Anticipatory Robot Path Planning in Human Environments

Akansel Cosgun[1], Emrah Akin Sisbot[2] and Henrik Iskov Christensen[1]

***Abstract*— Robot path planning in human environments benefits significantly from considering more than obstacle avoidance, and recent works in this area proposed safety and comfort considerations. One shortcoming of current approaches is that humans' behavior is modeled as independent of robot's motions. In this work, we aim to give this anticipation ability to a robot by simulating people's reaction to robot's motion during planning. Our approach is based on extracting a static plan using A* search on the grid map by minimizing safety, disturbance and path length costs and then refining it by simulating humans' reaction using the Social Force Model.**

With two example scenarios in simulation and two on the real system, we provide qualitative examination of the resulting robot paths and demonstrate that robots can exhibit social behaviors that is not possible to model with standard approaches. This work serves as a primer for quantitative user studies, and we hope will urge future robot path planners to consider a richer set of social capabilities.

I. INTRODUCTION

Robot navigation is a relatively mature field as demonstrated by an uninterrupted 26 mile run in an office environment [1]. Recently, there is a lot of interest in robot navigation in human environments [2]–[4]. Path planning for robot navigation is traditionally seen as a shortest-path problem. While this leads to correct and collision-free paths, the behavior of the robot is sometimes seen as unsafe or unnatural by human observers. Human-aware navigation necessitates considering the safety and comfort of humans to generate human-friendly paths. For example, sudden appearance of a robot can cause fear in humans or cutting in between two people while they are in a conversation is usually considered rude behavior. Approaches in human-aware navigation produce safe and socially acceptable paths; however, they assume that humans are independent agents and robot motions have no effect on their motions. However, mere presence of a robot in motion is likely to influence the motions of nearby people. Robot can potentially exploit this implicit cooperation between moving embodied agents. For example, consider the 'room problem' in Figure 1. The robot's goal is to navigate inside the room but there is a person standing at the door and blocking the path. Not only traditional path planners, but also planners that consider dynamic objects fail to produce a solution to this problem. The role of physical embodiment in human-robot interaction is significant [5], however it is ignored in robot navigation. A human-aware planner should anticipate that the human may give way to the robot if it expresses its intent to go inside the room. Extending this idea, by using anticipation a robot

[1]A. Cosgun and H. I. Christensen is with Georgia Tech, Atlanta, GA
[2]E. A. Sisbot is with Toyota InfoTechnology Center, Mountain View, CA

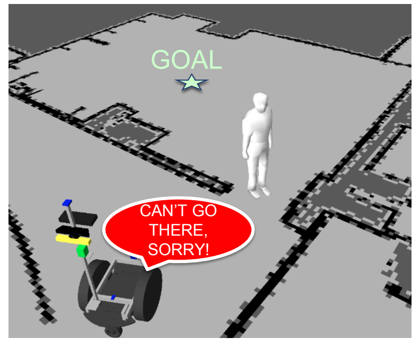


Fig. 1. Standard path planners fail to produce a solution to the 'room problem'. Our planner anticipates that the human can give way to the robot if it approaches towards its goal.

can reduce its time of travel and behave more human-like in general cases.

In previous work, we used a traditional path planner that treated humans as static obstacles in point-to-point navigation for service robotic applications [6], [7]. In current work, we propose a planner that considers reactions of humans to robot motion. Our planner consists of three parts: 1) a static planner that searches a grid map using A* and considers path length as well as the safety and disturbance of people. 2) a dynamic planner that refines the static plan by simulating people's reaction to robot's motion using Social Force Model [8]. 3) trajectory planner. In dynamic simulation, robots and humans repulse each other, and additional forces helps to stay away from obstacles and conserve formation in groups. Paths are re-planned when the world state changes or humans do not move as anticipated.

We demonstrate two example scenarios in simulation and two on the real system. We discuss the resulting behavior of the robot and demonstrate that our approach can produce social robot behavior that is not possible with standard path planners. We think that qualitative evaluation of robot behavior is a necessary primer for quantitative studies in socially aware navigation, and we leave user studies for future work.

A literature survey will be given in Section II, followed by a brief problem definition in Section III and a detailed description of our approach in IV. Implementation on a robot is discussed in Section V, results are presented in Section VI, followed by a conclusion in Section VII.

II. RELATED WORKS

In this section, we review the literature on robot navigation in human environments including social spaces, socially acceptable navigation, learning behaviors from humans and cooperative navigation.

A. Social Spaces

According to Lam [9], mobile robots should obey certain rules while navigating in human environments. These rules include: not colliding anybody, not entering the personal space of a human unless the task is to approach the human and waiting if robot unwillingly enters the personal space of a human. Humans are already good at obeying such social conventions. Therefore most works on robot navigation in human environments is linked to human-human spatial interactions. One of the first studies in such interactions is conducted by Hall [10]. This study presents the proxemics theory, which categorizes the distance between people in four classes. These distances, named intimate, personal, social and public, provide spatial limits to different types of interactions. Kendon [11]'s F-formation is based upon observations that people often group themselves in a spatial formation, e.g. in clusters, lines and circles. Huttenrauch [12] claimed that works of Hall and Kendon should be adapted to suit the dynamics of HRI.

