2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)
October 25-29, 2020, Las Vegas, NV, USA (Virtual)

Human-Aware Robot Navigation by Long-Term Movement Prediction

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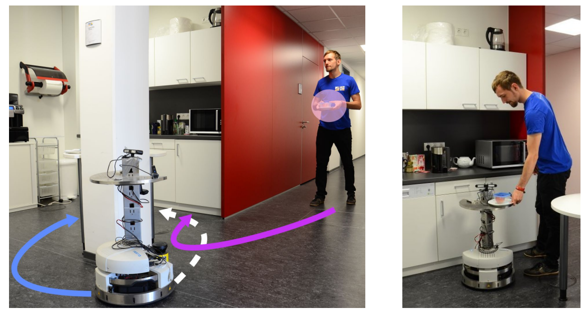
Abstract— **Foresighted, human-aware navigation is a prerequisite for service robots acting in indoor environments. In this paper, we present a novel human-aware navigation approach that relies on long-term prediction of human movements. In particular, we consider the problem of finding a path from the robot's current position to the initially unknown navigation goal of a moving user to provide timely assistance there. The navigation strategy has to minimize the robot's arrival time and at the same time comply with the user's comfort during the movement. Our solution predicts the user's navigation goal based on the robot's observations and prior knowledge about typical human transitions between objects. Based on the motion prediction, we then compute a time-dependent cost map that encodes the belief about the user's positions at future time steps. Using this map, we solve the time-dependent shortest path problem to find an efficient path for the robot, which still abides by the rules of human comfort. To identify robot navigation actions that are perceived as uncomfortable by humans, we performed user surveys and defined the corresponding constraints. We thoroughly evaluated our navigation system in simulation as well as in real-world experiments. As the results show, our system outperforms existing approaches in terms of human comfort, while still minimizing arrival times of the robot.**

I. Introduction

As robots become ever more present in human environments, so does the need for human-aware navigation policies. To be able to provide a real benefit for humans, a robot should coexist with them without causing discomfort. One common way to achieve this is to mimic human social behavior [1]. Humans are more than dynamic obstacles and special constraints need to be fulfilled to enable efficient robot navigation that still abides by social rules, ensuring human comfort. A prerequisite for this is the ability to predict human movements and foresee and avoid situations in which the robot could violate social constraints with its navigation policy.

In this paper, we present a novel approach to accomplish human-aware navigation of service robots in indoor environments. We solve this task using a framework to predict human movements based on their typical transitions between objects [2] in combination with time-dependent planning of the robot's path. We hereby plan the path in a time-dependent cost map that takes into account the user's predicted movements as well as compliance to human comfort. Both the prediction and the cost map are periodically updated based on new robot observations to deal with uncertainties and prediction errors. To specify robot behavior that abides by the rules of human comfort, we use existing knowledge [3], [1] as well as the results of an interview and online survey we conducted.

All authors are with University of Bonn, Germany. This work has been funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) BE 4420/2-1 (FOR 2535 Anticipating Human Behavior).



(a) (b)

Fig. 1: Motivating example of our approach. (a) The robot observes the moving user interacting with an object (pink circle) and predicts his most likely navigation goal and path (violet). Using the prediction, the robot is able to compute a short path to the navigation goal of the human (blue) while avoiding paths that would result in discomfort for the user (white). (b) Still, the robot arrives at the goal location before the user and early enough for direct assistance.

Fig. 1 depicts an application example of our approach. As can be seen, the robot chooses a path to the user's predicted navigation goal. It also tries to minimize discomfort of the human by avoiding the direct route which interferes with the human's path.

To summarize, our contributions are the following:

1) A human-aware navigation system based on long-term movement prediction, human comfort constraints, and path planning on a time-dependent cost-map.
2) The conduct of a survey about human comfort to evaluate different navigation strategies.
3) An evaluation of the complete system in terms of arrival time and human comfort in comparison to state-of-the-art methods [4], [5], [6], both in simulated environments with pre-defined metrics and in real-world experiments with direct human feedback.

