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A navigation model for side-by-side robotic wheelchairs for optimizing social comfort in crossing situations

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ABSTRACT

One challenge in designing side-by-side robotic wheelchairs is to improve the comfort of the users, caregivers and surrounding people in crowded environments. Among different scenarios that a side-by-side robotic wheelchair has to deal with, crossing pedestrians is a common situation. Yet techniques developed for tackling the problem of passing pedestrians have still failed to take into account enough factors related to human walking behavior, therefore the navigation plan is not natural. To tackle this problem, this paper proposes a novel navigation model for side-by-side robotic wheelchairs that considers the Friendly Link factor and Preferred Walking Velocity related to the comfort of wheelchair users, caregivers and pedestrians. The model is carried out based on an experimental observation and data collection. The developed model is then validated by comparing the distance errors between the moving solutions of the new model and previous methods with the real solutions of humans based on a natural walking scenario. The experimental results show that the performance of the proposed technique is significantly better than that of previous techniques.

1. Introduction

The world population is aging and the demand for in-house care for the elderly is increasing [1]. The number of disabled people has also increased [2]. Meanwhile, the proportion of people of working age has been decreasing, thus increasing the cost of labor-intensive services, including care services for the elderly and disabled. This has drawn the attention of robotic researchers for developing autonomous devices, including autonomous wheelchairs, to support them. As a result, many kinds of assistant wheelchair robots have been developed to support people [3–7].

Under this research direction, developing wheelchairs that can autonomously move with a caregiver in a peer-like manner is a relatively new initiative. In many situations, people using wheelchairs have difficulties in controlling them. As a result, in some environments, e.g. hospitals or nursing homes, a caregiver has to take control of the moving function of the wheelchair, thus putting an extra burden on the caregiver. Therefore, the idea of developing robotic wheelchairs that can move alongside a caregiver, thereby easing their workload, has drawn much attention recently.

However, to be truly acceptable to humans, robotic assistants in general, and robotic wheelchairs in particular, need to not only satisfy the technical requirements, but also meet the psychological needs of the users [8–10], i.e. they should give comfort to users and surrounding people while working. In the case of robotic wheelchairs, when walking in pairs, maintaining a side-by-side formation is a natural habit of humans (Fig. 1). It is a more comfortable motion pattern for a friendly pair rather than, for example, walking one after the other. This is explained referring to the psychological benefits it brings to both members of the pair [11–13]. Therefore, the robotic wheelchairs should be able to move alongside their caregivers in a suitable human-like manner; this is called a side-by-side robotic wheelchair.

Developing a side-by-side robotic wheelchair is not a trivial problem [3]. Many factors need to be considered, such as keeping a stable relative distance to the caregiver, moving at a preferred velocity, reducing the acceleration changes, avoiding static and moving obstacles, etc. [14–23].

During a navigation session, among various different scenarios that a side-by-side robotic wheelchair has to deal with, passing pedestrians is a common problem. Fig. 2 depicts five main modes in which a walking pair can pass another pedestrian walking in the opposite direction on a pathway (a to e).

In modes (a) and (b), the pair tries to maintain their side-by-side formation during the passing period. In modes (c) and (d), the pair switches from side-by-side formation to leader–follower formation, where one person follows the other person while passing. In mode (e), the pedestrian's trajectory disturbs the side-by-side formation of the pair. As can be seen from our observations, which are described in detail in Section 3, the majority of people

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Fig. 1. Maintaining side-by-side formation is a natural habit of humans in walking.

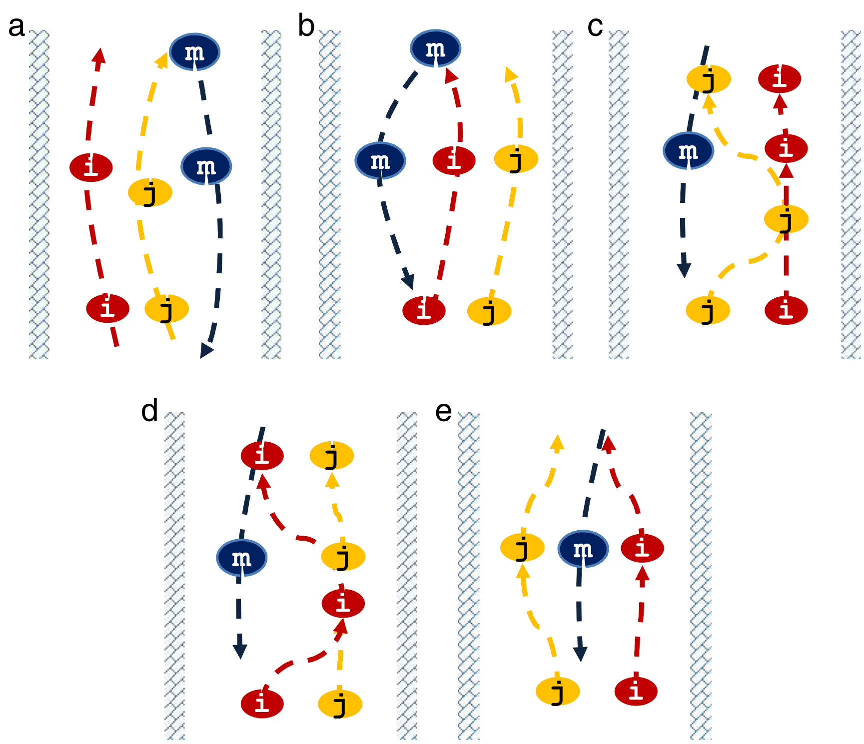

Fig. 2. Passing behavior between a pair and a pedestrian (i and j are a walking pair and m is a pedestrian walking in the opposite direction).

prefers the passing modes (a) or (b) if the pathway is not too narrow.

Based on our investigation, although a large number of studies have been conducted for passing pedestrians, most of those solutions are developed for robots moving alone; not with a human moving alongside. Among the few studies which were conducted for a side-by-side robot and human pair avoiding obstacles, there are three main approaches [3–5].

In the navigation solution developed by Sato et al. [5,24] the wheelchair goes to a side of the caregiver by default. While following the caregiver, assuming that agent i is the caregiver and agent j is the wheelchair, the wheelchair j changes its relative position with the caregiver i from side-by-side formation to leader–follower formation (wheelchair follows the caregiver) if an obstacle or a pedestrian is found, i.e. the robot always chooses passing mode (c). This allows both the caregiver and the wheelchair to avoid collisions with the obstacle or pedestrian. However, this model does not reflect the reality that people prefer passing modes (a) and (b) to other modes, i.e. this model is not capable of producing natural human-like motions; or it lacks the methods to maximize the comfort of people when passing pedestrians.

Ferrer et al. [4] developed a mobile robot to accompany a person based on social-force and proxemics concepts in which their model mainly focuses on maintaining a comfortable distance between the robot, its companion, and surrounding people. Yet, some important factors are ignored, e.g. in real-world scenarios, the robot not only has to take into account the navigation plan to move alongside a caregiver, but the caregiver himself and the surrounding people also have their own predictions and reactions based on the past and future actions of the robot. One of the main disadvantages of this method is that it does not have any mechanism for suggesting to the robot that modes (a) and (b) are the most preferred modes chosen by the caregiver and the pedestrian.

In a more comprehensive navigation model developed by Morales et al. [3], eight factors that influence the decisions of a walking pair are considered. Subsequently, an extended model was developed by the authors [21], considering nine factors. These navigation models have been developed under a hypothesis that a walking pair has to consider nine factors related to them before making a new step if they want to maximize their comfort. Technically, the pair tries to maximize a utility function of eight or nine variables, which are based on corresponding influencing factors. As a result, these navigation models are capable of moving a robotic wheelchair alongside a caregiver, allowing both the caregiver and the wheelchair user to maintain a comfort level similar to a normal walking pair of people. However, both these models are limited to certain static environments and do not take into account the presence of the pedestrian; they lack a suitable method to pass a pedestrian.

This paper presents an improved navigation model for side-by-side robotic wheelchairs by incorporating the Friendly Link factor, in order to overcome the above-mentioned limitations. In addition, the authors suggest a method to predict the next Preferred Walking Velocity of people. That helps the new model predict better the next positions that all people in the scene intend to take, hence the side-by-side robotic wheelchair can navigate alongside the caregiver as the caregiver's companion; the wheelchair is able to mimic the movements of a human. This model is created based on data collected by observing the behavior of walking pairs in a hallway. Using collected data, the model was developed, calibrated and validated. Later, using a different data set, the model was tested in order to verify its performance.

