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Approaching a Person in a Socially Acceptable Manner Using Expanding Random Trees

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***Abstract*— In real world scenarios for mobile robots, socially acceptable navigation is a key component to interact naturally with other persons. On the one hand this enables a robot to behave more human-like, and on the other hand it increases the acceptance of the user towards the robot as an interaction partner. As part of this research field, we present in this paper a strategy of approaching a person in a socially acceptable manner. Therefore, we use the theory of "personal space" and present a method of modeling this space to enable a mobile robot to approach a person from the front. We use a standard Dynamic Window Approach to control the robot motion and, since the personal space model could not be used directly, a graph planner in configuration space, to plan an optimal path by expanding the graph with the use of the DWA's update rule. Additionally, we give a proof of concept with first preliminary experiments.**

***Index Terms*— Social acceptable navigation, approaching strategy, expanding random trees, dynamic window approach**

I. INTRODUCTION

In the recent years, mobile robotics have been developing towards fields of applications with direct interaction with persons. There are several prototypical systems that aim to help elderly people to improve cognitive abilities [1], to assist care givers in hospitals [2, 3], be an intelligent video-conferencing system [4], guide people in supermarkets and home improvement stores [5, 6] or simply improve the well-being by providing an easy-to-use communication platform. All these scenarios have to consider persons, interacting with the robot system. Psychologists and gerontologists showed in the 90s that technical devices are treated and observed as "social beings", for example cars, television and computers [7, 8]. Also a robot system is recognized as a social being and also has to behave like one. One important part of the robots behavior is the socially acceptable navigation. Navigation commonly includes tasks like mapping, motion control, obstacle avoidance, localization and path planning. Social-acceptable navigation focuses on these tasks with keeping in mind that humans are within the operation area of the robot, and that an extra treatment is needed.

We are contributing to the ALIAS (Adaptable Ambient LIving ASsistant) project. ALIAS has the goal of developing a mobile robot system to "interact with elderly users, monitor and provide cognitive assistance in daily life, and promote social inclusion by creating connections to people and events in the wider world" [9].

A. The ALIAS robot and the navigation system

The ALIAS projects provides a variety of services, like auto-collecting and searching the web for specific events , a calendar function to remind the user, and, most important, a service to communicate by e-mail, social networks and voice- or video telephone, particularly adapted to the needs of the target group. All these tasks are provided by a mobile robot system (see Fig. 1). The benefit of a mobile system is the capability to move: the robot can be requested by the user and should autonomously drive to the user and approach him/her. Navigation has to be smooth and exact, therefore our motion controlling system is based on the Dynamic Window Approach [10]. Based on this approach, we present here how to approach a person with known pose while considering the "personal space" of the interaction partner. This provides a more natural, polite and unobtrusive approaching behavior of the robot. The personal space itself is not appropriate to use directly inside the DWA, so we need to apply a planning strategy to find an optimal approaching behavior.

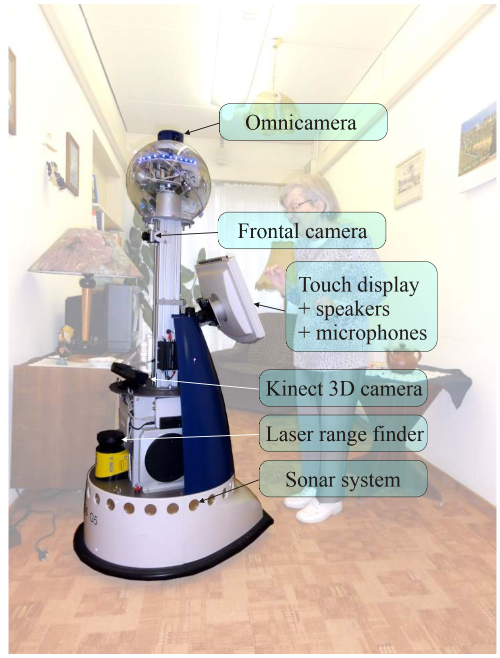

Fig. 1. The ALIAS robot, a SCITOS G5 platform of MetraLabs GmbH, with cameras, Kinect© 3D sensor and laser range finder. It interacts with the user by touch-display and7 speech output.