B. Socially Acceptable Path Planning

Socially acceptable robot navigation is considered in different applications such as person following [13], free navigation [14] and approaching people [2]. Some works used the personal space concept in cost-based general path planners [14], [15]. Our work is most similar to Sisbot [14], which models the social spaces as a ellipse-shaped Gaussian, and takes into account the safety, preferences and vision fields of humans for a robot that navigates from a location to another. The main difference of this work is that we consider the future dynamicity of humans in the environment. Kirby [15] presents a path planner that takes into account social conventions such as tending to one side of the hallways. A potential field based trajectory planner for dynamic human environments is presented by Svenstrup [16]. Rios-Martinez [17] presents a RRT-based planner that considers not just safety but also the disturbance of humans. In simulation, if interaction within a group of people is detected, the robot can either not disturb the interaction or join the group. Our approach is conceptually similar to this work, however we use grid search instead of RRT's, and Social Force Method instead of Kendon's formations. Lu [18] shows that using gaze cues and social navigation makes robot-human hallway passing more efficient.

C. Learning Navigation from Human Behavior

Behaving human-like in robot navigation is usually favored in the literature [19]. One way to simulate human navigation behavior is to use social cost maps that capture social conventions [20], [21]. Contrary to the imitation approach, [22] tries to avoid predicted paths, with the goal to minimize the risk of interference. Kuderer [4] presents a teleoperated robot that computes the policy of a desired interactive navigation by learning from observations of pedestrians. Pellegrini [23] trains a dynamic social behavior, that account for social interactions, using pedestrian data.

D. Human Cooperation in Robot Navigation

Robots can exploit human cooperation in certain scenarios. In populated environments, one way to move with the crowd is to follow individuals that move towards the robot's goal [24], [25]. Some of the recent works in the literature claim that the robot motions should be predictable so the human observers can judge the motive and future behavior of the robot. Observational study in [26] claims that three features can increase the predictability of robot navigation: straight lines, stereotypical motions and usage of additional gestures. In a user study conducted by Gockley [27], humans observers watched two ways of person following. People found direction-following more natural than exact path following.

Trautman [28] introduces the 'freezing problem', where traditional path planners fail to produce a feasible solution in crowded human environments. The difference of our work from this work is that we explicitly consider human formations. Muller [25] briefly mentions a 'shooing away' behavior, where the robot accelerates towards a human, hoping that he/she will get out of the way. Kruse [29] introduces an optimistic planner, which assumes that people will cooperate with robot movements. Their approach relies on assigning a non-infinite cost if a robot enters to a human's personal space, however the plan fails if humans doesn't move as expected because of the lack a local planner.

III. Robot Navigation Planning

Robot path planning involves finding a collision-free path from a start position (x_0, y_0) to a goal position (x_g, y_g). A common approach is to divide the path planning into two parts: global and local. Global planning extracts a set of waypoints from start to goal. One approach is to represent the floor plane as a discretized 2D grid therefore global path planning becomes a graph search problem. Local planning computes the velocities that would keep the robot pursuing the global plan as much as possible, while also handling obstacle avoidance.

Common metrics for human-aware navigation includes safety, comfort and naturalness. Safety ensures that robot doesn't make unwanted contact with humans. Comfort is different from safety in the sense that human observers may feel unsafe and in danger even if the robot is moving safely. Naturalness involves imitating human motion and behaviors on a robot. We describe our approach in the next section.

IV. Anticipatory Navigation

As mentioned in Section III, robot path planning is usually divided as global and local planning. We provide both functionalities, but further divide global planning into two planners: static and dynamic. Static planner finds a path on the map of the environment by considering the safety, disturbance of humans and path length and but doesn't consider the future movements of humans. Dynamic planner simulates the reaction of humans and re-computes robot's path assuming the robot wanted to follow the static path. It takes the static path and refines it by considering the predicted temporary goals of humans, reaction to the robot and group formations. Local planner is essentially a trajectory planner that computes the linear and angular velocities that should be applied to the robot to follow the dynamic path. The system overview is shown in Figure 2. We elaborate on the static, dynamic and trajectory planning in the following sections.

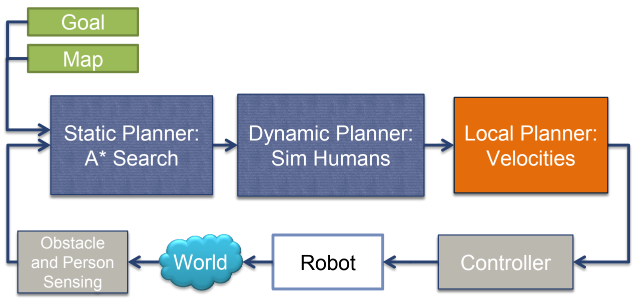


Fig. 2. System overview

A. Static Planner

Static planner takes the start and goal positions and a 2D grid map as input and aims to find a set of waypoints that connects the start and goal cells. The output path has the minimum cost with regards to a cost function with 3 parameters: path length, safety and disturbance. We use A* search with Euclidean heuristics on a 8-connected grid map to find the minimum cost path. The configuration space obstacles are found by inflating the map obstacles for as much as the radius of the robot with the assumption that the robot is circular.