II. Related Work

A vast amount of research has been invested to determine human-aware robot navigation policies. Typical tasks for human-aware navigation include socially acceptable person following [4], navigation through dense crowds [7], guiding people to goal positions [8] and providing unobtrusive assistance at different locations [9]. An overview was given by Kruse *et al.* [1]. The authors defined three metrics to evaluate human-aware navigation policies: human comfort (absence of annoyance and stress for humans), naturalness (similarity between robot and human behavior), and sociability (adherence to cultural conventions). Common imple-

978-1-7281-6211-9/20/$31.00 ©2020 IEEE

mentations of these metrics are proximity constraints w.r.t. the human [3], navigation rules [10] and user specific [11] or general anthropomorphic robot design [12] to increase the similarity between users and robots, both visually and behavior wise. The authors also highlighted that a reliable prediction about human movements is a prerequisite to achieve good results with these metrics [3].

According to Foka *et al.* [13], prediction systems can be classified into short- and long-term prediction. A short-term system primarily forecasts the human motions for the next few time steps while a long-term prediction system focuses on inferring navigation goals. Frameworks that target at following a user commonly use short-term motion prediction, e.g., Pradhan *et al.* [14] proposed to use predictive fields to avoid moving obstacles and Ferrer *et al.* [6] developed a variant of the social force model [15] in which they additionally use the position and orientation of the human to predict their next movement. Kollmitz *et al.* [16] presented a method to predict the users path to achieve a good local social navigation behavior of the robot. The authors proposed to model the sensitive area around the human using a Gaussian that decays with time to model the uncertainty in the prediction. The robot then takes into account the predicted occupied areas during planning to avoid interference. However, for applications that aim at generating foresighted robot behavior to reach the user's intended target locations, short-term motion prediction is not sufficient. Instead forecasting of the user's motion for a longer time horizon, i.e., long-term prediction, is necessary.

Long-term prediction systems often use a set of known paths [1] to predict the user's future motions based on observations. For example, Bayoumi *et al.* [5] developed a framework based on Q-learning to predict a user's navigation goal and determine the best robot actions. The learned policy is then applied to enable foresighted robot navigation. Usually, such approaches depend on a specific environment and typical human trajectories in it. Our system, on the contrary, uses human transition probabilities between objects instead of key points on a given map so that the learned transitions are independent of a specific map [2], [17].

In contrast to all the methods discussed above, our approach combines long-term motion prediction with human-aware navigation, making explicit use of the prediction at every time step. This allows to use time-dependent path planning to avoid situations in which the robot would cause discomfort to the user.

III. Constraints Derived From Studies About Human Comfort

An essential component of human-aware navigation is the identification and avoidance of robot actions that decrease human comfort. A detailed overview of research in this area is given by the surveys of Kruse *et al.* [1] and Rios-Martinez *et al.* [3] who analyzed that proximity rules are currently seen as most important for human comfort [18]. In our approach, we combine findings from these works with results from our own survey to define human comfort constraints as described in the following.

According to proxemic theory [19], humans have personal space regions around them in that others, including robots, normally cannot intrude without causing discomfort. The size and form of these regions depend on the familiarity of the intruder, e.g., a friend is allowed to move closer to a person than a stranger. To model the allowed proximity of entities in an unfamiliar social context the *social zone (SZ)* is used, which is a circular interpersonal space region around the human with a radius of 1.2 meter [19]. As a service robot represents a typical example of an unfamiliar entity inside social context, we model the SZ as a minimal distance that the robot must hold to humans. Furthermore, as noticed by Kitazawa *et al.* [20], objects inside a rectangular area with a length of 4 meters and a width of 1 meter in front of moving humans are considered as potential obstacles. This area is called *information process space (IPS)*. Moving inside the IPS does thereby by definition disturb the path planning of humans and a robot should avoid this area to reduce interferences.