The robot we use is a SCITOS G5 platform and is equipped with sonar based and laser based distance sensors, a high-res front camera, a Kinect© 3D camera from Microsoft (see Fig. 1), and a dual core PC. With these sensors obstacle recognition and also person detection is done to provide the navigation system with all needed information. The navigation system is only a small part of the overall ALIAS system

zone	interval	example situation
close intimate	0.0m - 0.15m	lover or close friend touching
intimate zone	0.15m - 0.45m	lover or close friend talking
personal zone	0.45m - 1.2m	conversion between friends
social zone	1.2m - 3.6m	conversion to non-friend
public zone	from 3.6m	no private interaction

TABLE I

PSYCHOLOGICAL DEFINITION OF THE PERSONAL SPACE AS DEFINED IN [11]. THIS SPACE CONSISTS OF 5 ZONES, EACH SUPPORTING DIFFERENT ACTIVITIES AND DIFFERENT COMMUNICATION INTENTIONS.

architecture, which also consists of the dialog controller, person recognition and detection system, speech recognition and speaker identification, and a set of applications presented to the user, which are enhanced with various web services.

II. STATE OF THE ART

Psychologists investigated the human-to-human interaction in public areas very carefully since the 70s of the last century. One of the foundations and most recognized publications is the work of Hall [11],[12], who first introduced the concept of different spaces around a human being to support different modes of interaction. There is a space for non-interaction, public interaction, interactions with friends and also an intimate space for interaction with very close relatives (see table I).

By formulating the theory that interaction is also coupled to spatial configurations between interaction partners, many investigations on this matter have taken place, and it could be shown that the configuration depends on many aspects like cultural background, age, sex, social status and person's character [13, 14, 15, 16, 17, 18]. But is the personal space a valid description for human robot interaction? As Reeves and Nass [8, 7] showed, complex technical devices are indeed seen as social beings and treated as such. So, we can assume that a robot with a person-like appearance is treated like a person. Additional proof is given by exhaustive experiments done within the COGNIRON project, where wizard of oz methods showed that a spatial configuration between robots and humans exists [19] and that this configuration also changes depending of the task of interaction (e.g. talking, handing over an object)[20], or such constraints like sex or experience with robots [21].However, non of these works tried to autonomously approach a person in a socially acceptable manner. But the wizard of oz experiments could find out useful spatial parameters to autonomously approach a person.

Despite the thorough psychological background work, only few publications exist that describe an actual autonomous approaching behavior. Often a simple control policy is used, where a fuzzy controller [22], a PID controller [23, 24], or a similar technique is used to keep the robot at a certain distance to the person. The used distance thresholds or fuzzy-rules are always hand-crafted and set by the designer without sufficient psychological justification. Some can only approach a person from the front [23], since face detection is needed, and some simply do not consider the upper body orientation of the person and approach the person from any direction [22].

There are only a few works, more aware of the concept of personal space, which use this space to approach a person or drive around a person without intruding the person's personal zone. For example Pacchierotti [25] uses an elliptical region around a tracked person in a corridor to signal avoidance towards the person by changing the robot's driving lane in a corridor at an early stage of approaching, where collision avoidance would not have suggested such a driving behavior. The distance of the lane changing where tuned by hand and the distance threshold for driving by was determined by evaluating a questionnaire. A hand-made approaching scenario was also presented by Hoeller [26], where different approaching regions where defined, each with a different priority. At least one of these regions had to be free from obstacles and the region with the highest priority was the current target region. Hoeller uses also expanding random trees[26] to plan the next motion step in an optimal fashion. The work of Svenstrup and Andersen [27] models the personal space explicitly and without the need of any thresholds, so they could create a dense representation of the personal space and approach a person by using a potential field method. Although their results do not consider any obstacles and could get stuck in local minima, they were the first with an actual mathematical model of the personal space. Sisbot [28] investigates in his work other aspects of planning a path towards a person. So the robot has to be visible, should not hide behind walls and also should not drive behind a person. He uses an adapted A* planner to derive a planning path but does not show how to include these results into the motion planning concept.

Other authors do not consider the personal space, but also have the need to approach a walking person from the front to catch customer attention [29]. Here, the trajectory of the person is predicted, and a point on that trajectory is chosen as the goal, to give the robot enough time to turn towards that person and approach her from the front.