Path length cost: Each action a of the robot (moving to one of the 8 adjacent cells) has a non-negative action cost $Cost_a(x_i, y_i, a)$. If the destination cell is occupied by a configuration space obstacle, then the action cost is infinite. Otherwise, it is the distance in meters. The action cost is thus defined as:

$$Cost_a(x_i, y_i, a) = \begin{cases} u & \text{if } a = \text{N, E, S, W} \\ u\sqrt{2} & \text{if } a = \text{NW, NE, SW, SE} \\ \infty & \text{if } Cell(x_{i+1}, y_{i+1}) \text{ in obstacle} \end{cases}$$

where N,NW,.. are the grid cell expansion directions and u is the grid cell size. The resulting path length cost of a path P is then the sum of all action costs:

$$Cost_{path}(P) = \sum_{a \in P} Cost_a(x_i, y_i, a)$$

Safety cost: The notion of safety is the absolute need of any human-robot interaction scenario. This cost is a human centered 2D Gaussian form of cost distribution and aims to keep a distance between the robot and the humans in the environment. While some approaches used un-isotropic cost functions to account for human orientation, we use a isotropic Gaussian for its simplicity. Each cell coordinate around a human contains a cost inversely proportional to the distance. Since the safety loses its importance when the robot is sufficiently far away from the human, safety cost becomes zero after a threshold distance. If there are multiple people in an environment, the safety cost of a cell takes its value from the closest human.

$$Cost_{safety}(x, y) = \begin{cases} u \max_{h \in H}(\mathcal{N}(\mu_h, \sum)) & \text{if } d < d_{max} \\ 0 & \text{if } d \geq d_{max} \end{cases}$$

where d is the distance to the closest human, H is all humans, $\mu_h = (|x - h.x|, |y - h.y|)$ and $\sum = \begin{pmatrix} 0.5 & 0 \\ 0 & 0.5 \end{pmatrix}$ is a fixed covariance matrix. The multiplication by the grid cell size compensates for the grid map resolution. Otherwise, for example, if a very fine map was used, safety cost would dominate the path length and disturbance costs, which are independent of the map resolution.

Disturbance cost: This cost is aimed to represent the cases where the robot potentially disturbs the interaction of a group of humans. For example, if two people are facing each other and talking, then the robot should not cross between them. We model this with a disturbance cost that is introduced if a path crosses between two people. We do not detect if there actually is conversation between the people, but estimate the disturbance cost using body poses of agents. This cost increases if body orientations of two people are facing each other and is inversely proportional on the distance between the two humans. It serves as a computationally efficient approximation of the amount of interaction between two people.

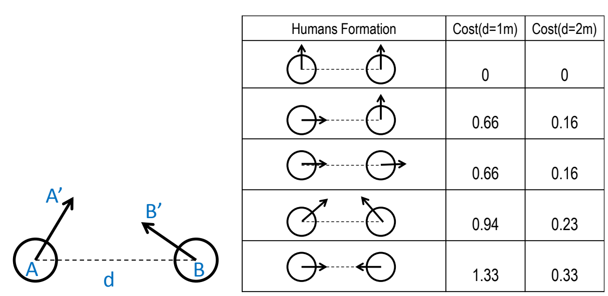
For each step taken in the grid, we check if the line segment from the current position to the projected position intersects a line segment between all pairs of humans. To illustrate, let's assume the robot crosses the line between human A and human B in Figure 3(a).

The disturbance cost is calculated as:

$$Cost_{dist}(x, y, a) = \max(0, f(d).(\vec{AA'}.\vec{AB} + \vec{BB'}.\vec{BA}))$$

$$f(d) = \frac{1}{d} - \frac{1}{d_{max}}$$

where all the vectors are normalized and d_{max} is the maximum distance between the humans that returns a disturbance cost. Figure 3(b) illustrates several examples of disturbance costs with $d_{max} = 3$ meters.



(a) (b)

Fig. 3. Disturbance costs in different human-human configurations and distances. A path that crosses the dashed lines incurs the disturbance cost calculated on the right side.

Total Cost: The total cost of a path P is computed with a weighted average of path length, safety and disturbance costs. We use A* search to find the minimum cost static path.

$$Cost_{Total}(P) = Cost_{path} + w_s.Cost_{safety} + w_d.Cost_{dist}$$

Note that the weights significantly affect the resulting robot behavior. In the current system, the weights were determined empirically, however further investigation is required on how to choose them for optimal behavior.

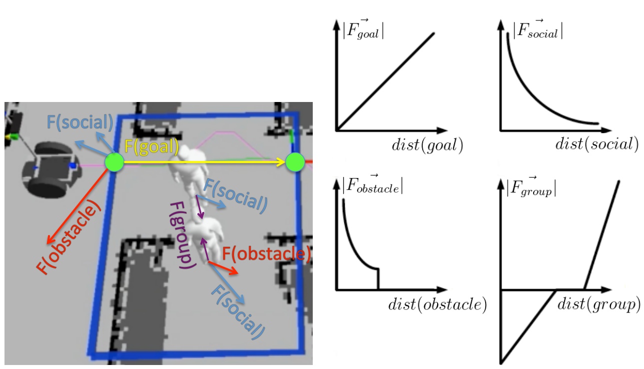
B. Dynamic Planner

Dynamic planner is responsible for reasoning about how people will react to robot motions. Moreover, paths from static plans are not smooth, therefore robot motion might not be easy to understand for human observers. Dynamic planner receives the static plan and simulates only parts of it where humans are close. We use Social Force Model (SFM) [8] to simulate the motions of both humans and the robot. Interaction between people are modeled as attractive and repulsive forces in SFM, similar to the Potential Field Method for robot navigation. The solution to the goal is found iteratively, as forces are recomputed for every robot position during planning.

