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Socially-Aware Navigation Planner Using Models of Human-Human Interaction

Meera Sebastian[1], Santosh Balajee Banisetty[2], and David Feil-Seifer[3]

***Abstract*— In this paper, we revisit a real-time socially-aware navigation planner which helps a mobile robot to navigate alongside humans in a socially acceptable manner. This navigation planner is a modification of *nav_core* package of Robot Operating System (ROS), based upon earlier work and further modified to use only egocentric sensors. The planner can be utilized to provide safe as well as socially appropriate robot navigation. Primitive features including interpersonal distance between the robot and an interaction partner and features of the environment (such as hallways detected in real-time) are used to reason about the current state of an interaction. Gaussian Mixture Models (GMM) are trained over these features from human-human interaction demonstrations of various interaction scenarios. This model is both used to discriminate different human actions related to their navigation behavior and to help in the trajectory selection process to provide a social-appropriateness score for a potential trajectory. This paper presents an evaluation done in simulation while utilizing data from real human interactions.**

I. INTRODUCTION

As robots become more integrated into people's daily lives, interpersonal navigation becomes a larger concern. In the near future, Socially Assistive Robots (SAR) will be working closely with people in public environments [1]. Strong research has rightly been directed towards the problem of making a robot safely navigate in the real-world environment [2]. However, for robots to effectively interact with people, they will need to exhibit socially-appropriate behavior as well. The real-world environment is full of unpredictable events; the potential social cost of a robot not following social norms becomes high. Robots that violate these norms risk being isolated and falling out of use, or even being mistreated by their human interaction partners [1]. Additionally, the navigation behavior of the robot can communicate intent to communicate [3] or lack of desire to interact [4]. The behavior of the robot must, therefore, be crafted correctly to account for the dynamic social rules of its environment, and to correctly communicate its own intentions.

Socially-Aware Navigation (SAN) plays a vital role in an efficient and effective Human-Robot Interaction. A robot should behave in a way that people feel safe and comfortable interacting with it. One example is that when interacting with others, humans generally respect others' personal space according to common social norms [5]. Robots earn social acceptance if they can fit in to existing human personal space and other social norms related to navigation. However, the robot should also be able to, like people, push the boundaries of acceptable behavior when necessary to accomplish an important goal. Some interaction scenarios (such as passing through narrow spaces) commonly result in behavior that may not follow strict distance-based rules.

People are more likely to interact with robots that obey rules of proxemics and interpersonal distance. Human-human social distance transmits significant social and communicative information. Such interpersonal distance plays an important role in the quality of interaction between two or more people. Similarly, interpersonal distance plays a significant role in interaction quality in human-robot interaction as well [6], [7]. Consequently, by studying and modeling human-human interpersonal interaction and using that to guide a robot's movement, the robot is more likely to exhibit socially-appropriate navigation behavior.

In an ethnographic study of an autonomous hospital delivery robot [1], the participants felt "disrespected" by the robot as the robot took precedence in the hallways. This is because a traditional navigation planner [8] treats any detected occlusion from a robot sensor as an obstacle. This is a reasonable assumption when navigating in static environments or when navigating in proximity to people accustomed to robot navigation and its limitations. It is acceptable to treat furniture as static obstacles, but people may feel uncomfortable interacting with a robot if it does not clearly communicate its intentions by respecting traditional social norms.

The robots may better perform a navigation task by respecting the social space and social norms of their human partners. By recognizing the social and personal space of people, a robot should adapt to environment treating humans as social (and mobile) beings rather than obstacles. What's more, the zones of personal space may change depending on the robot's orientation with respect to a person, the current navigation action both person and robot are taking with respect to each other, and relationship of a person to other people or the environment itself [9]. Maintaining safe distance from a piece of furniture is acceptable when passing it but when passing a human, the robot should take persons' social space into consideration, and that social space may change depending on the current social action taken.

The focus of this work is to augment a people-aware navigation planner to handle a larger range of person-oriented navigation behaviors utilizing a multi-modal distribution model of human-human interaction. Prior work [10] utilized

Department of Computer Science & Engineering University of Nevada, Reno, Reno, NV, 89557
[1]Email: meerasebastian@nevada.unr.edu
[2]Email: santoshbanisetty@nevada.unr.edu
[3]Email: dave@cse.unr.edu

a fitted interpersonal distance model based on features which could be detected real-time using on-board robot sensors. Such models can be used to discriminate between a set of human actions and provide a social appropriateness score for a potential navigation trajectory. These models are used to weigh the trajectories and select the most appropriate action for the given situation. This robot navigation mimics the adherence to social norms while simultaneously adhering to a stated navigation goal as well. The goal of this system is to sense interpersonal distance and choose a trajectory that jointly optimizes for both social-appropriateness and goal-orientedness.