2. Related studies

2.1. Walking habits of pairs

Common walking habits of humans, as individuals and as pairs, have been investigated in several studies [12,13,17,23,25,26]. Helbing & Molnar [23] describe factors that affect people during walking as a combination of attractive and repulsive forces. According to their explanation, these hidden forces drive people to walk from a starting point to the destination in a safe manner, avoiding collisions with static and dynamic obstacles in the pathway. Later, Xu et al. [26] improved that model with a new factor called 'bonding force'. Around the same period, Costa et al. [12] discovered that when people walk in pairs, they normally move in side-by-side formation rather than in other formations, unless the environment is particularly crowded or the pathway is too narrow. Moussaid et al. [13] had similar observations when they studied human walking behavior.

Several authors proposed concepts represented as 'personal space' and 'social distance'. The concept of proximity was proposed by Hall [17], who discovered the presence of certain social distances, called hidden dimensions, between people when they are standing in a group or in a public location. When people maintain these social distances, they normally feel more comfortable. Kendon et al. [25] proposed further personal spaces and social distances when they studied people's positions in conversations. Although some of these studies are conducted in static environments, they can be generalized into moving situations as well [3,4,9].

A common finding of all the above studies is that, when people stand, walk or chat, they normally obey hidden rules of social and personal factors including spatial formation, distances between people in a group, or distances between one person and other people or obstacles in the environment. When these rules are obeyed, people normally feel more comfortable; their psychological needs are better satisfied.

2.2. Walking alongside a robotic wheelchair

Realizing the factors affecting moving or chatting, many efforts have been made in developing a robotic wheelchair that can act more naturally in crowded environments. A preliminary effort relevant here is the study of Gockley et al. [27], whose robot can follow a human in a natural manner. Iwase et al. [28] developed a robotic wheelchair with a pre-defined non-reactive area that allows it to move alongside a caregiver and stop when the caregiver stops. A more sophisticated solution come from Kobayashi et al. [5,24,29–31], in which their robotic wheelchair can not only move alongside a caregiver but can also detect the caregiver's posture to change its moving direction. Moreover, their robotic wheelchair can implement the leader–follower mode to avoid collision with a static obstacle or a pedestrian from the opposite direction, or multiple wheelchairs can move with only one caregiver.

In another direction, Prassler et al. [32] developed a side-by-side robotic wheelchair with a prediction model. This model predicts the partner's velocity in the next step based on past discrete trajectories. Therefore the robotic wheelchair is able to move more smoothly alongside the caregiver, and is more comfortable for the wheelchair users and their partners. Later, Wu et al. [6] proposed a prediction method based on Neural Network for a robotic wheelchair. Their model can learn from the statistical data to predict the next positions that the caregiver intends to move. That helps their robot move alongside a caregiver in a static environment with no obstacles.

We consider that the solution provided by Morales et al. [3] is the most advanced model that can be employed by a side-by-side robotic wheelchair. The model employs the largest number of related factors that affect robots and humans in a side-by-side walking session. As a result, the robot takes into account many related factors before making a decision for its next movements. The solution was developed further for a situation in which the pair needs to pass a static obstacle in the pathway [21]. So far, this model has only been developed for passing static obstacles in static environment.

In this paper, we rely on [3,21] to develop a model that can tackle the passing problem with a pedestrian. Our model enables the robot to pass a pedestrian, based on reasoning about the movements of all people in the scene. By adding a new factor discovered in our study, our model can better predict the next movements of all people in the scene and can propose movement plans similar to human behavior, hence it helps the side-by-side robotic wheelchair to be able to mimic the movements of a real human during a walking session with his partner.

3. Data collection set up

The purpose of the data collection step was to understand human decisions in side-by-side walking mode when crossing pedestrians. Particularly, we focused on walking sessions of a caregiver and a disabled person or patient sitting in a robotic wheelchair. In a walking session with a caregiver and a robotic wheelchair, normally we have a leader (the caregiver) and a follower (the robotic wheelchair) moving along with the leader. However, we believe that the wheelchair user will feel more comfortable if he does not need to entirely depend on leader while walking. In some circumstances, based on the observation of actions and reactions of the leader and other people in the scene, the follower may actively propose and execute a plan, as humans normally do. Therefore, we set up a walking scenario in which both members of the pair

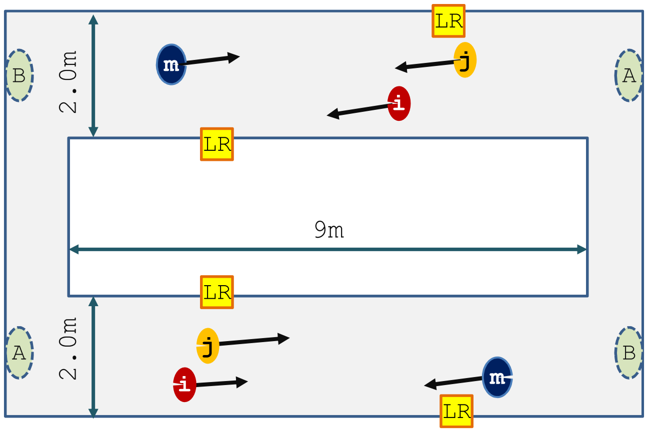

Fig. 3. Data collection: the walking environment settings.

were treated as equal; they simply walked as a pair, maintaining their relationship during the walk but one person did not need to entirely depend on the other.

This data collection step needed to answer two questions: when a pair encounters a pedestrian, how does the passing process happen? Apart from the factors that we know, what are other factors that affect this process?

3.1. Data collection

The scenario of the data collection involved a pair and a pedestrian walking around in two parallel indoor corridors as illustrated in Fig. 3. The width and length of both corridors were 2.0 m and 9.0 m respectively. Along with the Gonzalez et al. study [33] that considered only a 5.0 m length for the passing procedure of two people, we believe that this 9.0 m length gave enough time and space to allow three people to walk and cross each other in a natural manner.

Here, LRs are the laser range finders with a maximum radius of 5 m, set up at 10 Hz scanning speed. m is a pedestrian moving inversely to the member i and his partner j. A and B mark the midpoints at each end of the corridors, and are the starting point and the destination of the pairs respectively. In the opposite direction, B and A are the starting point and the destination of the pedestrians respectively. In the setting, people knew in advance the final destinations of their walking sessions. We employed the work of Leigh et al. [34] to record the trajectories of people in the scene. In addition, we marked the ground with stickers and used two video cameras to record the walking sessions. The data from LRs and video camera were used to determine positions of people in the scene, in which the videos help to refine the people's positions in cases of doubt about the recorded data from the LRs. We also observed people's views of the pathway and of the other people in the scene. All the data that could be used to identify people in the study was eliminated, hence volunteers participated anonymously.

We set up the scenarios with moving rules for the walking sessions. In both corridors, both people i and j started walking from A at the same time and in the same direction toward the same destination B. While walking, the pair was asked to act as friends by starting a friendly conversation at the starting point before moving, and maintain their intimate relationship during the walking session. Also, both members of the pair were asked to actively move in a natural way to bring comfort to their partners and other pedestrians in the scene as humans normally do. By arranging this setting, we simulated factual scenarios in which a caregiver escorts a patient/disabled person to wander around or move from one location to another. In the opposite direction, one person was asked to act as a pedestrian moving from B to A. He started walking at the same time the pair started. Participants were asked not to walk in a rush, but to consider their walking sessions as strolling around a park or on a street.

Table 1
Data collection: the crossing sessions. Crossing modes refer to Fig. 4.

No	Passing mode	Quantity
1	a	15
2	b	11
3	c	0
4	d	0
5	e	1

Fourteen participants joined our study; their ages ranged from 45 to 65 with the average age around 55, three were men and the others were women. All the people lived in one residential area. They had no research relation to our project. We randomly mixed them in groups following the above settings; each group had one or two walking sessions in each corridor, then they swapped to form another group. People were asked to obey the above moving rules, and all had their own conversations during the walking sessions, without any prepared scripts.

After eliminating some walking sessions from the final results because they violated the moving rules (some pairs did not try to maintain the relationship, or all the people in the scene suddenly stopped in the pathway to start a new conversation of three people, or two members of the pair start walking at the same time, etc.), a total of 27 sets of crossing sessions were recorded, and are summarized in Table 1. This data was used to establish a novel navigation model for the side-by-side walking mode in crossing situations.

3.2. Trajectory standardization

To make it easier to analyze the data, we applied a standardization process for collected trajectory sets as follows:

- We defined the time when the pedestrian crosses the first person of the pair as the central point C of each trajectory set T. Each trajectory set T is comprised of three trajectories of three people in one corridor.
- From C, we moved forward each trajectory in T for 1 s and discarded the rest of them. Because we only focused on the passing procedure, and after $C + 1$ s, the passing procedure was totally completed, we did not need to analyze the parts after $C + 1$ s.
- From C, we moved backward each trajectory in T for n seconds, where n is a natural number, until we reached the starting point of that trajectory, or to a point that we cannot move backward further. Yet, because we have three individual trajectories in one set T, thus with each T, we may have more than one value of n corresponding to it. In those cases, we chose the smallest value of n. We kept all the trajectory parts from $C - n$Sec to $C + 1$ s. All the outside portions of the trajectories were discarded from the trajectory data.
- Because the movements of each person in the upper corridor were in the opposite direction to those in the lower corridor, we rotated all the trajectory sets in the lower corridor by 180° so that all the pairs' moving directions (and hence, all the pedestrians' moving directions) are the same.