A. The Dynamic window approach

To move a robot, there must be decisions taken which action to be executed as next. Here, two parts are important. First, the robot has to know to which position it has to drive, and second, which trajectory it has to drive to reach a good position. As mentioned before, we use the Dynamic Window Approach [10] for motion planning and therefor can only support physical plausible paths towards the target. We can assume two things when decide upon the next action. First, we can measure the robots position and speed, and second we know the current obstacle situation. The Dynamic Window Approach's key idea is to select a rectangular region of rotation- and translation speeds around the current rotation- and translation speed, and decide which next speed pair is the best by evaluating different so called objectives. Each Objective focuses on one aspect of navigation like avoiding obstacles, heading towards the target, drive at a certain speed and so on. The window's outer bounds are only based on physical constraints, like the robot's acceleration capabilities and maximum allowed speeds. The voting values of the objectives are summed up weighted, and the minimum vote of the current speed window is chosen to be the next valid action. Our goal is to design an objective for the DWA, which uses a personal space model to approach a person. The model of the personal space is described in the next section. After that section we show, how to include the model into the DWA's objective.

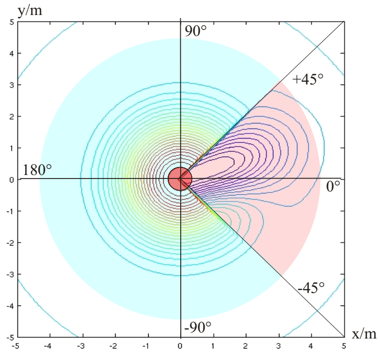

Fig. 2. Two regions of our personal space model. The front region is within an $\pm 45°$ interval (in red). The back region is the rest (in blue). Note, that the regions are not limited in radial extension, like it is done in the illustration.

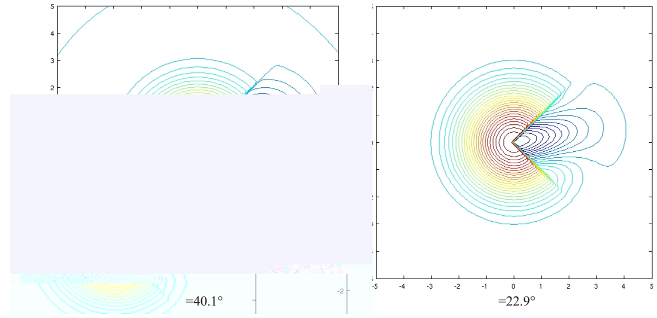

Fig. 3. Two example configurations for different approaching directions.

III. Model of the personal space

As described in section II, the model of the personal space is the key component to approach a person. Similar to the work of Dautenhahn [19], we also want the robot to approach a person from the front, but with a slight aberration from the direct front, since most user perceive such a behavior more comfortable. For this purpose, obviously we need the position and viewing direction of the person to calculate the configuration of the personal space model. The space configuration should enable the robot to drive around the person in a comfortable distance and turn towards the person when a "front position" is reached. Like in [27], we model the personal space with a sum of Gaussians. The space relative to the persons upper body direction is separated into two regions: a front-region, which is considered to be within $\pm 45°$ around the persons upper direction, and a back-region, which is the rest (see fig. 2).

In both areas we define a distance function to keep the robot out of the user's personal zone but within his/her social zone while approaching the person. The function is defined relative to the persons upper body direction.

$$a(x, y) = \frac{\alpha}{2\pi\sigma_1} \cdot e^{-\frac{x^2+y^2}{\sigma_1^2}} - \frac{\beta}{2\pi\sigma_2} \cdot e^{-\frac{x^2+y^2}{\sigma_2^2}} \quad (1)$$

The variables $\alpha, \beta, \sigma_1, \sigma_2$ describe a classical Difference of Gaussians function and are set in our case (see Fig. 2) to $\alpha = 0.6, \beta = 0.3, \sigma_1 = 2m, \sigma_2 = \sqrt{7}m$ to form a minimum cost region in a distance of 3.5 meters around the person. The front region is treated additionally with an "intrusion function" $i(x, y)$. This is also a Gaussian function and is simply added to $a(x, y)$.