First, groups of people are found on floor plane by clustering with respect to their positions. Simple euclidean distance thresholding is used for clustering. In our current implementation, a group region is defined as a rectangle, although other shapes are also possible. Dynamic planner receives the static plan and finds out where it enters and exits each group region if it intersects the region. Goal of the dynamic planner is to find a sub-plan between those two points. Forces apply to all agents, including the robot and humans. We defined 4 forces acting on the agents:

- F_{goal} : attraction towards a sub-goal
- F_{social} : repulsion from other agents
- F_{obs} : repulsion from nearest obstacle
- F_{group} : attraction or repulsion towards group members

The forces acting on the robot at the first iteration of dynamic planning are illustrated on the robot in Figure 4(a). The force magnitudes with respect to distances between entities are plotted in 4(b).



(a) (b)

Fig. 4. a) (Best viewed in color) Social forces acting on the robot, including F_{goal},F_{social},F_{obs}, are shown at the first iteration of the dynamic planner. b) Social forces with respect to the relevant distances.

Starting from the first group region that intersects the static plan, the following procedure is applied within every group region: At every iteration, first the resultant force vector acting on the robot is found. Then the planner takes a step in the direction of the F vector for a fixed step size. Then each of the humans in the group takes a step towards the resultant force that is acting on them. The planner continues the iterations until a solution is found. If a solution is found, the calculated sub-plan replaces the static plan in this group region. Potential fields are prone to getting stuck in local minima, and the planner might go into infinite loop. We stop the planner after a number of iterations and accept the static plan in the corresponding group region if that happens.

We assume that humans have a cognitive model of the robot, by thinking that the robot has a limited Field of View (FOV). When the robot has gone past a human (out of the FOV), then we make the repulsion force $F_{social} = 0$.

C. Trajectory Planner

The trajectory planner is responsible of computing the linear and angular velocity necessary to follow the dynamic path. We use Dynamic Window Approach (DWA) [30] for obstacle avoidance of non-holonomic robots. DWA samples linear and angular robot velocities and simulates the robot trajectory for each of them. First, a waypoint on the dynamic path is chosen as a sub-goal. At every control iteration, the waypoint is chosen as the first point ahead of the robot that is further than a distance threshold. We found that a threshold of 0.25 meters was sufficient. Robot is simulated with each velocity combination and the trajectory that gets closest to the sub-goal is sent to the motor controllers.

V. Implementation

We implemented the system on a Segway robot that is running ROS. The robot is able to localize itself in the map, track the poses of humans and avoid obstacles during navigation.

A. Person Tracking

A torso-level Hokuyo laser scanner is used for person tracking. When a laser scan is received, it is first segmented into clusters by using a Euclidean distance threshold metric. Tracking of a cluster is activated if it does not match human hypotheses and if it is person-sized. We fit an ellipse to the tracked torso cluster, and treat the center of the ellipse as the position of the person. Shorter principal axis of the ellipse is used to estimate the orientation of the human. To disambiguate the orientation modulo front/back of a person, we assume that people are facing the sensor when they are first detected. While this is a significant limitation our current system, in future we hope to add other sensor modalities for person detection. Nearest neighbor data association is used for tracking.

We evaluated the torso tracking approach from a dataset collected from torsos of 23 people. More details about the experimentation can be found in [31]. The mean positional tracking error in all experiments was about $0.05m$ regardless of the distance and the bearing of the human. The mean orientation tracking error was $14.5°$. Least orientation error was achieved when people were facing the sensor $4°$ and the error was the most (about $25°$) when people were perpendicular. This analysis is valid with the assumption that a correct initial detection is made. In our experience, we have seen that the initial detection was not very robust, and led to sub-optimal robot behavior in some demonstrations. This is one of the aspects of the system could be improved.

B. Navigation

Map of the environment is extracted beforehand using SLAM and the robot is localized with AMCL. For trajectory planning, we uniformly sample linear velocities from 0 to 0.45 m/s with 0.02 m/s resolution and angular velocities from -0.7 to 0.7 rad/s with 0.02 rad/s resolution. We used the following parameters for the static planner: $w_s = 0.5$,$w_d = 5$, $d_{max} = 3$.

As the robot moves in the environment, previously unseen obstacles and humans must be taken into account in the plan. This is achieved by re-planning the static and dynamic paths when necessary. Static plan is found periodically whereas dynamic plan is found if and when one of the 3 events occur:

- A new human is detected or lost from the view
- One or more humans change his/her position
- A static plan is found

Obstacle avoidance usually works as expected, however, since human motions are very dynamic, in certain cases the robot can get very close to people. We took 2 measures in an attempt to prevent unwanted contact with humans. First one is that, when the robot is in a group region, it navigates at half speed. We think that it not only improves safety, but also improves legibility of the robot as a clear reduction in speed signals to human bystanders that the robot is aware of them. We think that this behavior fits the requirement of robot predictability as a 'stereotypical motion' in Lichtenthaler's work [26]. Second measure is a collision protection system using the ankle-level laser scanner. The robot reads its velocity and simulates where its tipping point will be in 0.25 seconds. If a collision is imminent, it stops and waits for a period of time. If the danger is removed, then the robot continues its path. Otherwise, it waits some more. This feature implements the "waiting rule" of Lam's work [9].