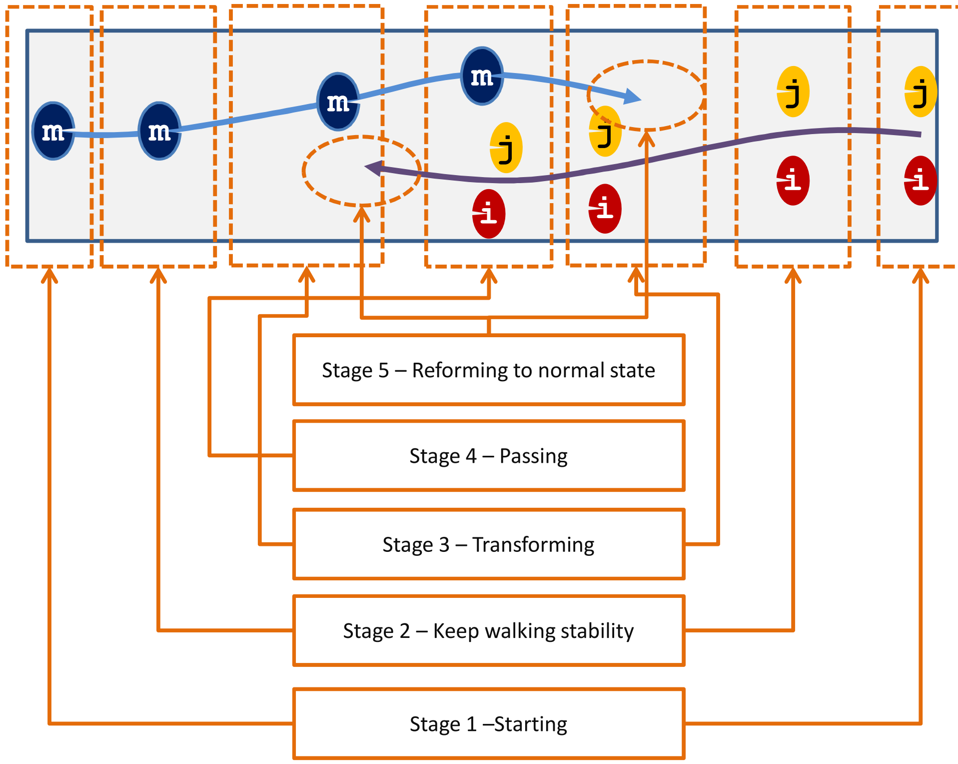

Fig. 4. Five passing stages observed in the study.

3.3. Observation

3.3.1. Five passing stages

We analyze the collected data for understanding the passing behavior. In each walking session, it was seen that participants underwent five stages, from Stage 1 to Stage 5, as illustrated in Fig. 4. At Stage 1, people started walking. They needed a few movements to reach a stable walking status, including their own velocities, direction to the destination, and side-by-side formation (for the pair), etc. When people entered Stage 2, they achieved a stable walking status. At this stage, people moved directly to the destination. After continuing walking, people entered Stage 3, called Transforming, in which they started finding a way to avoid collision with the moving obstacles. Stage 3 was completed when people completely proposed a trajectory plan for passing the moving obstacles in front of them, and then they entered Stage 4—Passing. In this stage, people simply performed their proposed trajectories to pass people in front. After passing, people entered Stage 5—resuming their normal walking behavior to the destination.

In the above stages, we consider that Stage 3 has the major role in the passing process. As illustrated in detail in Fig. 5, Stage 3 starts happening when the pedestrian starts diverting from his straight pathway to the destination to move toward one side of the corridor (to the corridor's wall).

When the pedestrian m enters Stage 3, from time t the pedestrian starts diverting his trajectory from a straight line to the destination. As a result, the angle γ_t^m starts increasing from zero to a value higher than zero. Stage 3 is completed when the pedestrian starts redirecting his route directly to the destination, or from time $t+q$ the angle γ_{t+q}^m starts reducing to zero. Similarly, the same process happens to the pair.

By analyzing the trajectory data, Stage 3 may start immediately after people start walking or after a few steps, and then finish at the time people cross each other, or one or two steps before that. To implement this process smoothly, all the people had to observe others to consider the proposed trajectories that their partners intended to process. In many cases, not all three people in the scene started Stage 3 at the same time, but one person acted as a "starter", meaning that he was the first person who decided to make one, or several, movements that deviated from his straight path to the destination.

The other people rapidly recognized his intention, accepted his decision, and responded to his actions by starting rerouting, and then Stage 3 was initiated for everyone. In some situations, when two or more people simultaneously acted as a "starter" but quickly realized that their proposed walking plan may create a conflict, e.g. these plans may lead to a collision or to a state that they would not feel comfortable with, they abandoned their initial intention and then rerouted the walking path.

In all these sessions, people were able to act quickly without the need of verbal negotiation with their partners. Normally, Stage 3 did not stop at the same time for all people. Some people rapidly moved toward to one side of the corridor and completed Stage 3 but others walked gradually, following a diagonal path, and Stage 3 was only completed at the crossing time. Through these observations, we believe that the "starter" here can be anyone, i.e. the passing process can be carried out smoothly regardless of who is the "starter".

Because of random pairing, in some cases some participants were unfamiliar with their partners. Nevertheless, their passing processes were smoothly executed, i.e. people implicitly understood the pathway that the others would take. Hence, we believe that these crossing behaviors are prevalent, not confined to a particular group of people.

3.3.2. Friendly link

In our observation, we noted another phenomenon. In most situations, people chose the modes (a) and (b) for passing. There was no clear distinction between these two modes. Not many people chose modes (c), (d) and (e). This statistical fact demonstrated an

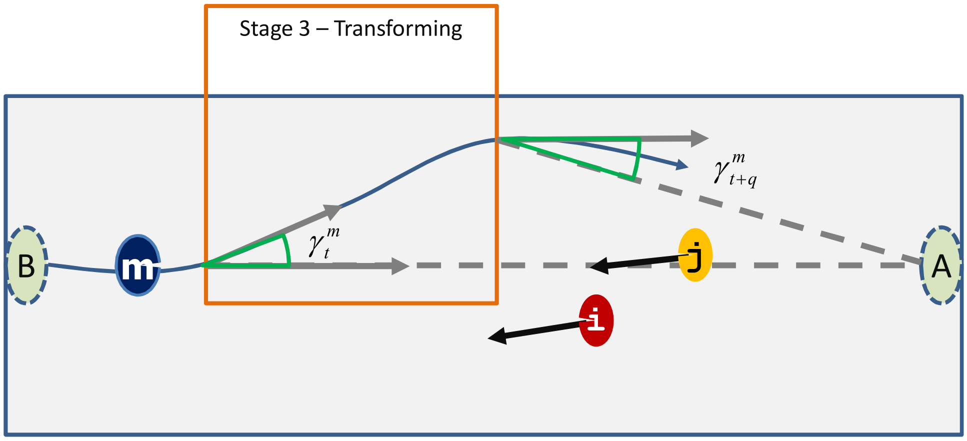

Fig. 5. Stage 3 of the Passing procedure.

invisible link between the two people in a pair, which was recognized by the pedestrian m, who as a human always tried to respect the relationship of the pair, and avoid breaking that connection. When the pairs were asked to keep a friendly relationship, aside from trying to maintain their side-by-side walking formation, they themselves also tried to keep the links from being disrupted by a third person. From this observation, we assume that when two people walk together in a friendly manner, they should not be considered as two entities moving freely but as a linked unit. The link between them is relatively tenacious and can be implicitly realized and respected by everyone in the situation without it being expressed in words. We call this connection the Friendly Link (*FL*).

4. Modeling

Our target was to create a navigation model for a robotic wheelchair that can move alongside a caregiver in harmony, like humans in dynamic environments. This model needed to collect parameters as humans do, and then create a decision for its next position which can maximize the comfort for all people in the scene as well as maintaining the optimal relationship for the pair. In addition, the model should bring to wheelchair users a feeling of freedom in navigation, i.e. the feeling of a normal, healthy person, not an invalid who totally relies on caregivers.