To evaluate the validity of our approach for proposed planner, we include in this paper performance metrics related to a human-robot interaction scenario. Prior work sometimes neglects the human performance alongside a robot. In this article, we include objective parameters related to both human and robot's performance, and adherence to a model of social behavior.

The remainder of this paper is organized as follows. In the next section, we briefly discuss related work. Next, we describe the design and architecture of the system. We then will detail how the system was evaluated, the results of that validation.

II. Related Work

Proxemics, the perception and use of space, is a fundamental social behavior for human-human interaction. Hall classified human interactions based on a concept of distance. He coined the term "social distance." Social distance characterizes the situation in which people talk to each other for the first time [5]. Several studies have proved that robots must display appropriate proxemics for a successful human-robot interaction [4], [11]. Mead and Matarić [9] investigated how user proxemics preferences changed to improve the robots understanding of human social signals.

The robot needs to know the relative locations of people to factor social consideration into an interaction. Vision and distance-based sensors can be used to detect and track people in the environment. Prior work has utilized ubiquitous sensing for this detection [6], [12], [13]. This often has the advantage of providing a clear picture of all the people that exist in a social scene, but with the drawbacks of heavily restricting the size of the environments in which such a system could operate. Developing socially-aware navigation systems that utilize egocentric sensors can be a far more challenging task, since these sensors frequently provide a more limited perspective of the environment.

On-board, egocentric sensors can enable the robot to detect a person human from a distance [14]. People can be detected by finding distinctive features of a person (such as their legs) in laser range data [15]. In this work, Arras, et al., applied AdaBoost to train a strong classifier from simple features or group of neighboring beams corresponding to legs in range data. This approach has been implemented and used in clustered office environments and obtained detection rates of over 90%. Most of the current research in socially-aware navigation relies on either ego-centric or exocentric vision for human detection and tracking. Using vision capabilities like face detection and use of RGB-D cameras to track humans in dynamic environments has drawbacks such as limited field-of-view, range and positional accuracy. In contrast, our approach uses an on-board laser range scanner to detect and track people yielding better positional accuracy, greater range, and a much-needed wider field of view.

Detecting people is significant for interpersonal social interaction. Additionally, predicting a person's future position based on their position *and* motion is the key factor in planning a socially appropriate path. Kushleyev [16] developed a method for planning with dynamic objects using a graph structure called time bounded lattice. This method merged short-term planning with the currently-observed scene with long-term planning based on *a priori* knowledge of the environment. This model helped to generate real-time trajectories which enabled the robot to reach a goal, while avoiding obstacles. Using a soft-max Markov Decision Process (MDP), Ziebart [17] predicted future pedestrian trajectories, while accounting for decision uncertainty. Thompson [18] also developed a similar system that could predict human motion. Mainprice [19] proposed a planner that generated acceptable, legible and collision-free paths. A path was initially generated using a randomized cost-based exploration method. The quality of the path was improved with a local path optimization method. Lu[20] modified the existing ROS navigation to make the robot navigate in a socially appropriate manner by adding Gaussian based cost values around a detected human. This causes the robot to take socially appropriate path in a hallway setting. Gaze behavior was also implemented for an enhanced interaction.

While interacting with humans, a robot should be able to perceive its surroundings, predict intended human behavior, and act accordingly. Satake [21] developed a model of approach behavior that anticipated the future behavior of people. SVMs (Support Vector Machines) were utilized to classify 2-second snippets of a trajectory into four behavior classes: fast-walking, idle-walking, wandering and stopping. An evaluation of the system conducted with human users found that people enjoyed interacting with the robot. Feil-Seifer [4] demonstrated that user state could be determined using autonomously sensed distance-based features, and that such an approach resulted in more "leading," more "helpful," and more "attentive" than a standard navigation planner. In this system GMMs were utilized to better capture the inherent multi-modality of interpersonal navigation data than an SVM-based system. We have used a similar approach to classify a person's navigation behavior from a set of human demonstrated actions [10], which had 94.74% accuracy.