VI. Results

We present simulation and real-world demonstrations in this section in order to validate our approach on anticipatory navigation. In simulation, we first re-visit the room problem and then show that the plans change drastically with the state of the humans in an office environment. In real experiments, we show how robot adapts to the changes in the human positions while it is moving to its goal.

A. Simulation

Room Problem: In this scenario, the robot is outside the room and a point inside the room is given as the goal (Figure 5). Traditional planners can not return a solution in this scenario because there is not enough space for the robot to navigate inside. There are two people standing at the doorway and there are two more standing people inside. The static plan and dynamic plans are shown in green and orange, respectively. This path is planned for the current time but makes assumptions about future positions of humans. Note that the dynamic planner modifies only the parts of plan inside group regions (blue rectangles). In the first group region (doorway), the static plan involves going between the humans. Dynamic simulation suggests that people will get closer to each other if the robot drives towards the side. In the second group region, since two humans are oriented to each other, going between them would add a high disturbance cost, therefore the static plan avoids going between them. Safety costs encourages staying far from the humans, but not too far because a longer path would increase the path length cost. The robot is further led to stay closer to the room boundaries in the dynamic planner due to the repulsive forces from both humans.

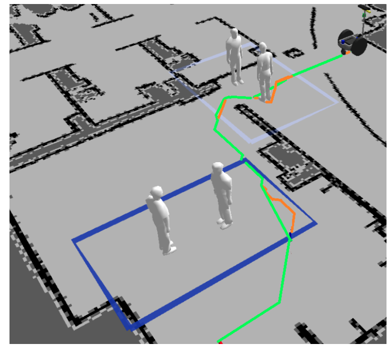


Fig. 5. (Best viewed in color) "Room Problem" revisited. The resulting static plan and dynamic plans are shown in green and orange, respectively.

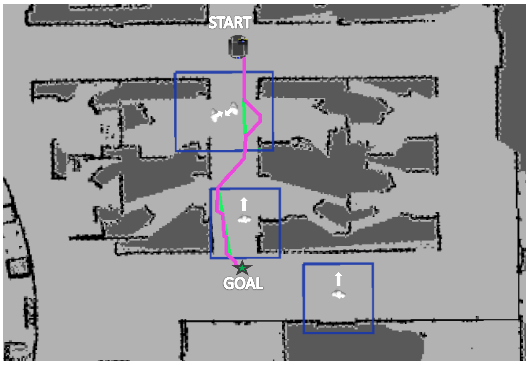
Office Environment: Goal of the robot is to navigate to a goal position in an office environment with 4 standing people (Figure 6). In this scenario, we show how the planned path is drastically changing with the poses of humans even though the start and goal position of the robot doesn't change. There are 3 main ways the robot can navigate to its goal: left, center or right corridor.

In the first configuration in Figure 6(a), two people are grouped together as they are looking at each other and likely conversing. The robot decides to take the center corridor, first slightly disturbing the speaking duo, then switches sides in the corridor and reaches its goal. In the figure, the dynamic path (pink line) is overlaid on the static path (green line).

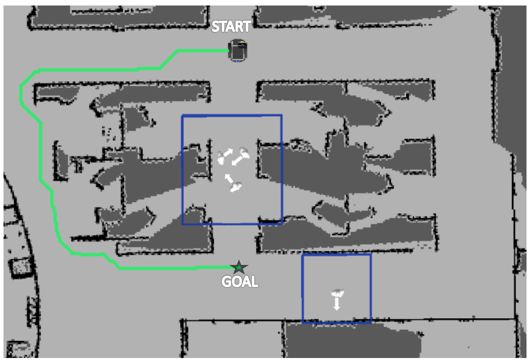
In the second configuration in Figure 6(b), The third person at the center corridor joins the conversation. Now we have 2 group regions (rectangles) in the scene. Since passing through a group of 3 people would introduce a high disturbance cost in addition to the safety cost, the robot decides to take a longer route (left corridor). Since this path does not intersect any group regions, no dynamic simulation is done.

B. Real robot

We demonstrate our anticipatory navigation planner on the real system in two environments: hallway and kitchen. Each



(a)



(b)

Fig. 6. (Best viewed in color) Paths differ drastically with the poses and grouping of humans. a) The robot takes shortest route, traveling in the vicinity of a group of two and another individual. b) third individual joins the group. Robot takes a longer path that doesn't have humans on path.

scenario is run twice under different human positions and behaviors in order to show how the planner responds. People in the environment were familiar with the robot's motions, and asked to move under the specific scenarios, to see what path the robot would take.

Hallway passing: In this scenario (Figure 7), robot's goal is to navigate to the end of the hallway. There are two people in conversation forming a group. The robot assesses that both people will move aside to let the robot move between them. Once the robot is close, both persons act as predicted by the robot. In the second run, the users decide to keep their conversation and move close to each other. The robot, which previously predicted that the persons will move aside, reacts to this change and immediately recalculates its path and moves to the side. In both cases, the initial plan is to disturb the interaction by going between the two. This is because the safety cost for getting close to one of the humans was more dominant than the disturbance cost.