4.1. Setting assumptions

At this step, we assumed these conditions for the model:

- Two people are walking together as a pair, one is the leader and the other is the follower.
- The starting point A and the destination B are known.
- The leader actively processes a trajectory to the destination. However his leading role does not eliminate the active status of the follower, i.e. the follower needs to reason about his environment to propose an action or reaction, not totally rely on the leader.
- Both members of the pair try to maintain a friendly relationship while walking, as a result the side-by-side walking formation is the preferred mode.
- While walking, the pair encounters a pedestrian moving in the opposite direction from B to A.
- We assume that all people in the scene not only consider the best route to their destinations but also respect the movements of the others.

Once the model was developed, the follower would be replaced by a robotic wheelchair with a wheelchair user sitting in it. The new model should allow the robotic wheelchair to take the wheelchair user to the destination as naturally as that user himself walks.

4.2. Passing process hypothesis

Based on the setting above, we assumed that the passing process of a person s ($s = i, j, m$) undergoes the following steps:

- At time t, at Step (1), the person s determines the past and current positions and other information (velocity, acceleration, walking direction, etc.) corresponding to movements of all the people, including himself, in the scene.
- At Step (2), the person s does a scan on all the positions which he is able to move to, called "feasible positions set".
- With each position in his feasible positions set, he predicts all the next feasible positions that other people are able to move to. Each set of all the people i, j, m's next positions forms a feasible moving plan $\mathbf{P}$.
- At Step (3), person s compares all the feasible moving plans $\mathbf{P}$. The plan that he believes can bring the most comfort to all the people in the scene is called the optimum plan $\mathbf{P}^*$.
- At Step (4), the person s processes his move to the new position in his feasible position set which forms $\mathbf{P}^*$. This step is finished at time $t + 1$.
- To continue the next movement for the time $t+2$, the person s repeats from Step (1) until he finishes the passing process.

4.3. Friendly link factor

So far, we know that the movements of a pair are affected by nine factors. These factors include distance to other pedestrians and obstacles O [14], moving toward subgoals S [15,16], relative distance between two people R_d [17], relative angle R_α [18], relative velocity R_V [19], relative vision R_β between two people in the pair [20,21], moving acceleration M_a [14,22], moving velocity M_V [23], and angular velocity M_w [14]. When a pair walks together, both members of the pair have a desire to keep all the above factors at the optimum values. Similarly, with the exception of the desire to maintain the relative factors (because he is moving alone), the pedestrian also has a desire to maintain the factors at the optimum values.

From the data collection setting in Section 3.1, it can be seen if there is no pedestrian in front of the pair, and there is no walking pair in front of the pedestrian, there is no reason for them

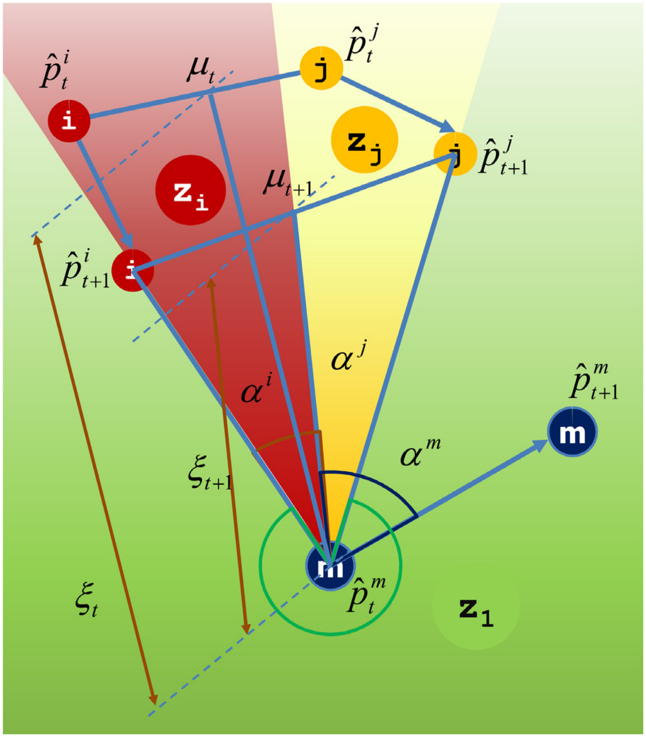

Fig. 6. Friendly link factor.

to suddenly change their moving directions, velocities, or other factors; i.e. after achieving the optimum status in Stage 2, there is no reason to explain the occurrence of Stage 3. However, with the arrival of the people walking in the opposite direction, their trajectories are changed. It means that the interaction between the pair and the pedestrian leads to the occurrence of Stage 3, i.e. there are some factors lead to this occurrence.

Of the nine factors above, one factor which may lead to the changing walking direction of the pair is the desire to keep far away from obstacles, in which the pedestrian himself is a moving obstacle. However, if people simply want to avoid obstacles, then we cannot explain why their passing modes mostly converge to two modes (a) and (b). We may also think that the pair wants to keep their relative vision factor, they may not feel comfortable when they cannot see each other if the pedestrian disrupts them, therefore they want to change the walking direction to avoid that. Yet, the pedestrian moves alone, i.e. he does not need to protect the relative vision factor, therefore we still cannot explain the convergence of crossing modes to the two modes (a) and (b).

As discussed in the previous Section 3.3 about the existent of the *FL*, we have to consider that the convergence is driven by the *FL* factor, i.e. the *FL* factor has an important role in passing.

We define several variables and their functions to represent the role and effect of the *FL* factor in the crossing situation between a pedestrian and a pair as follows:

It can be seen that the *FL* is threatened to break if the pedestrian moves directly toward the space in between the two members of the pair. This threat is inversely proportional to the distance between the pair and the pedestrian. We illustrate this problem in Fig. 6.

Variables and notations used in Fig. 6 are introduced in the following:

- $\hat{p}_t^m$ and $\hat{p}_{t+1}^m$ are respectively the current position at time t and proposed position at time $t+1$ of the pedestrian m. Similarly, $(\hat{p}_t^i, \hat{p}_t^j)$ and $(\hat{p}_{t+1}^i, \hat{p}_{t+1}^j)$ are the respective current positions at time t and proposed positions at time $t+1$ of the agent i and the agent j.
- μ_t is the midpoint of the straight line between two points $\hat{p}_t^i$ and $\hat{p}_t^j$; μ_{t+1} is the midpoint of the straight line between two points $\hat{p}_{t+1}^i$ and $\hat{p}_{t+1}^j$.
- ξ_t is the distance between $\hat{p}_t^m$ and μ_t; ξ_t is the distance between $\hat{p}_t^m$ and μ_{t+1}
- z_i and z_j are the parts of the Euclidean plane covered by two angles α^i and α^j respectively. Their values depends on the moving directions of the pair and the pedestrian. z_1 is the rest of the Euclidean plane after subtracting z_i and z_j.

$$z_i = \begin{cases} A_{ang}(\alpha_{t+1}^i) & \textbf{if } \xi_{t+1} < \xi_t \\ A_{ang}(\alpha_{t+1}^i) - A_{tri}(\hat{p}_{t+1}^i, \mu_{t+1}, \hat{p}_t^m) & \textbf{if } \xi_{t+1} \ge \xi_t \end{cases} \tag{1}$$

$$z_j = \begin{cases} A_{ang}(\alpha_{t+1}^j) & \textbf{if } \xi_{t+1} < \xi_t \\ A_{ang}(\alpha_{t+1}^j) - A_{tri}(\hat{p}_{t+1}^j, \mu_{t+1}, \hat{p}_t^m) & \textbf{if } \xi_{t+1} \ge \xi_t \end{cases} \tag{2}$$

$$z_1 = A_{EP} - z_i - z_j \tag{3}$$

$$\alpha^m = angle(\overrightarrow{\hat{p}_t^m \hat{p}_{t+1}^m}, \overrightarrow{\hat{p}_t^m \mu_{t+1}}) \tag{4}$$

$$\alpha^i = angle(\overrightarrow{\hat{p}_t^m \hat{p}_{t+1}^i}, \overrightarrow{\hat{p}_t^m \mu_{t+1}}) \tag{5}$$

$$\alpha^j = angle(\overrightarrow{\hat{p}_t^m \hat{p}_{t+1}^j}, \overrightarrow{\hat{p}_t^m \mu_{t+1}}) \tag{6}$$

$$\xi_t = distance(\hat{p}_t^m, \mu_t) \tag{7}$$

$$\xi_{t+1} = distance(\hat{p}_t^m, \mu_{t+1}). \tag{8}$$

Here, A_{ang} is a part of the Euclidean-plane area, determined by the inside area covered by an angle variable α. A_{tri} is the inside area of the triangle determined by three vertices $(\hat{p}^s, \mu, \hat{p}^m$ where $s = i, j)$. A_{EP} is the entire Euclidean-plane area.
We define an incidence variable θ as follows:

$$\theta_{t+1} = \begin{cases} \delta + \dfrac{(\alpha^i - \alpha^m)}{\alpha^i} & \textbf{if } \hat{p}_{t+1}^m \in z_i \\ \delta + \dfrac{(\alpha^j - \alpha^m)}{\alpha^j} & \textbf{if } \hat{p}_{t+1}^m \in z_j \\ 0 & \textbf{if } \hat{p}_{t+1}^m \in z_1 \\ \delta + 1 & \textbf{if } \alpha_{t+1}^m = 0. \end{cases} \tag{9}$$

Here, δ is an adjustment coefficient, it is a constant.