To find further constraints, we conducted an interview survey with 8 student participants from the University of Bonn. Each interview lasted around 15 minutes. Participants were asked about their feelings towards service robots, for which tasks they could envision to use robots, how they would design them, and whether there was any behavior that they saw as desirable or undesirable. All participants favored unobtrusive robot behavior. Interestingly, this was even more important than efficient working of the robot for most participants. Most participants also disliked behavior in which the robot would follow them, move silently or unpredictably, or would come too close to them.

Based on those findings, we conducted a follow-up online survey[1] with 261 participants, distributed via Clickworker [21]. We restricted the survey to German participants to stay consistent with our interview survey and our later real-world experiments. We did not have any other formal requirements for participants and aimed for a cross section of the population. In the survey, we asked participants how they feel about robots following them, which distances to robots they prefer (based on pictures) and how they rate unobtrusive robot behavior against efficient working of robots.

We found that 61% of the participants did not want the robot to follow them and 57% would accept a reduced work performance if the robot would then behave more unobtrusively supporting the trend of our interview study. Regarding the robot distance, we found that 77% of the participants had no problem if the robot was moving at approximately 3 meters in front of them (as long as the robot did not enter their IPS) while only 58% would say the same if the robot was moving at the same distance behind them. However, this number increased to 70% if the robot was at least 5 meters behind the human.

[1]The survey questions are available on our website https://www.hrl.uni-bonn.de/publications/comfort_survey.pdf

Fig. 2: Example of our approach. The human (dark violet) started their movement after interacting with a sofa. The robot (light blue) observed the interaction and started to plan its movement with our approach. The computed likelihood of the objects to be the user's navigation goal are shown in green, the darker the color the higher the likelihood. Cost values of possible robot positions are shown in blue, the darker the color the lower the cost. The position with the lowest cost value is shown as blue cross. (a) Based on the initial observation the robot predicts that the human will head to a nearby office and moves accordingly. However, the robot then observes that the human is moving in another direction, concluding that its initial prediction is false. (b) The robot updates the prediction accordingly and computes a new navigation goal and path to it. The robot cannot pass by the user in the corridor as it does not want to enter their SZ or IPS (light violet). As other paths are not available it chooses to follow the user at 5 meter distance. (c) Once the user reached a wider corridor, the robot is able to pass by the user and reach a position close to their true navigation goal.

We therefore derived the following constrains: the robot should not enter the SZ and IPS, it should minimize close following of the human and prioritize these constraints over its work efficiency. The formal representation of these constraints and resulting path planning is presented in the next section.

IV. Human-Aware Time-Dependent Path Planning

We tackle the scenario of a service robot that needs to provide assistance to the user at certain locations. The objective is to find a path from the robot position to the initially unknown navigation goal of a moving user, that minimizes the robot's arrival time and complies with the user's comfort. Our solution consists of the following steps:

1) Prediction of the user's navigation goal by applying Bayesian inference, using prior information about the transitions between objects and the knowledge about their locations as well as current observations.
2) Computation of a time-dependent cost-map based on the predicted user positions at future time steps and social constraints, determined as described in Sec. III.
3) Solving the time-dependent shortest path problem [22] on the given cost map and executing the returned path.

These steps are regularly executed to update the prediction and recalculate the best robot navigation action based on new observations. Fig. 2 demonstrates the functioning of our system for an example scenario. In the following, we explain the individual steps of our approach in detail.

A. Prediction of the Navigation Goal

To predict the user's navigation goal, we use an updated version of our previously published object interaction based system [2]. We thereby assume that humans move between objects and that knowledge about typical object transitions can therefore be used to predict future navigation goals. In contrast to our previous system, we now use a less complex Bayesian inference approach. As before, we assume that a map of the environment as well as the locations of relevant objects is known.

The prediction relies on a so-called interaction model I that models the user's transition probabilities between different object classes. To learn the model, we used data sets of human interaction sequences with objects as described in our previous work [17]. I then acts as prior knowledge and provides the probability that given a previously observed interaction with an object of class A, the user will interact next with an object of class B.