$$\begin{aligned} i(x, y) &= \frac{\gamma}{2\pi\sqrt{|\Sigma|}} \cdot e^{-\vec{x}^T\Sigma^{-1}\vec{x}} \quad (2) \\ \Sigma &= \begin{bmatrix} \sigma_x & 0.0 \\ 0.0 & \sigma_y \end{bmatrix} \cdot \begin{bmatrix} \cos(\phi) & -\sin(\phi) \\ \sin(\phi) & \cos(\phi) \end{bmatrix} \end{aligned}$$

Here the variables σ_x and σ_y define an elliptical region, that is rotated towards the needed approaching direction ϕ, as seen from the persons perspective. The vector $\vec{x}$ is simply a column vector $(x, y)^T$. The variables are set to $\gamma = -0.5$, $\sigma_x^2 = 2.9$ and $\sigma_y^2 = 1.1$. Only ϕ and σ_x need to be set at runtime to regulate the approaching distance and direction. These parameters defining the form of the personal space can be obtained by investigating the familiarity of the user with robots, but for the sake of simplicity have been chosen manually for our first trials. All other parameters are constant and are chosen to reflect the properties of the personal space definition in [11]. So, the final definition of the personal space $p(x, y)$ relatively to the person coordinates $x = 0, y = 0$ and upper body pose towards the x-axis is defined as follows:

$$p(x, y) = \begin{cases} a(x, y) & \text{, if } \langle x, y \rangle \text{ in back-region} \\ a(x, y) + i(x, y) & \text{, if } \langle x, y \rangle \text{ in front-region} \end{cases} \quad (3)$$

To compute the personal space in a real world application, each point $(\acute{x}, \acute{y})^T$ has to be transformed to the person-centered coordinate system $(x, y)^T$ presented here. In our trials we use the given person's upper body pose, representing the "most likely" pose. Figure 3 shows an example of two configurations of the personal space with two different approaching directions.

IV. Planning with expanding random trees and the Dynamic Window Approach

Up to that point, we have shown how the personal space can be described, if the upper body pose of a person is known. We also stated, that this space is used within an objective for the DWA. The basic idea of the DWA is to decide what next action is best in a local optimal fashion. The local driving command is only valid for a certain Δt, than the next window configuration is evaluated. The model of the personal space could be used directly within the Dynamic Window objective. It is possible to predict for every speed pair V_{rot}, V_{trans} the trajectory within the interval Δt and simply evaluate the value of the personal space at the end point of each trajectory. This is shown in Fig. 4. The minimal value results in the most supported driving decision. By using the personal space directly, multiple driving decisions may lead to the same minimal value and a unique local optimum can not be guaranteed.

So we have to reformulate the search problem to guarantee a function with a unique local minimum, and, by sequentially following the local minima, a function that leads towards the global minimum (or target position). It is known that planning algorithms can provide such functions. We choose a random tree planner[30] for two reasons. First, classical

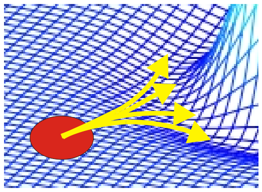

Fig. 4. No distinct speed decision is possible, when the personal space model is used directly. Here, several actions can lead toward the same minimal value.

planning approaches like A*,D* and E* are defined only in metric grid-based maps (and not in the configuration space the DWA is defined in) and have to explore a large area of the grid to finish the plan. The second reason is, that random trees need to touch only a small area of the planning grid. Here, computation time can be saved by computing only the needed cells of the personal space grid and also by covering only a sparse portion of the planning space. In the following sections we describe how the random tree graph is constructed and how it fits to the Dynamic Window Approach. The basic idea is simply, to use the global optimal pose, extracted from the personal space, and use the mentioned planning algorithm to overcome local minima in the personal space by also finding a cost optimal path to the global optimal pose.