As can be seen from this definition, if the pedestrian m walks directly to the midpoint of two people in the pair, θ will get the maximum value $\delta + 1$. If the pedestrian m walks directly to the leader or the follower, θ will get the value δ. If m is moving far away from the pair, or following them at a relatively far distance in which his next step will not interfere with the pair, then θ will get the minimum value 0. In other cases, if the pedestrian m walks toward the pair, θ will get a value in between δ and $\delta + 1$.

If we define a Friendly Link utility that describes the desire to maintain *FL*, as f_P, in which f_P will get the maximum value if no threat to *FL* is existent, and f_P will get the minimum value if the threat to *FL* is greatest, then we have:

$$f_P(\xi, \theta) = \begin{cases} f(\xi, \theta) & \textbf{if } \hat{p}_{t+1}^m \in z_i \cup z_j \\ argmax(f_P) & \textbf{if } \hat{p}_{t+1}^m \in z_1. \end{cases} \tag{10}$$

4.4. Moving utility of one member in the pair

For the purpose of distinguishing this work from the previous studies, here we briefly describe the results presented in [3] and [21].

Morales et al. [3] suggested that at a particular time t, both members of a pair try to determine their next positions at time $t+1$, in which those positions should bring the optimum comfort to them. They define a utility function U that will receive the maximum value at time $t+1$ if both people achieve the optimum comfort at time $t+1$. U is affected by eight factors mentioned in Section 4.2. These factors include distance to other pedestrians and obstacles O, moving toward sub-goals S, relative distance between two people R_d, relative angle R_α, relative velocity R_V, moving acceleration M_a, moving velocity M_V, and angular velocity M_w.

Morales et al. proposed a utility function for member i in the pair (i, j) as follows:

$$U^i(\hat{p}^i|\hat{p}^j) = k^i_O f^i_O + k^i_S f^i_S + k^i_{R_d} f^{ij}_{R_d} + k^i_{R_\alpha} f^{ij}_{R_\alpha} + k^i_{R_V} f^{ij}_{R_V} + k^i_{M_a} f^i_{M_a} + k^i_{M_V} f^i_{M_V} + k^i_{M_w} f^i_{M_w}. \quad (11)$$

Here, $f_O,\ f_S,\ f_{R_d},\ f_{R_\alpha},\ f_{R_V},\ f_{R_\beta},\ f_{M_a},\ f_{M_V},\ f_{M_w}$ are individual utility functions of the eight factors $O, S, R_d, R_\alpha, R_V, M_a, M_V$, and M_w of the person i respectively. k values are the weight constants.

Morales et al. modeled the function f_O by using a step function as follows:

$$f_O(x) = -|(\frac{x}{a})^{-2b}| \quad (12)$$

and the other f functions are modeled by using a bell function as follows:

$$f(x) = \frac{1}{1 + |(\frac{x-c}{a})^{2b}|} - 1. \quad (13)$$

In Eqs. (12) and (13), a, b, c are co-efficients, they are constants. Each individual utility f has a unique set of a, b, c. x is a variable, it is one of the eight factors $O, S, R_d, R_\alpha, R_V, M_a, M_V$, and M_w.

At time t, both members will try to consider the next positions for time $t+1$ which allow the function $U^i(\hat{p}^i|\hat{p}^j) + U^j(\hat{p}^j|\hat{p}^i)$ to be maximized. By applying this model, the wheelchair robot should be able to optimize the relationship with the caregiver when the pair is passing a static obstacle located at a side of the pathway.

Morales et al.'s above model [3] does not consider cases where obstacles are placed in the middle of the pathway. To tackle the problem of passing a static obstacle located in the middle of the walking pathway of a pair, the authors suggested that a vision factor R_β should be added to the utility function U mentioned above [21]. Here, the individual utility function $f^i_{R_\beta}$ of the agent i should get the maximum value if the agent i can fully observe his partner and it should get the minimum value if the agent i cannot see his partner at all. Similar to the utility function of eight factors above, function f_β is also modeled by the bell function Eq. (13).

The utility function U proposed in our previous work, which incorporates f_β is given below. This is an improved version of Morales et al.'s utility function.

$$U^i(\hat{p}^i|\hat{p}^j) = k^i_O f^i_O + k^i_S f^i_S + k^i_{R_d} f^{ij}_{R_d} + k^i_{R_\alpha} f^{ij}_{R_\alpha} + k^i_{R_V} f^{ij}_{R_V} + k^i_{R_\beta} f^{ij}_{R_\beta} + k^i_{M_a} f^i_{M_a} + k^i_{M_V} f^i_{M_V} + k^i_{M_w} f^i_{M_w}. \quad (14)$$

Yet, a moving pedestrian is not included in the above previous studies. Therefore, in the work presented in this paper, we take another step forward by proposing a further improved utility U considering moving a pedestrian.

Assume that i is one member of the pair (any member) positioned at position $\hat{p}^i$, then the member i will have a utility of U^i toward his partner positioned at $\hat{p}^j$ and a moving pedestrian positioned at $\hat{p}^m$ as follows:

$$U^i(\hat{p}^i|\hat{p}^j, \hat{p}^m) = k^i_O f^i_O + k^i_S f^i_S + k^i_{R_d} f^{ij}_{R_d} + k^i_{R_\alpha} f^{ij}_{R_\alpha} + k^i_{R_V} f^{ij}_{R_V} + k^i_{R_\beta} f^{ij}_{R_\beta} + k^i_{M_a} f^i_{M_a} + k^i_{M_V} f^i_{M_V} + k^i_{M_w} f^i_{M_w} + k^{ijm}_P f^{ijm}_P. \quad (15)$$

In this equation, the function f_P (Eq. (10)) described in Section 4.3 is added. k values are the weight constants of each individual utility. When two people walk together as a pair, they normally try to optimize these ten factors by maximizing corresponding individual utility functions. When a factor reaches the optimum value, the corresponding function f will reach the maximum value. In some cases it may not be possible to maximize all individual utility functions. In such cases, they normally try to reach the best state they can. i.e. the overall function U is maximized for the given situation. In other words, before making a new step, both members i and j will try to select the next position that can maximize the value of their utilities U^i and U^j.

4.5. Moving utility of the pedestrian

The overall utility of a member in the pair given by Eq. (15) is the combination of personal utilities considering the relationship between the two members in the pair. Similarly, the utility of the pedestrian toward the pair can be calculated. However, only some of the factors out of the 10 factors mentioned in Eq. (15) are relevant in the case of a pedestrian moving toward the pair.

$$U^m(\hat{p}^m|\hat{p}^i, \hat{p}^j) = k^m_O f^m_O + k^m_S f^m_S + k^m_{M_a} f^m_{M_a} + k^m_{M_V} f^m_{M_V} + k^m_{M_w} f^m_{M_w} + k^{mij}_P f^{mij}_P. \quad (16)$$

Similarly to members of the pair, before making a new step the pedestrian will try select a next position that can maximize the value of the utility U^m.

4.6. Moving utility of the scene

We assume that everyone in the scene not only try to maximize their personal utilities at each step but also try to respect the others by cooperating with them to maximize their utilities. Otherwise, their behavior would not be socially acceptable. Thus, everyone in the scene contributes toward the quality of the environment. This can be incorporated into another utility called "scene utility".

Assume that, at time t, the positions of the two members i and j of the pair, and the pedestrian m in the environment are represented by the set $\mathbf{P}_t = \{\hat{p}^i_t, \hat{p}^j_t, \hat{p}^m_t\}$. $\mathbf{P}_{t+1} = \{\hat{p}^i_{t+1}, \hat{p}^j_{t+1}, \hat{p}^m_{t+1}\}$ is one positions set among all feasible positions sets that they can move to. Then, at time t, the overall utility of the scene for the next step is calculated as follows:

$$\Psi_{t+1}(\mathbf{P}_{t+1}) = U^i_{t+1} + U^j_{t+1} + U^m_{t+1}. \quad (17)$$

The new positions set $\mathbf{P}^*_{t+1}$ is most likely to be chosen if:

$$\Psi_{t+1}(\mathbf{P}^*_{t+1}) = argmax(\Psi_{t+1}). \quad (18)$$

4.7. Modeling the friendly link utility

By considering the role of the *FL* factor, the passing process should be tackled by people as follows:

- All people in the scene continuously collect information relating to ten factors (nine traditional factors plus the *FL* factor) to calculate the answer for utility Ψ (Eq. (17)) for determining the next best positions $\mathbf{P}^*$ that they should take.