Narrow corridor: In this scenario (Figure 8), robot's goal is to drive towards the exit door. There are 3 people nearby the robot, and the environment is constraint by the kitchen counters. In the first run the robot's path is completely blocked, resulting a previously unsolvable scenario. However using the anticipatory navigation method, the robot deducts that the person ahead will move aside to let the robot pass. In the second run there are two people ahead of the robot. This time the robot calculates that it is more costly to move both people to the side, and more comfortable for everybody to take a longer route. The second run shows that the robot may take a longer route if the disturbance and safety costs are going to be large.

VII. Conclusion and Future Work

We presented a human-aware path planner that takes into account humans' reactions to robot's motion. Our approach relies on a 1) static planner that conducts search on a grid map and 2) a dynamic planner that refines the static plan by iteratively simulating humans' reaction. We consider proximity of humans, path length and disturbance of groups of people in the static planner. Attractive and repulsive forces between humans and the robot sets base of the dynamic simulation. Traditionally, humans are considered independent actors in robot path planning. We showed that robots could use the fact that they could affect how people around them move and this insight can help planners find solutions to problems that are insolvable by standard methods. Considering this new dimension will likely generate interesting new research challenges in the areas of motion planning and HRI.

We think implementation and qualitative validation of robot behavior is a critical first step for navigation planning algorithms. In this paper, we showed that our approach produced sound solutions in a number of example scenarios. As future work, we would like to conduct user studies to compare our approach with current planners. We will evaluate the efficiency of the paths and how natural and safe human observers will find the robot behavior. Another interesting topic to explore for future work is the the legibility of robot motions. Watanabe [32] has an interesting proposal to provide explicit social cues by highlighting the future trajectories with light projection. Such kind of an approach, combined with a social planner could facilitate interaction with the robot in many cases.

References

[1] E. Marder-Eppstein, E. Berger, T. Foote, B. Gerkey, and K. Konolige, "The office marathon: Robust navigation in an indoor office environment," in *IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2010, pp. 300–307.

[2] S. Satake, T. Kanda, D. F. Glas, M. Imai, H. Ishiguro, and N. Hagita, "How to approach humans?-strategies for social robots to initiate interaction," in *4th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. IEEE, 2009, pp. 109–116.

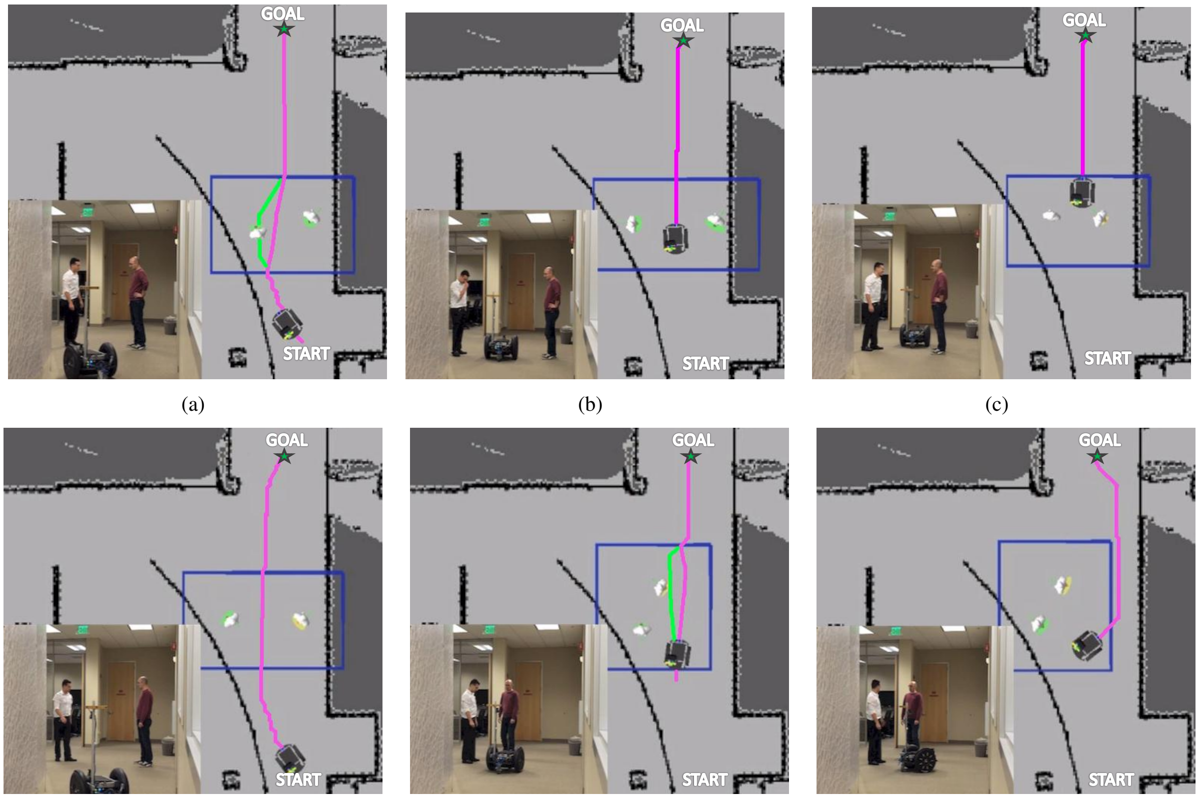
[3] D. Vasquez, P. Stein, J. Rios-Martinez, A. Escobedo, A. Spalanzani, C. Laugier, *et al.*, "Human aware navigation for assistive robotics," in *13th International Symposium on Experimental Robotics (ISER)*, 2012.