A. *Expanding Random Trees*

For planning purposes we use so called expanding random trees [30]. These trees are used to generate a path towards a *target pose*, so one aspect of planning is to define the target pose to reach (see IV-C), the graph's state definition (inside this section) and also the directed expansion of existing graph nodes towards the target (section IV-B). If the target is reached by one node of the graph, it is guaranteed that a cost minimal path toward the target is found. The benefit of an expanding random tree is, that only a sampled set of possible actions are used per node to expand that node. This makes the tree efficient and still suitable for complex planning tasks. Formally a random tree is quite simple: it consists of a set of nodes $S = (s_1, s_2, ..., s_n)$, each representing a state s_i of the system. Our tree uses a five dimensional state space consisting of rotational speed V_{rot} of the robot, translational speed V_{trans}, position and orientation of the robot x, y, ϕ. What makes this approach useful is the creation of successive states by using a random transition function $tr(s_i)$ and using the state update equation from the DWA. This function generates a set of next states by considering the current node's state s_i and applying a set of random actions on that state to generate a set of next system states (see Fig. 5 b)). This process is also called the "expansion" of a node. We use as the transition function a motion model for a differential drive robot with left wheel speed and right wheel speed. Given a pair of these speeds, we can create the trajectory for a given time interval Δt. Since translation speed and rotation speed is convertible to left wheel- and right wheel speed, we can sample a set of speed pairs from a virtual dynamic window, centered at the current speed states of the given node (see Fig. 5 b).

B. *Expanding the graph*

To expand the graph, the method of A* [31] is used. A* uses heuristics to implement a directed search (unlike other planners like E* or Dijkstra) and could significantly speed up the search for the optimal path. Each node of the planning graph also carries a cost value c_i which is incrementally increased with the graph nodes parent c_{i-1} , the real costs to travel from node s_{i-1} to node s_i (denoted by the cost function $C(s_{i-1}, s_i)$ and the heuristic for node s_i. So, a cost update is:

$$c_i = c_{i-1} + C(s_{i-1}, s_i) + h(s_i) \tag{4}$$

The traveling cost function $C(s_{i-1}, s_i)$ is described in more detail in section IV-D. The heuristic is quite simple. We use the 5D euclidean distance of the nodes' state vector to the minimum cell $(\acute{x}, \acute{y})$ of $p_{min}(\acute{x}, \acute{y})$ with target speeds $V_{rot} = 0$ and $V_{trans} = 0$. All nodes with updated costs are put to the active node list. From that list, the node with the lowest costs c_i is selected, expanded and removed from the list of active node. If a node reaches the target cell with correct speed and viewing direction, the planning task is complete.

The graph is initialized by using the current configuration of the dynamic window. The root node is the current robot position, view direction and rotation- and translation speed. The dynamic window is used to give a fully specified set of next actions, which are applied to that node and the graph expands. All subsequent nodes are expanded by using only a sampled subset of the corresponding dynamic window, valid only for each node (see Fig. 5 c)). Than the sequence of best motion actions is applied to the robot's driving system. The deviation from the best path is measured and if the difference reaches above a threshold, complete replanning is done. The same is done when the person changes his/her position too much.

C. *Extracting the target region*

To navigate with the Dynamic Window, we use local occupancy maps to represent the surrounding obstacle situation around the robot. In this grid representation, we have to rasterize also the personal space values $p(\acute{x}, \acute{y})$ to merge the costs of the personal space with the costs of obstacles to create an optimal path. Each planning algorithm has to know the target, to which state the system has to drive to. Since we have a rasterized personal space, we are able to easily extract the minimum value $p_{min}(\acute{x}, \acute{y})$. For a grid based planner this would be sufficient to be the target region, but for expanding random trees it is very unlikely to hit exactly that single cell. So the target region has to grow to increase the probability to hit a target cell. We do so by adding a ϵ value to the minimum and each cell with a value below $p_{min}(\acute{x}, \acute{y}) + \epsilon$ is called a target cell (see Fig. 5 a)). For each target cell we also store the needed orientation of the robot towards the person. Planning is complete when the first lattice of the graph hit a target cell, when the speed of the robot at that cell is near zero and the viewing direction of the robot is nearly towards the person to approach.