- At time t, a person s ($s = i, j, m$) considers that his personal utility will be rapidly decreased if he continues walking in the same direction as in the past. As discussed above, one of the main reasons that leads to this thought is the desire to protect FL, i.e. to maintain the value of f_P. Simultaneously, he may also judge that utilities of related people walking in his pathway are being reduced. As a result, this leads to the down-trend of Ψ. Subsequently, the person s tries to maintain Ψ by starting changing his trajectory to a new direction. In this situation, s is the "starter". At the time t, all the others in the scene may not simultaneously have the same feeling as person s, i.e. in their viewpoint, the value of Ψ may remain unchanged if they keep moving in the same direction as in the past. However, at time $t + 1$, after the person s processes his new direction, the equilibrium of the past state is changed. Afterward, all people start recomputing Ψ following new changes. Finally, all the others process new reactions to adapt these impacts. When all the reactions of the people in the scene lead to a new equilibrium, a new trajectories set is determined to prepare for passing process—Stage 3 is started for all people in the scene.

Based on characteristics of Stage 3 and the reasoning above, the Friendly Link utility should have the following characteristics:

- In a far distance between the pair and the pedestrian, i.e. ξ gets high values, this utility should not greatly affect the overall utility of each person. This can be seen from the real world scenarios, when people are far from each other, e.g. 100 m, they prefer to walk directly to the destination rather than considering a detour, i.e. Stage 3 should not happen too soon. Thus, in this condition, the value of f_P should be approximately maximum.
- When people come close enough, i.e. when ξ is small and θ is large, the value of this utility should be rapidly decreased, reflected in the relatively short lifetime of Stage 3.

Based on these characteristics, we modeled the utility f_P as a step function as follows:

$$f_P^s = -\theta * |(\frac{\xi}{a})^{-2b}| \quad (s = i, j, m) \tag{19}$$

where a and b are coefficients. In this equation, we set the maximum value of f_P to zero to coordinate with other utilities in Eqs. (15) and (16).

4.8. Implementing the passing process in the robotic wheelchair

Based on the discussion on the passing process of humans in Section 4.7, it can be seen that each person may estimate different values of f_P (and even other individual utilities) in each circumstance. For this reason, the time that Stage 3 occurs is not fixed and the person who is the "starter" can be anyone. However, the passing process can still be performed smoothly without any problem. Therefore, we implement the utility Eq. (15) on the robotic wheelchair as follows:

- Because the robot is the follower, we put the priority to initialize the passing process on the leader and the pedestrian. If the leader or the pedestrian starts Stage 3, the robot simply adapts to the change.
- If the leader and the pedestrian keep walking, and do not start Stage 3 at a given threshold, the robot will initiate the process and act as the "starter". The threshold is just enough for the robot and all people to perform the necessary maneuvers to successfully start and complete Stage 3. All co-efficients need to be adjusted to ensure that Stage 3 can happen at this threshold.

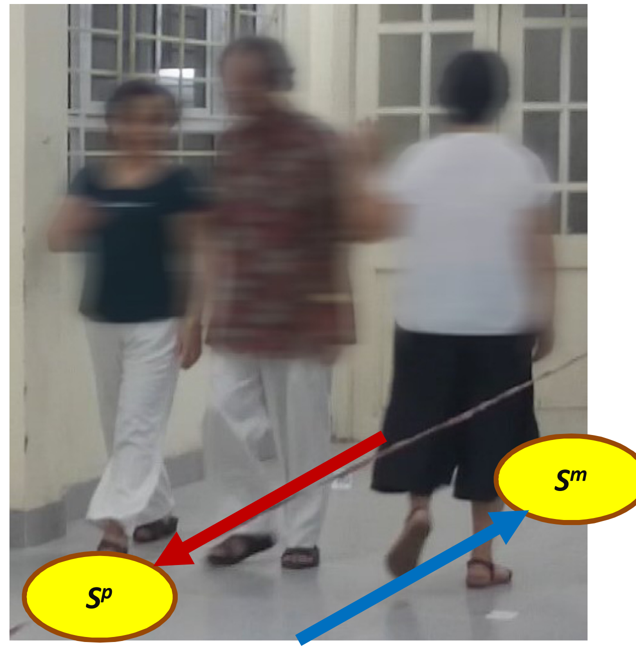

Fig. 7. Sub-goal illustration: positions of people at passing time.

Because the values of these coefficients are not known in advance, they need to be estimated. The next section will describe the Parameter calibration.

4.9. Sub-goal estimation

Another important factor contributing to the smooth crossing process is the ability to predict the sub-goals, which are the positions that people intend to take when they pass each other. Fig. 7 illustrates these sub-goals. By predicting the sub-goals of others in passing, people can prepare their trajectories for smooth passing and for avoiding conflicts. Hence, if the robot knows in advance the sub-goals of people in passing, its motions can be more natural and bring more comfort to the people in the scene.

First, we analyzed the positions of all three people at passing time C for determining their potential sub-goals. The statistical data is illustrated in Figs. 8 and 9. In Fig. 8, the x-axis shows the positions of the pedestrian along the width of the corridor; those positions are considered sub-goals that the pedestrian wants to pass to before reaching their destination. The y-axis represents the number of times these sub-goals occur, i.e. the frequency of these sub-goals. Similarly, Fig. 9 shows the sub-goals of midpoint μ of the pair and their frequency.

From this statistical data, positions of μ and the pedestrian tend to converge to some specific locations in the corridor, hence we can use these locations as the sub-goals for them through the following procedure:

- The pedestrian may have two sub-goals: S^m_{left} and S^m_{right}, in which S^m_{left} is the midpoint of the left side of the corridor, and S^m_{right} is the midpoint of the right side of the corridor.
- Similarly, the pair may have two sub-goals: S^p_{left} and S^p_{right}, in which S^p_{left} is the midpoint of the left side of the corridor, and S^p_{right} is the midpoint of the right side of the corridor.

These sub-goals are illustrated in Fig. 10. There may be a slight difference between the sub-goal's positions in the above definition and the statistical data. However, the corridor is pretty narrow

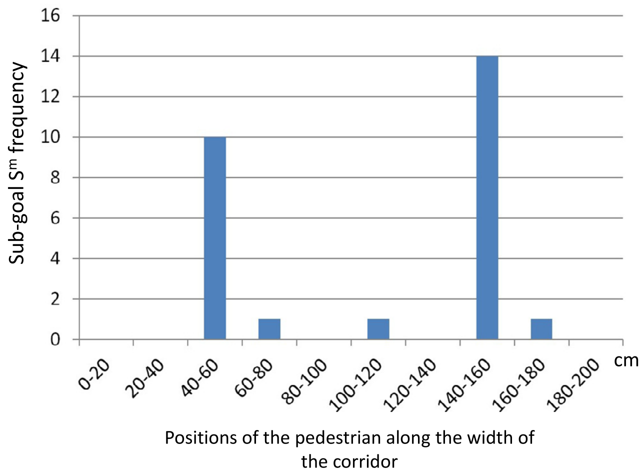

Fig. 8. Positions of the pedestrian at passing time.

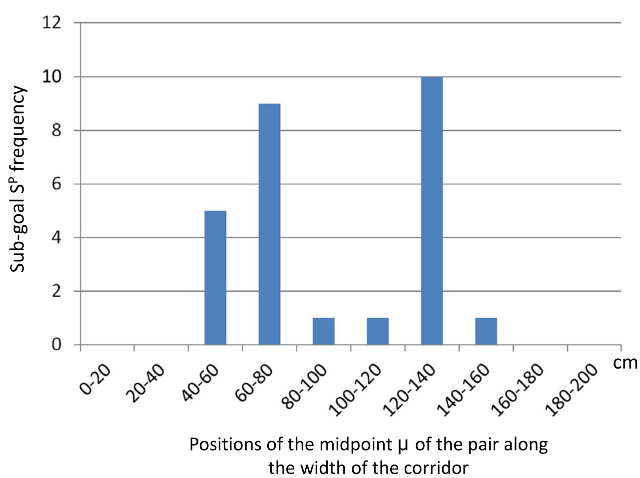

Fig. 9. Positions of the midpoint μ of the pair at passing time.

and our main purpose is to anticipate whether the pair and the pedestrian want to go to the left or to the right of the corridor, therefore the exact sub-goal positions are not important.