[4] M. Kuderer, H. Kretzschmar, and W. Burgard, "Teaching mobile robots to cooperatively navigate in populated environments," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2013, pp. 3138–3143.

[5] J. Wainer, D. J. Feil-Seifer, D. A. Shell, and M. J. Mataric, "The role of physical embodiment in human-robot interaction," in *15th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*. IEEE, 2006, pp. 117–122.

[6] A. J. Trevor, A. Cosgun, J. Kumar, and H. I. Christensen, "Interactive map labeling for service robots," in *IROS Workshop on Active Semantic Perception*, 2012.

[7] A. J. Trevor, J. G. Rogers III, A. Cosgun, and H. I. Christensen, "Interactive object modeling & labeling for service robots," in *Proceedings of the 8th ACM/IEEE international conference on Human-Robot Interaction (HRI)*. IEEE Press, 2013, pp. 421–422.



(a) (b) (c)

(d) (e) (f)

Fig. 7. (Best viewed in color) The Hallway scenario. 2 runs are shown in first and second rows.The static plan (green line) and dynamic plan refinement (pink line) are shown. First run: a) Navigation starts. The dynamic planner anticipates that people will give way to the robot when it starts to move towards them. b) Humans notice the robot, and give way by increasing the separation between them. The robot has entered the group region, therefore the velocity is halved. c) The robot continues towards its goal and humans regroup. Second run: d) both the static and dynamic plan involves going in between humans again e) human on the right gets closer to the other person. Since a human made significant movement, dynamic planner re-plans. Plan no longer involves going in between. f) static planner periodic re-plan triggers, leading to robot to stick to the wall to the right.

[8] D. Helbing and P. Molnar, "Social force model for pedestrian dynamics," *Physical review E*, vol. 51, no. 5, p. 4282, 1995.

[9] C.-P. Lam, C.-T. Chou, K.-H. Chiang, and L.-C. Fu, "Human-centered robot navigation towards a harmoniously human–robot coexisting environment," *IEEE Transactions on Robotics*, vol. 27, no. 1, pp. 99–112, 2011.

[10] E. T. Hall, "The hidden dimension." 1966.

[11] A. Kendon, *Conducting interaction: Patterns of behavior in focused encounters*. CUP Archive, 1990, vol. 7.

[12] H. Hüttenrauch, K. S. Eklundh, A. Green, and E. A. Topp, "Investigating spatial relationships in human-robot interaction," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2006, pp. 5052–5059.

[13] A. Cosgun, D. A. Florencio, and H. I. Christensen, "Autonomous person following for telepresence robots," in *Robotics and Automation (ICRA), 2013 IEEE International Conference on*. IEEE, 2013, pp. 4335–4342.

[14] E. A. Sisbot, L. F. Marin-Urias, R. Alami, and T. Simeon, "A human aware mobile robot motion planner," *IEEE Transactions on Robotics*, vol. 23, no. 5, pp. 874–883, 2007.

[15] R. Kirby, R. Simmons, and J. Forlizzi, "Companion: A constraint-optimizing method for person-acceptable navigation," in *18th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*. IEEE, 2009, pp. 607–612.

[16] M. Svenstrup, T. Bak, and H. J. Andersen, "Trajectory planning for robots in dynamic human environments," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2010, pp. 4293–4298.

[17] J. Rios-Martinez, A. Spalanzani, and C. Laugier, "Understanding human interaction for probabilistic autonomous navigation using risk-rrt approach," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2011, pp. 2014–2019.

[18] D. V. Lu and W. D. Smart, "Towards more efficient navigation for robots and humans," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2013, pp. 1707–1713.

[19] T. Sasaki and H. Hashimoto, "Human observation based mobile robot navigation in intelligent space," in *IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2006, pp. 1044–1049.

[20] L. Scandolo and T. Fraichard, "An anthropomorphic navigation scheme for dynamic scenarios," in *IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2011, pp. 809–814.

[21] M. Luber, L. Spinello, J. Silva, and K. O. Arras, "Socially-aware robot navigation: A learning approach," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2012, pp. 902–907.

[22] M. Bennewitz, W. Burgard, G. Cielniak, and S. Thrun, "Learning motion patterns of people for compliant robot motion," *The International Journal of Robotics Research*, vol. 24, no. 1, pp. 31–48, 2005.