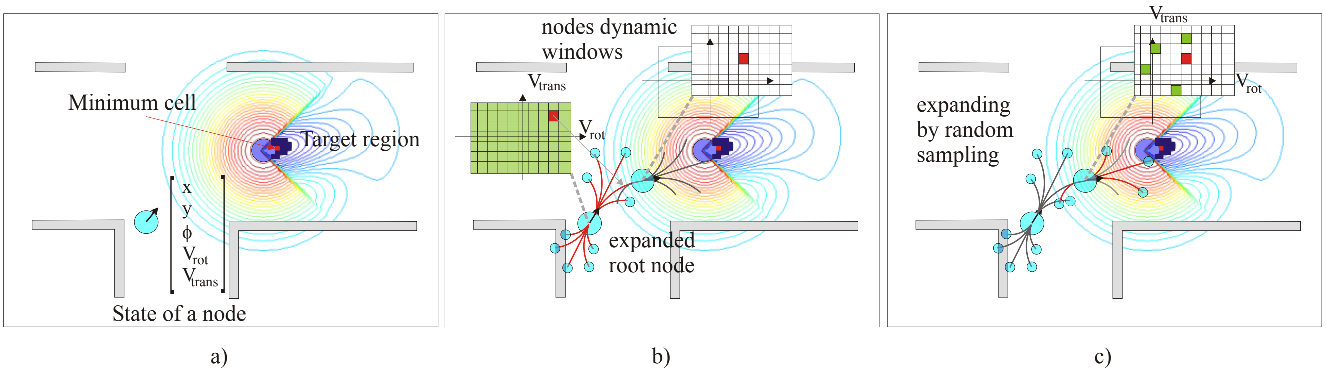

Fig. 5. Different stages of creating the expanding random tree. In a) the root node at the current robot state is created and expanded with the actions from the full dynamic window. Also the target region is defined. Each node gets new state variables. In b) in each node a new individual dynamic window is constructed, to define a set of new possible trajectories. In c) only a subset of these trajectories are used per node to expand the graph towards the target region.

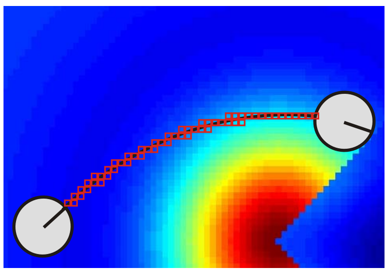

Fig. 6. To estimate the personal space costs, the trajectory is rastered and personal space costs along the trajectory are summed up.

D. The cost function

The last piece (and core component) to understand the graph structure is the calculation of the traveling cost function $C(s_{i-1}, s_i)$ from one node to the next. It consists of two components. One is the cost component from the personal space and the second is the traveling time. In a differential drive system the robot can only drive strait lines or piecewise defined circles. The radius of the circles is simply V_{trans}/V_{rot}. So, when V_{rot} reaches zero, the radius is infinitely large. Given V_{rot} and the prediction time interval Δt one can easily calculate the rotation angle $(V_{rot} \cdot \Delta t)$ and the length of the line segment l_{ij}.

To compute the traveling time t_{s_i,s_j} we calculate $t_{s_i,s_j} = l_{ij}/V_{trans}$. The costs of the personal space are harder to calculate. We use here the rasterization of the trajectory and sum up all costs on the the rasterized trajectory (see Fig. 6). For each cell $\langle x_i, y_i\rangle$ which is part of the trajectory. The costs $k(s_i, s_j)$ are:

$$k(s_i, s_j) = \sum_n p(\acute{x_n}, \acute{y_n}) \text{ if } x_n, y_n \in traj(s_i, s_j) \quad (5)$$

If the trajectory hits an obstacle, the traveling costs are set to infinity. The resulting costs are the sum of both values: $C(s_{i-1}, s_i) = t(s_{i-1}, s_i) + k(s_{i-1}, s_i)$

V. Experiments

A problem on approaching a person is the estimation of the person's position and the associated measurement noise. We plan to detect the upper body pose by fusing two standard tracker methods, namely the leg-pair detector of [32] by using the laser range scanner and the OpenNI full body pose tracker by using the Kinect. To test the stability and robustness of the approach towards that noise, we investigated two scenarios, one in a narrow space and one in a large room of our lab. We use a simulator to avoid the problems of person detection and to control the (simulated) measurement noise of the person's and robot's pose. We could also proof in first test, that the approach is running well on the real robot, but here you have to face the challenging task of upper body pose estimation. To investigate the stability of the approaching behavior, the position of the person and the robot was chosen randomly to approach in a circle around a marked position. The robot and the person should face towards a given direction each. For each of the two locations, we define two person positions with different viewing angles and performed ten runs for each position. So, we had a set of four trials with a sum of 40 single runs. The variance of the final positions of the robot and the variance of the person position are shown in table II.