Because in most cases, people prefer passing modes (a) and (b), we can assume that the sub-goals of the pair and the pedestrian are different in one passing situation. Therefore if the sub-goal detection process determines that:

- (1) if $S^p \equiv S^p_{right}$ and $S^m \equiv S^m_{left}$: the robot will set its sub-goal to $S^{robot} \equiv S^p_{right}$.
- (2) if $S^p \equiv S^p_{left}$ and $S^m \equiv S^m_{right}$: the robot will set its sub-goal to $S^{robot} \equiv S^p_{left}$.
- (3) if ($S^p \equiv S^p_{left}$ and $S^m \equiv S^m_{left}$) or ($S^p \equiv S^p_{right}$ and $S^m \equiv S^m_{right}$): these are atypical situations in which the pedestrian will move in between two members of the pair, thus the robot should wait for the next detection loop to re-determine the sub-goals until situation (1) or (2) is detected, or until the Friendly Link utility f_P affects the overall utility at a threshold that situation (1) or (2) happens, depending on whichever comes first. During this waiting period, the robot keeps the final destinations of all the people as their sub-goals.

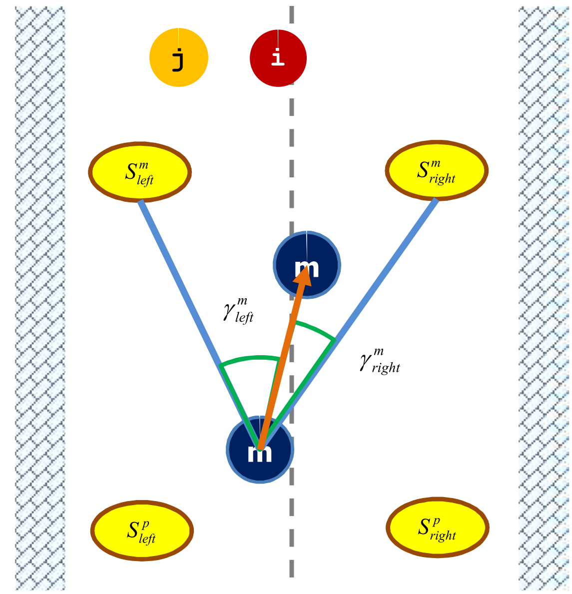

Fig. 10. Sub-goal detection in passing.

To determine the sub-goals of the pair and the pedestrian, we developed the idea proposed in Murakami et al.'s study [35] for detecting sub-goals in the new setting showing in Fig. 10 as follows:

$$S^m = \underset{\{S^m_g | S^m_{visible}\}}{argmin} \{\gamma^m_g\} \tag{20}$$

$$\gamma^m_g = angle(\overrightarrow{p^m_{t-1}p^m_t}, \overrightarrow{p^m_{t-1}S^m_g}) \tag{21}$$

$$S^P = \underset{\{S^P_g | S^P_{visible}\}}{argmin} \{\gamma^P_g\} \tag{22}$$

$$\gamma^P_g = angle(\overrightarrow{\hat{p}^{leader}_{t-1}\hat{p}^{leader}_t}, \overrightarrow{\hat{p}^{leader}_{t-1}S^P_g}) \tag{23}$$

where $g = (left, right)$, $S_{visible} = \{S_{left}, S_{right}\}$. *leader* is the caregiver, as we set the priority of the caregiver higher than the robot. In this situation, if agent i is the *leader*, then agent j is the robot and vice versa.

4.10. Preferred walking velocity

From the modeled function of the utility f_{M_v}, this utility will reach the maximum value when $M_v = c_{M_v}$. In Morales et al.'s study [3], the coefficient c_{M_v} is determined as the average value of the statistical walking velocities. Morales et al. assume that people always prefer to walk at the velocity $M_v = c_{M_v}$ at any time in any walking session.

In our data, the average value of the walking velocity M_v of the pedestrians and the pairs is $c_{M_v} = 0.79$ m/s; lower than the average velocity in Morales et al.'s study [3] ($c_{M_v} = 1.10$ m/s). The high average age, low average height, purpose of the participants' walk (strolling) may lead to this change. Yet, in real world scenarios, walking velocities of pedestrians are affected by many other reasons as well, e.g. if pairs focus more on their conversations, their walking velocities tend to be slower. Even when a person wanders alone, if he suddenly directs his attention to something on the pathway, his walking velocity also may also increase or decrease. Therefore, it is not reasonable to assume that all people prefer to walk at a constant velocity c_{M_v}, even if that velocity is the average value of all the observed walking velocities. Sviestins et al.'s study [36] has addressed this issue and proposed a solution to predict the next preferred walking velocity of a pair. However the method is not fully developed and has not considered all the situations as discussed above. Therefore in this study we proposed the following solution:

We employ an n-gram model with $n = 2$, $\Delta t = 1$ s to analyze the data and compare the actual walking velocity of people at time $t + \Delta t$ (i.e. $t + 1$) with the following equation:

$$c_{M_{v_{t+1}}} = \frac{M_{v_{t-1}} + M_{v_t}}{2}. \tag{24}$$

The result indicated that, with an error threshold of 10%, the value of $c_{M_{v_{t+1}}}$ in Eq. (24) and the real walking velocity M_v matched in over 81% of samples. Whereas the value of M_v in the real walking velocity and the constant value c_{M_v} matched in less than 75% of samples.

Hence, we used Eq. (24) to compute the value of c_{M_v} at time $t+1$ instead of using a constant value of c_{M_v}, i.e. the coefficient c_{M_v} of the utility f_{M_v} is continuously updated during a walking session. Thus, at time $t + 1$, f_{M_v} reaches its maximum if $M_v = c_{M_{v_{t+1}}}$.

4.11. Standard navigation model

For the purpose of verifying the effectiveness of the new model and the current models for side-by-side walking robotic wheelchairs, we employed the Morales et al.'s model [3], which we believe is one of the state-of-art navigation models for side-by-side robotic wheelchairs. However, because this model was developed only for static environments with static obstacles, we slightly modified the model, adding a pedestrian, as follows:

Walking utility of the agent i in the pair:

$$U^i_{standard}(\hat{p}^i|\hat{p}^j) = k^i_O f^i_O + k^i_S f^i_S + k^i_{R_d} f^{ij}_{R_d} + k^i_{R_\alpha} f^{ij}_{R_\alpha} + k^i_{R_V} f^{ij}_{R_V} + k^i_{M_a} f^i_{M_a} + k^i_{M_V} f^i_{M_V} + k^i_{M_w} f^i_{M_w}. \tag{25}$$

Walking utility of the pedestrian:

$$U^m_{standard}(\hat{p}^m) = k^m_O f^m_O + k^m_S f^m_S + k^m_{M_a} f^m_{M_a} + k^m_{M_V} f^m_{M_V} + k^m_{M_w} f^m_{M_w}. \tag{26}$$

The formula of overall walking utility Ψ of the entire environment is as follows:

$$\Psi_{standard} = U^i(\hat{p}^i|\hat{p}^j) + U^j(\hat{p}^j|\hat{p}^i) + U^m(\hat{p}^m). \tag{27}$$

5. Parameter calibration and performance evaluation

5.1. Parameter calibration

The coefficients needed to be calibrated in order to have a working model; we set up the following steps:

(1) We used the trajectory data for calibrating the new model. After eliminating the walking sessions that did not follow modes (a) and (b) because they were atypical, 26 crossing sessions, or 26 trajectory sets, remained.
(2) A simulator was developed for calibrating coefficients. A grid was applied to the navigation environment with cell dimensions of 20 × 20 cm.
(3) We replaced one member of the pair with our simulated agent, which represents our robotic wheelchair. Because the pair has two members, we ran two rounds; on the first round, the agent i was replaced by the robot, then on the second round, the agent j was replaced by the robot. By doing this, the role of the robot was treated as equal to its partner.

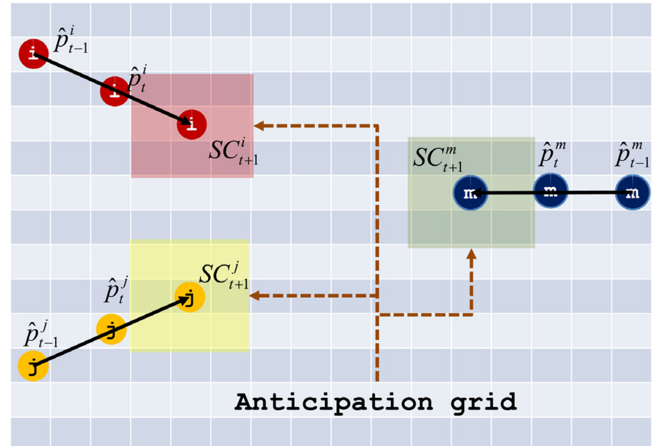

Fig. 11. Anticipation grid in the simulator.