Given an observation about the user's state $S = (\mathcal{X}_h, \theta)$, with $\mathcal{X}_h$ as their position in a map of the environment and θ as their orientation, our framework calculates the belief about the user's navigation goal as described in the following. Let $O = \{o_1, o_2, ..., o_n\}$ be the set of all relevant objects in the environment with $o_i = (\mathcal{X}_{o_i}, \tau_{o_i})$ where $\mathcal{X}_{o_i}$ is the location and τ_{o_i} the class of object o_i. The belief about the navigation goal is computed using Bayesian inference.

$$P(o_i|S) = \frac{P(S|o_i)P(o_i)}{\sum_{o_j \in O} P(S|o_j)P(o_j)} \quad (1)$$

The prior knowledge $P(o_i) = I(o_i|\tau_L)$ is hereby given by the learned object transition probabilities encoded in the interaction model I and the class of the last object τ_L the user interacted with. This simplifies Eq. (1) to

$$P(o_i|S) = \eta \cdot P(S|o_i)I(o_i|\tau_L) \quad (2)$$

with $\eta = (\sum_{o_j \in O} P(S|o_j)P(o_j))^{-1}$ as a normalizer. Note that it is also possible that the robot did not observe the last object interaction. In this case, we use the marginalized interaction probability over each possible last object

$$I(o_i) = \sum_{o_j \in O_L} I(o_i|o_j) \tag{3}$$

where $O_L \subseteq O$ is the set of all objects in the environment that are "behind" the user considering their walking direction. In this case Eq. (1) transforms to

$$P(o_i|S) = \eta \cdot P(S|o_i) \cdot I(o_i). \tag{4}$$

In both equations, $P(S|o_i)$ corresponds to the likelihood of the user's observed state $S = (\mathcal{X}_h, \theta)$, given the navigation goal o_i. To evaluate this likelihood, we use the assumption that the user moves on the shortest path towards the navigation goal. We therefore compute the shortest path $\mathcal{P}_{h \to o_i}$ from the user's position $\mathcal{X}_h$ to the object location $\mathcal{X}_{o_i}$ in an occupancy grid map of the environment with A^*. Let $\mathcal{L}(\mathcal{P}_{h \to o_i})$ be the length of $\mathcal{P}_{h \to o_i}$. Furthermore, we compute the difference $\Delta a(\theta, \theta_{opt})$ between the user's current orientation θ and the orientation θ_{opt} the user would have if they moved from $\mathcal{X}_h$ to the next grid cell on $\mathcal{P}_{h \to o_i}$.

Accordingly, the likelihood of the observed user state given the navigation goal o_i is defined as

$$P(S|o_j) = \mathcal{L}(\mathcal{P}_{h \to o_i})^{-1} \cdot \Delta a(\theta, \theta_{opt})^{-1}. \tag{5}$$

Finally, $P(o_i|S)$ can be computed according to Eq. (2) and Eq. (5) as

$$P(o_i|S) = \eta \cdot \mathcal{L}(\mathcal{P}_{h \to o_i})^{-1} \cdot \Delta a(\theta, \theta_{opt})^{-1} \cdot I(o_i|\tau_L). \tag{6}$$

Using Eq. (6), the robot has an estimate about the navigation goal of the moving user, which is regularly updated based on new observations.

B. Time-Dependent Path Planning

Given the computed belief, the robot needs to determine a path from its current position to the user's predicted navigation goal. We assume that enough space is available in the environment for the robot to navigate. The path should minimize the robot's arrival time while complying with the comfort of the user. To calculate the path, we use a cost grid and apply time-dependent shortest path planning. The grid costs are hereby defined based on the distance of cells to the user's possible navigation goals and human comfort constraints.

