to move within crowds of people	1

Regarding the third point of the interview about any future intention to use the robot system, seven participants reported that they would definitely use the robot, six reported that they would not use it and seven stated that they would like to use it if it could be improved (points in Table 3). These results are shown in Fig. 16.

Table 3. Points to be improved in the side-by-side robot

Points to improve	Number of participants mentioning the point
The turns were stiff	13
Speeding up / slowing down (continuous change of speed)	8
The robot should be interactive (move head, hands, and talk)	8
Robot being sensitive to movement (overreacting)	7
Robot moving in crowds of people	3

Figure 16. Graph showing the intentions of the participants toward using the side-by-side robot.

We further asked for detailed reasons from participants who mentioned that they would not use the robot. One mentioned that the use of robots in real environments could be very dangerous, i.e., if a child suddenly appeared running fast close to the robot and they collided. Solving such concern would require more thorough preparation of other sub- systems, such as safety computing and hardware design.

A couple of participants commented on its motion limitation. Two participants mentioned that the robot should be faster, and two participants mentioned that it should be smoother. Our model tried to adapt to the walking of the partner; however, walking styles of people naturally differ. A couple of participants mentioned that a robot should be faster another participant mentioned that the robot was too fast:

I am a very small person who walks very slow; I thought that the robot was sometimes a little bit too fast for me.

The parameter around the robot's preferred velocity was set to 1.1 m/sec. Two participants, in providing their free impressions, mentioned that it must have been difficult for the robot to keep pace with different people, for example,

I was thinking that each person walks at different pace, so it must be difficult to be able to walk with different types of people.

We would need to adjust this speed aspect to adapt to each individual in the future using an approach like found in Sviestins, Mitsunaga, and Kanda (2007). We considered that the implementation of our anticipation model in a robot and the realization of the demonstration's results in real environments gave us insight of the problems faced in the field. For instance, the localization of the robot in a shopping center was relatively less stable: since the environment constantly changes, the precision of the localization decreased, sometimes resulting in brief jittering movements. In the end, these implementation issues are important but independent from the side-by-side walking model.

7. Discussion

7.1 Contributions

Through both laboratory experiment and field demonstration, we showed the pragmatic value of side-by-side walking capability. It is not yet perfected, and some participants in the field trial found problems to be improved before real use, while some already considered the utility to be immediately useful.

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 a 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. Other applications could include robotic physical therapy companions and elderly walking companions.

A contribution for the general context of the HRI field is the development and evaluation from simulation to real world experiments of a collaborative model between a person and a robot based on human behavior observations. This kind of collaborative model in which a robot anticipates human behavior before performing an action could be utilized for many other types of applications.

7.2 Validity of the Model: Completeness vs. Simplicity

We have only tested our model in limited scenarios until now, thus the generalizability of the model beyond what we have tested is arguable. We consider that some parameters are not necessarily generalizable across different cultures, e.g., social distance and preferred speed. Thus, we believe that parameters might need to be re-adjusted depending on such differences in culture or other environmental conditions.

Furthermore, one could argue that, even with adjusting parameters, the equation might not be sufficient enough to fully describe side-by-side walking. The model in this work is simplified; while it includes all relevant elements (e.g., distance, orientation, velocity, and acceleration), it assumes an additive contribution of each model element. This means that each element, derived from distributions in humans' data, is treated independently from every other element. Here, it is arguable that there can be correlations between the elements, thus such an additive model is not sufficient to describe some part of behavior in side-by-side walking.

There are, in fact, some correlations among the eight utility factors that we tested; however, they are weak. A correlation (0.34) existed between linear velocity (f_{M_v}) and acceleration (f_{M_a}). This correlation can be interpreted as a tendency to behave with larger acceleration when velocity is higher. To explain such correlations, we may need a more complex model, such as a multiplicative or quadratic term function (as $f_{M_a \cdot M_v}$).

Nevertheless, we chose to use an additive model as a simple way to combine the different walking parameters. Our belief is that the model proposed in this work offers a good trade between simplicity and accuracy. Including such quadratic terms requires parameters for them too, and hence we would need computations for adequate and complex parameter combinations. The question here is, to what extent would behavior observations will be accurate with such additional complexity? What we know is that the simplified model was proved to work in a side-by-side walking scenario without major fault. Furthermore, simple models are oftentimes more applicable to wider contexts (well known as Occam's razor), and hence, we consider that our simplified model would be more easily generalizable to other contexts than a model with more complex parameters.

7.3 Extending the Model.

So far, the model is only intended 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 this utility is very close to the general idea in robotics to use potentials. The potentials field method and its extension are widely used in robotics.

Our method requires subgoal information and assumes that when people walk, they share 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 situational aspect to provide interesting future work.

7.4 Limitations

In this study, the parameters were not systematically calibrated, though it would be important to develop a method to calibrate them. In particular 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 alters along with context (Hall, 1966).

We did not specifically adjust parameters in favor of the proposed method for the experiment with the robot, although one could argue that the results would be due to the specific parameters we used. We believe that there are quantitative differences across the methods. For example, the *standard prediction method* and the *self-anticipation method* lacked the capacity to quickly make a space for the partner (see Fig. 1b and Fig. 13), as it did not predict the partner's motion constraints related to obstacles (see Fig. 1a and Fig. 12). The *standard prediction method* further lacked 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.

An assumption of the model presented in this work is that the robot knows the path (list of subgoals from a start to a goal location) that is going to be traversed. This study only addressed peer-type relationships between people who walk side by side, but leader-follower relationships would considerably change the situation. For example, as reported by Kobayashi et al. (2011) and Prassler et al. (2002), in cases where 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 was missing in the *standard prediction method* is a capacity to take a lead and move toward the goal; experimental results showed that this was

crucial in side-by-side walking with peer-type relationships. The extension to handle different formations according to the knowledge (or lack of) of the next subgoal is left for future work.

8. Conclusion

We developed a human computational model for side-by-side walking. A utility model describing how people prefer to move was built based on recorded trajectories of human side-by-side walking pairs. Parameters for this model were chosen that 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. Finally, the model was implemented in a robot moving at human walking velocities, proving to be effective as it was able to walk in a side-by-side formation with participants through the corridors of a shopping mall.

We believe that this model can be generalized to other situations and scenarios. In this case, parameters might need to be adjusted if, for example, the social distance or walking speed would vary for different cultural groups of people.

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