(4) We set the simulation step with $\Delta t = 1$ s. At time t, by applying Eq. (17) for the new model and Eq. (27) for standard model, the simulator needed to estimate the positions of the follower in the scene at time $t + 1$. We defined SC^s_{t+1} as a point on the line stretching between two points $\hat{p}^s_{t-1}$ and $\hat{p}^s_t$ with $s = (i, j, m)$ toward the destinations. The distance between SC^s_{t+1} and $\hat{p}^s_t$ was a length determined by the velocity M_v in Eq. (24) multiplied by Δt. To find the value of U in Eqs. (17) and (27) at time $t+1$, the simulator scanned a region of 5 × 5 cells around SC^s_{t+1}, as illustrated in Fig. 11. We skipped the first step because the overall utility Eqs. (17) and (27) need information from previous steps for calculating. Also, at the second step, because we did not have enough data on the two previous steps for the input of Eq. (24), hence we set $c_{M_{v_{t+1}}} = c_{M_v}$.
(5) Initially, all the coefficient values found by previous studies [3,21] were kept.
(6) With f_P, at the beginning we set $\theta = \delta + 1$. The coefficients a, b and the weight constant k needed to be determined in order for f_P to start changing rapidly when $\xi = 5$, i.e. the robot should actively start Stage 3 if the distance from the pair to the pedestrian m is less than 5 m in a condition that the pedestrian m keeps walking directly to μ. Thus, we started with $a = 20$, $b = 0.4$, and $k = 1$.
(7) At time t, after the values of Ψ in Eq. (17) and $\Psi_{standard}$ in Eq. (27) are found, the new position at time $t + 1$ for the simulated follower is determined. Then, the follower moves to the newly determined position. The leader and the pedestrian do not move to the new positions determined by the model, but move to their real positions recorded in the data corresponding to the time $t+1$. By simulating that way, the robotic wheelchair always had to use the real positions of the leader and the pedestrian to calculate its next step. All calculations for the step $t + 1$ is finished here.
(8) The model continues calculating the position of the simulated follower at time $t + 2$ and so on.

We adjusted the coefficients so that trajectories of the follower built by the models were as close as possible to the real trajectories in the recorded data. At each step t, we measured the distance Λ between the simulated agent position and the real agent position in the recorded data. We employed our new model with the subgoal detection and the preferred velocity estimation (Eq. (24)),

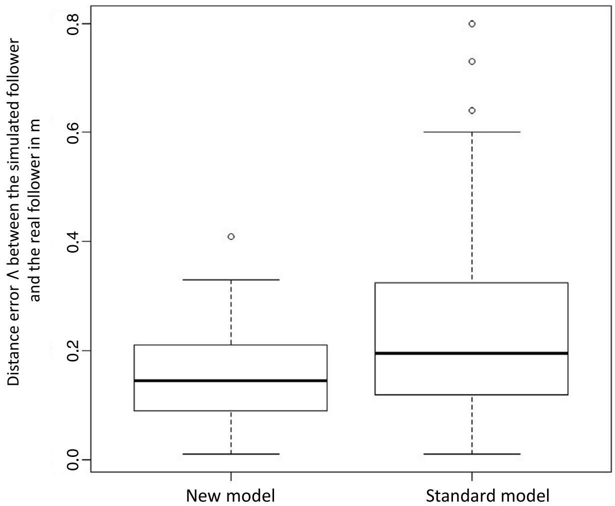

Fig. 12. Testing on the data set A: The values of Λ in the y-axis represent the distance errors in meters between the positions proposed by the simulated follower and the real follower's positions.

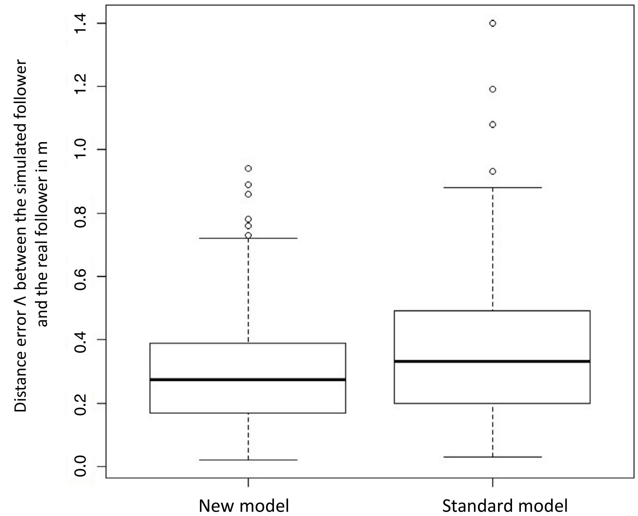

Fig. 13. Testing on the data set B: The values of Λ in the y-axis represent the distance errors in meters between the positions proposed by the simulated follower and the real follower's positions.

whereas the Standard navigation model is employed with the sub-goal detection only.

The new coefficient values are listed in Table 2. Most values of coefficients from previous studies were kept, though some values of k were changed. In addition, we set $\delta = 0.3$.

5.2. Performance verification

The one-way repeated-measure analysis of variance (ANOVA) was employed to evaluate performance of the new model by comparing the distance errors Λ between our new model and the Standard navigation model.

In the first step, the performance was tested by using the data collected in Section 3.1, we called this testing data set A. The result $F = 13.13$, $P = 0.00042$ was found, showing a significant difference between the two models. With our new model, the Mean was 0.158 m, Standard Deviation was 0.085, whereas with the Standard model, the Mean was 0.248 m and Standard Deviation was 0.179. These values are illustrated in Fig. 12.

However, because the testing data set A is also used to calibrate the coefficients of the model function, an over-fitting problem may occur. Therefore, in the second step, we carried out a new study following the same procedure of the first study, described in Section 3.1, to collect new, independent data to verify the performance of the new model.

This time, eight volunteers participated in the study, two women and six men, their ages ranging from around 20 to over 40. We did not ask their ages, but estimated their average age to be around 30. All the participants were lecturers or students, however they had no research relationship to our study. All the steps described previously to collect data were repeated, although we took notes to eliminate some atypical walking sessions instead of using a video camera. Participants were asked to pretend that they were strolling around a mall and therefore should not walk as they were late for work. We also applied some filter steps as described in Section 3.1. For example, one participant suddenly told the other participants that they wanted to walk in a particular way, and that attitude have affected the natural walking behaviors of all the people in the scene, therefore that walking session was eliminated. In addition, only the walking modes (a) and (b) were kept. The Trajectory standardization step in Section 3.2 was also applied. Finally, 50 crossing sessions remained; we call this testing data set B. The average velocity of this data set $c_{M_v} = 0.74$ is determined.

Table 2
Determined coefficients for the navigation model.

Parameters	a	b	c	k^l, k^f	k^m
f_{R_d}: Social relative distance (m)	0.25	2.00	0.75	0.1	–
f_{R_a}: Relative angle (rad)	0.08	3.00	$\pi/2$	0.3	–
f_{R_v}: Relative velocity (m/s)	0.20	1.20	0.00	0.01	–
f_O: Distance to Obstacles (m)	20.0	0.40	–	0.02	0.04
f_S: Angle to sub-goal (rad)	0.45	1.00	0.00	0.3	2.5
f_{M_v}: Velocity (m/s)	0.30	1.60	0.79	0.05	0.5
f_{M_w}: Angular velocity (rad/s)	0.70	4.40	0.00	0.01	0.5
f_{M_a}: Acceleration (m/s^2)	0.20	1.00	0.00	0.01	0.01
f_{R_β}: Vision (%)	0.3	2.00	1.00	0.6	–
f_P: Friendly Link	10	0.4	–	0.05	0.1

Data set B was then sent to the simulator to test the distance errors. The result $F = 20.78$, $P = 5.93\text{E} - 06$ was found, proving that the two models were significantly different. With our new model, the Mean was 0.296 m, Standard Deviation was 0.170, whereas with the Standard model, the Mean was 0.356 m and Standard Deviation was 0.206. The results are illustrated in Fig. 13.

As can be seen from the results achieved from both testing steps, the performance of our new model was significantly better than the previous model.

6. Conclusion

This paper presents a novel navigation model for side-by-side robotic wheelchairs for optimizing the social relationship and the comfort of the involved parties in a crossing situation; i.e. the wheelchair user, caregiver and a third-party pedestrian. Based on our observations, we propose a navigation solution considering human factors in a friendly side-by-side walking session. By applying our model with calibrated parameters, the robot has a better mechanism to generate a reliable and reasonable decision to optimize benefits for both wheelchair users and the caregiver in a crossing situation with a human; i.e the robot is able to mimic the decision-making process of humans, tackling the limitations of navigation functions in previous studies. Although this study is conducted in a straightforward environment which has only one pedestrian, we believe that this model can be applied to more complex environments where the pair has to encounter more than one pedestrian.

On the other hand, this model still has some limitations that need to be developed further. The model was developed based on an assumption that the destinations of all the people in the scenes were known. However, in real scenarios, the robot might encounter dynamic environments where the destinations of the pair and the pedestrians are uncertain. In those circumstances, more factors might need to be combined into this navigation model to let the robot understand the future actions and reactions of the caregiver, the pedestrian and surrounding people.

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