Given the observed user state S, our approach assigns costs to each cell $\mathcal{X}$ that is not occupied with a static obstacle. To do so, we sum up the distances from $\mathcal{X}$ to each possible navigation goal $\mathcal{X}_{o_j}$ weighted by their probability

$$C_{dist}(\mathcal{X}) = \sum_{o_j \in O} P(o_j|S) \cdot \mathcal{L}(\mathcal{P}_{\mathcal{X} \to \mathcal{X}_{o_j}}) \tag{7}$$

with $\mathcal{L}(\mathcal{P}_{\mathcal{X} \to \mathcal{X}_{o_j}})$ as the length of the A* path from $\mathcal{X}$ to $\mathcal{X}_{o_j}$.

Furthermore, our approach considers the constraints derived from the studies about human comfort introduced in Sec. III. To do so, we need to predict the user's path given the belief about their navigation goal. Let us assume that the current observation $S = S^0$ was done at time $t = 0$ and that

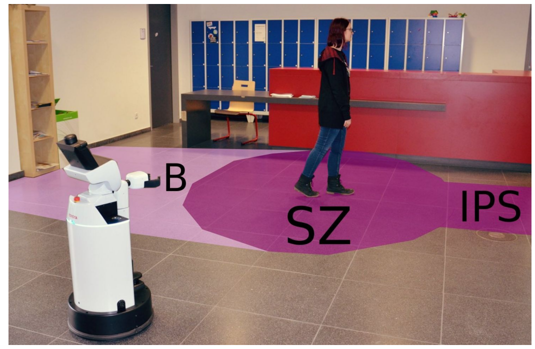


Fig. 3: Visualization of the regions around the human that the robot should not enter, based on our surveys. The social zone (SZ), with a radius of 1.2 meters, and the information process space (IPS), with a length of 4 meters and a width of 1 meter, are impassable regions depicted in dark violet. The area behind the human (B), with a length of 5 meters and a width of 2.4 meters depicted in light violet, can be entered by the robot but has increased costs since a robot in this region would likely be perceived as a follower.

o_g is the user's most likely navigation goal according to the observation and the prediction as described in Eq. (6). To predict the user's path, we assume that they follow the A* path from their current position $\mathcal{X}_h$ to o_g on the grid map with their current velocity until the next observation takes place. Let us further assume that the user reaches o_g at time step t_f according to the current velocity.

Based on the results of Sec. III, we have 3 human comfort constraints: minimizing time inside the SZ, IPS, and the region up to 5 meters behind the human. Furthermore our survey showed that, if they must decide, humans prefer non-disturbing robot paths over efficient working of the robot. We also observed that humans dislike situations in which the robot follows them. We therefore choose the following modeling: The SZ and IPS are impassable regions for the robot, as by definition humans are disturbed if a robot enters these areas. For the same reason positions up to 5 meters behind the human have increased cost, the closer to the human the higher. As a result, the robot only enters this area if no alternative paths are available and only to reach more cost efficient positions, e.g., in front of the human.

Formally, this results in the following time-dependent cost function for the grid cells

$$C_h^t(\mathcal{X}) = \begin{cases} \infty \text{ if } \mathcal{X} \in SZ(\mathcal{S}^t) \\ \infty \text{ if } \mathcal{X} \in IPS(\mathcal{S}^t) \\ \frac{5}{dist(\mathcal{X}, \mathcal{X}_{o_j})} \text{ if } \mathcal{X} \in B(\mathcal{S}^t) \\ 1 \text{ else} \end{cases} \tag{8}$$

with $SZ(\mathcal{S}^t)$ and $IPS(\mathcal{S}^t)$ as the SZ and IPS at time t, respectively, and $B(\mathcal{S}^t)$ as the backwards extended SZ or back area of the human, which corresponds to a rectangular region with a length of 5 meters, a width of 2.4 meters and its center 2.5 meters behind the human, orthogonal to their movement direction at time t. This area represents the region in which humans tend to view a robot as a follower. Fig. 3 visualizes these areas.