Robot	σ_{pers}	σ_{rob}
scen. 1(I)	$(0.3, 0.1)$	$(0.3, 0.1)$
scen. 1(II)	$(0.2, 0.1)$	$(0.4, 0.2)$
scen. 2(I)	$(0.2, 0.1)$	$(0.2, 0.2)$
scen. 2(II)	$(0.2, 0.2)$	$(0.2, 0.4)$

TABLE II
THE VARIANCE OF THE END POSITION OF THE ROBOT VS. THE VARIANCE OF THE PERSONS UPPER BODY POSITION.

From the experimental setup we have uncertainties of 0.1m to 0.3 meters in the person position. The question to be answered in our experiments is, how the uncertainty of the target position of the robot will increase when approaching a person. To do so, we record the trajectory of the robot and calculate the mean and standard deviation of the final robot poses. The results are also shown in table II.

The average distance from the person is 0.7 meters, the variance is usually within the same magnitude as the variance of the person's pose. In two cases, the variance in one direction is increased by 0.2 m, which is a result of the target region calculation with its simple threshold heuristic. Figure 7 shows the path and the mean person position with variance of all four test cases. The quality of the trajectories also gives an impression on the stability of the method. Scenario 2 shows, how the upper body pose heavily influences the trajectory of the robot. Scenario 1 shows, that in narrow spaces the trajectory has to follow the physical restrictions and only the upper body pose is considered. The personal space has to be intruded, if there is no other chance.

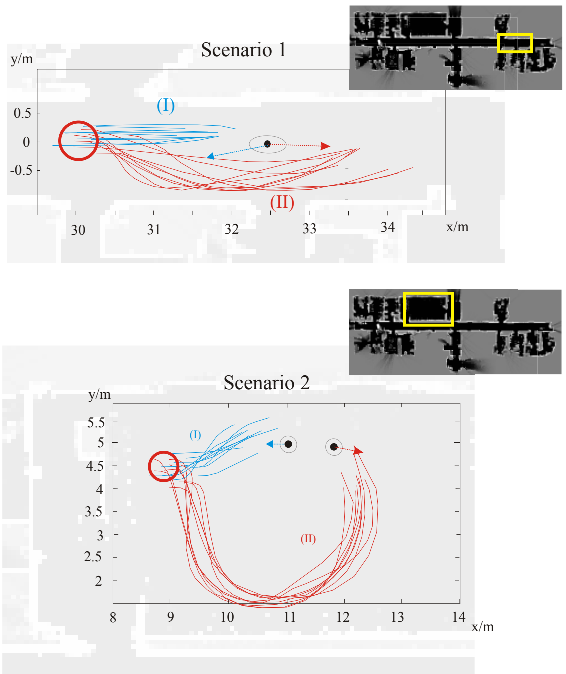

Fig. 7. Resulting trajectories of the two tested scenarios. Per scenario two different poses are evaluated by the user (I and II). The mean positions of the user are shown as black dots, the mean upper body poses as arrows. In each scenario the blue lines denote the robot's trajectories corresponding to the first person setup, while the red lines show trajectories of the second setup. Red circles denote the mean starting position of the robot. Both scenarios show, how the upper body pose influences the approaching trajectory. Scenario 2 also shows, that the social zone is respected if there is room to navigate.

VI. Conclusions

In this paper we presented a method, working within the Dynamic Window Approach, to approach a person by considering his/her personal space. We could demonstrate, by using a planning strategy, that a stable and reliable solution could be achieved. Nevertheless the method of extracting the target region could be improved in future work. We also want to include obstacles into the personal space model, to improve planning quality and focus on the task of real time replanning, when the person changes his/her pose while the robot approaches. And off course we plan to couple the planning approach with data from a real person tracker to show these results at the conference.

Acknowledgment

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