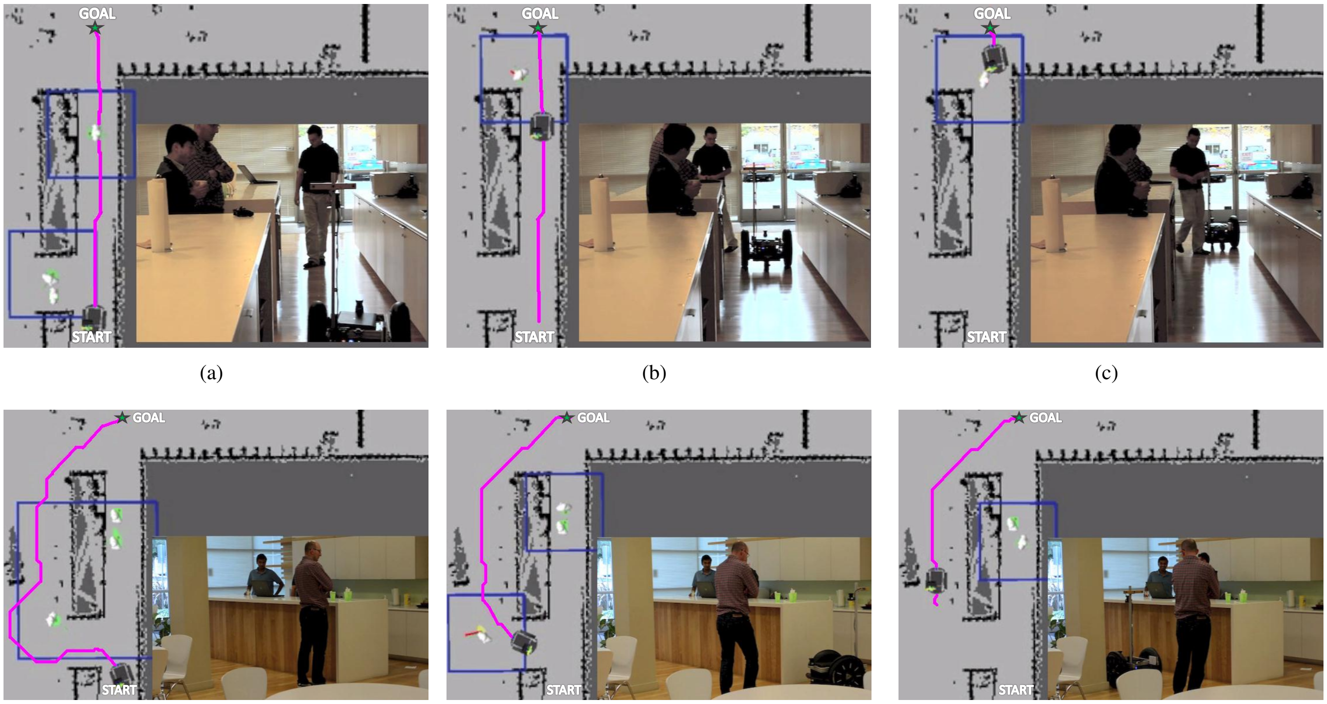
[23] S. Pellegrini, A. Ess, K. Schindler, and L. Van Gool, "You'll never walk alone: Modeling social behavior for multi-target tracking," in *12th IEEE International Conference on Computer Vision*. IEEE, 2009, pp. 261–268.

[24] P. Stein, A. Spalanzani, V. Santos, C. Laugier, *et al.*, "Robot navigation taking advantage of moving agents," in *IROS Workshop on Assistance and Service robotics in a human environment*, 2012.

[25] J. Müller, C. Stachniss, K. Arras, and W. Burgard, "Socially inspired motion planning for mobile robots in populated environments," in *Proc. of International Conference on Cognitive Systems*, 2008.

[26] C. Lichtenthäler and A. Kirsch, "Towards Legible Robot Navigation - How to Increase the Intend Expressiveness of Robot Navigation Behavior," in *International Conference on Social Robotics - Embodied Communication of Goals and Intentions Workshop*, 2013.

[27] R. Gockley, J. Forlizzi, and R. Simmons, "Natural person-following



(a) (b) (c)

(d) (e) (f)

Fig. 8. (Best viewed in color) The Kitchen scenario. In the first run, there are two people blocking the path to the left and one person at the narrow corridor. a) robot decides to take the shorter route, because it would disturb one person instead of two. There is not enough space to pass, and dynamic planner assumes the person would get out of the bottleneck to give way. b) human behaves as robot anticipated and gets out of the narrow passage. robot slows down because it enters the human region. c) person gets back to his original position, robot reaches the goal. In the second run: d) there are two people at the narrow corridor and one person on the left. The robot decides to take the longer route and pass the third person from left. The safety cost from the two others would be too high if the robot took the direct route. e) the person steps back as he recognizes the robot. since the person has moved, the dynamic planner re-plans and decides to pass from right. f) after the robot passes the person, it proceeds to its goal.

behavior for social robots," in *ACM/IEEE international conference on Human-robot interaction (HRI)*. ACM, 2007, pp. 17–24.

[28] P. Trautman and A. Krause, "Unfreezing the robot: Navigation in dense, interacting crowds," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2010, pp. 797–803.

[29] T. Kruse, A. Kirsch, E. A. Sisbot, and R. Alami, "Exploiting human cooperation in human-centered robot navigation," in *IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*. IEEE, 2010, pp. 192–197.

[30] D. Fox, W. Burgard, and S. Thrun, "The dynamic window approach to collision avoidance," *Robotics & Automation Magazine, IEEE*, vol. 4, no. 1, pp. 23–33, 1997.

[31] A. Cosgun, A. Sisbot, and H. Christensen, "Guidance for human navigation using a vibro-tactile belt interface and robot-like motion planning," in *IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2014.

[32] A. Watanabe, T. Ikeda, Y. Morales, K. Shinozawa, T. Miyashita, and N. Hagita, "Communicating robotic navigational intentions," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2015, pp. 5763–5769.