The final cost of a cell $\mathcal{X}$ at time t is then given as

$$C^t(\mathcal{X}) = C_{dist}(\mathcal{X}) \cdot C_h^t(\mathcal{X}). \quad (9)$$

according to Eq. (7) and Eq. (8). Let $\mathcal{X}_{min}$ be the position with the lowest cost at time t_f

$$\mathcal{X}_{min} = \min_{\mathcal{X}} C^{t_f}(\mathcal{X}) \quad (10)$$

and $\mathcal{X}_r$ be the robot's position at time $t = 0$. As described above, t_f corresponds to the estimated time step when the user reaches the predicted navigation goal. Given the time-dependent cost function C^t, we can now solve the time-dependent shortest path problem from $\mathcal{X}_r$ to $\mathcal{X}_{min}$ using A* following the algorithm of Zhao *et al.* [22].

Once the path is computed the robot starts following it and after a fixed time interval performs a new prediction about the user's navigation goal based on a new observation. Afterwards, the best path for the robot is recalculated using an updated cost map. The process is repeated until the user has reached their destination.

V. Experimental Evaluation

To evaluate our approach, we performed a quantitative evaluation in simulation with 140 trajectories and a real-world experiment in our lab with 11 participants. For the quantitative evaluation, we used as metrics the *human comfort* (HC) and the *difference in arrival time* between the robot and the user (ΔT). Positive ΔT values indicate that the robot arrives at the goal before the user. The higher this value the earlier the robot will be at the true navigation goal of the human. To quantify HC, we measured the ratio of the number of robot positions outside of the SZ or IPS and the robot's overall number of positions as *social distance compliance* (SDC) as well as the average *human-robot distance* (HRD). Based on our surveys, an optimal human-aware robot path has an SDC of 1.0 and a high average distance. During the real-world experiment, we asked the participants to rate their comfort with the robot navigation behavior on a 5-point Likert scale rating from very uncomfortable (1) to very comfortable (5).

In all experiments, we compared our results with three existing approaches. The social force approach by Ferrer *et al.* [6], which applies a short-term prediction system, the reinforcement learning approach by Bayoumi *et al.* [5], which uses long-term prediction but no time-dependent path planning, and the follower approach by Tee *et al.* [4], which does not use a prediction system and was configured to follow the user at a distance of 2 meters.

A. Quantitative Evaluation

For the quantitative evaluation, we created five different simulated office and home environments with sizes between $100\,m^2$ and $150\,m^2$, a grid resolution of 0.25 meter and up to 110 different objects from 15 different classes using the V-REP editor [23]. We randomly sampled a set of 140 test trajectories over all environments and based on a training set of 128 previously recorded human object interactions. The same set of test trajectories was used for all evaluations.

	Avg. SDC	Std. SDC	Avg. HRD	Std. HRD	Avg. ΔT	Std. ΔT
Our approach	0.97	0.009	**8.7m**	1.9m	8.6s	2.9s
Social force approach [6]	**0.99**	0.004	2.5m	0.4m	-4.5s	1.7s
Reinforcement learning approach [5]	0.87	0.04	4.2m	0.8m	**9.5s**	2.8s
Non-predictive approach [4]	0.50	0.05	2.0m	0.4m	-9.0s	1.4s

TABLE I: Results of the quantitative evaluation with 140 trajectories in five different simulated environments. As can be seen, our approach achieves by far the highest average human-robot-distance (HRD), while simultaneously achieving the second highest average social distance compliance (SDC) and difference in arrival time (Δ T). We refer to the text for a detailed definition of these metrics and discussion of the results.

Tab. I shows the evaluation results. As can be seen, our approach archives the highest HRD and the second highest SDC and ΔT. Social distance violations were mostly encountered when the user moved unexpectedly while the robot was trying to pass them. Typically, the robot would pass by the user as early as possible and wait at key points of the map to update its prediction. In contrast to that, the reinforcement learning approach [5] focuses on reaching the most likely goal position as fast as possible. Early predictions tend to be false, which resulted in unnecessary movement of the robot and some passes through the SZ and IPS. When using the social force approach [6], the robot followed the user outside of their SZ. However, while the robot was able to predict the user's short-term movements and anticipate and avoid situation in which it would enter the SZ, it was not able to reach the goal before the user nor hold a high distance to the user. The small HRD and the fact that the robot could not predict long-term goals resulted in the behavior of closely following the user. The non-predictive approach [4] performed similarly. However, as no prediction system was used the robot was not able to anticipate changes in the user's movement pattern and many intrusions inside the SZ happened.

We performed a paired t-test to check whether there is a significant difference between the individual approaches, with a alpha level of 0.05. We found that the difference in SDC and ΔT between our approach and the best performing other approaches is not significant, with p-values of 0.83 and 0.52 respectively. However the difference between the HRD values of our approach and the second best approach is significant, with a p-value of 0.002. We can therefore conclude that no approach is significantly better than our approach regarding SDC and ΔT, while we significantly outperform the other approaches in terms of HRD.

B. Real-World Experiments

For the qualitative evaluation, we designed a wizard of Oz real-world user experiment with 11 student participants from different departments of the University of Bonn. The task of the participants was to follow a specific trajectory, while a robot would predict and navigate to their movement goal using our approach as well as the three different methods

	VC (5)	C (4)	N (3)	U (2)	VU (1)	Avg. value	Std. value
Our approach	27%	**63%**	0%	9%	0%	**4.1**	0.8
Social force approach [6]	18%	27%	**36%**	18%	0%	3.5	1.0
Reinforcement learning approach [5]	9%	9%	18%	**45%**	18%	2.5	1.6
Non-predictive approach [4]	0%	0%	9%	36%	**54%**	1.5	0.7

TABLE II: Results of the qualitative evaluation with 11 participants. Participants rated the robot's behavior on a Likert scale with five values, ranging from 1 to 5: very uncomfortable (VU), uncomfortable (U), neutral (N), comfortable (C), very comfortable (VC). As can be seen, our approach achieves the highest rating and was on average seen as comfortable (4.1). We refer to the text for a more detailed discussion of the results.

introduced above. After the experiment, the participants had to rate their feeling of comfort for each of these approaches on a Likert scale with five values, ranging from 1 to 5: *very uncomfortable* (VU), *uncomfortable* (U), *neutral* (N), *comfortable* (C), *very comfortable* (VC). Tab. II depicts the results of the qualitative evaluation. We observed the same trend as in our previous surveys. Participants felt uncomfortable to very uncomfortable if a robot passed through their SZ and or IPS (reinforcement learning, non-predictive) and comfortable to very comfortable if a robot would not enter these areas (our approach, social force). Participants also particularly disliked if the robot would just follow them (non-predictive). We also observed that participants felt more comfortable if they thought that the robot had a policy to actively avoid them (our approach, social force). As these results demonstrate, the navigation strategy produced by our approaches achieves the highest rating and was on average seen as comfortable.

VI. Conclusion

In this paper, we presented a novel solution to human-aware navigation for assistant robots in indoor environments. As new contribution, we apply a long-term prediction of human motions that utilizes prior knowledge about human object transitions, in combination with time-dependent path planning under consideration of human comfort constraints.

As we demonstrated in a quantitative evaluation, our approach achieves a high average distance between the robot and the human and avoids interpersonal space breaches, which are seen as uncomfortable by humans. At the same time, our framework leads to efficient navigation behavior, so that the robot is often able to arrive before the user at their navigation goal. Furthermore, our qualitative evaluation with a real robot and participants in our lab shows that the robot behavior resulting from our approach is rated as comfortable and outperforms existing methods based on social forces [6], reinforcement learning [5], and non-predictive following [4]. We therefore achieved our goal of realizing a human-aware robot navigation framework using long-term movement prediction that minimizes travel time and maximizes human comfort.

Acknowledgments

We would like to thank Sandra Höltervennhoff, Bettina Esser, and Jenny Mack for their help during our experiments.

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