Inverse reinforcement learning (IRL) has been used to learn human-like navigation behavior based on real human example paths [22]. The capabilities were demonstrated on a realistic crowd flow simulator. The planner learned to guide the robot along the flow of the people in a crowded environment. Kim [23], used a framework for socially adaptive path planning in dynamic human environments which involve three modules: feature extraction, inverse reinforcement learner, and a path planner. This framework used an RGB-D camera to extract features such as velocities, densities of obstacles to characterized the state space. The learner used a set of expert demonstrated trajectories to learn a social cost function that was later utilized by a planner module. Ramirez [24] used IRL to learn paths and locations to approach humans. The learned costmap was combined with other costmaps to generate an appropriate path using Dijkstra's algorithm. Okal [13] developed a flexible graph approach to capturing suitable task structure, extended Bayesian IRL to use these sampled trajectories from the graph representation to learn to navigate with social normativeness.

Beyond person and activity detection, the architecture of a collision-avoiding motion planner is crucial as well. A collision avoidance method for a mobile robot that estimates motion and personal space was proposed by Ohki where the future position of the individual is determined by considering the planned motion and personal space [25]. Tadokor developed a motion planning method for mobile robots that coexist and cooperate with a human being to avoid a collision [26]. A motion predictor using a stochastic process model predicts future human motion.

The above methods only considered trajectory prediction, not explicit social factors. Trautman utilized Gaussian Decision Processes to generate motion trajectories that fit with a prior-trained model of human behavior in a crowded social scene [12] that more explicitly modeled social behavior. Chung [27] presented a spatial behavior cognition model (SBCM) to outline the spatial effects existing between human and human, human and environment. This model predicted human intentions and trajectories and exhibited socially acceptable motion. Our planner architecture does not rely on explicitly-modeling the future position of a person, but instead uses a model of human demonstrations of a task to score potential movements for social appropriateness.

III. System Design and Architecture

Our SAN planner has three main modules: the feature extractor, the SAN model (presented in [10]) and the modified trajectory planner (contribution of this paper). The feature extractor collects distance-based features that build our model which represents various social scenarios. The modified trajectory planner detects the current social scenario, scores every possible trajectory end point to get an appropriateness score for that scenario. The trajectory end point with highest appropriateness score is chosen to execute a socially appropriate path to the goal. We chose the PR2 for implementation of this planner, but it could easily be implemented on any robot that is nav_core compliant and has on-board sensing.

Hallways are one of the places that are frequently used at workplace and have a high potential for interaction. To validate our approach, we identified three common hallway scenarios:

- Scenario I - one person passing another in a hallway;
- Scenario II - two people meeting in a hallway; and
- Scenario III - people walking together away from a common starting point;

to focus our development. The following sections will describe our approach in more detail.

A. Feature Detection

The goal of this work was to improve upon prior work [4] which utilized ubiquitous sensing to detect features in the environment. In this work, we only utilized on-board sensing to detect features relevant to the social scenario. For the proposed social scenarios, information regarding where an agent was located with respect to the hallway, with respect to the other agents in a scene, and how much a given action has progressed was necessary in order to observe the social scenario. We hand-selected several of these interpersonal features and used them to build the social model and score for appropriateness.

These features included: the normalized time, distance traveled by the robot, the lateral position of human with respect to the hallway, the distance between the robot and human; and the lateral distance between human and the robot with respect to the hallway. A SAN feature extractor node was developed to calculates a set of required features based on the possible future trajectory points the robot could select and published them for the developed model to analyze.

The detection of obstacles, hallways, people etc. was achieved using a floor-level laser scanner on-board the PR2 robot. People were detected using the *leg_detector* package, which finds people by looking for leg shapes in the laser scan [20]. The position of people in the scene were found by pairing detected legs together. People were detected in the scene and assigned a unique ID. Hallway walls were detected in the floor-level laser data using Hough Transforms to find a parallel straight line pair.

B. Model Formulation

The central contribution of this paper is the utilization of multiple models of human-human social interaction to choose more socially-appropriate trajectories for a robot to reach a given goal. Human-human navigation data for three scenarios described above were collected [10]. We recorded the positions of two people exhibiting the given navigation behavior using a floor-level laser scanner, and detecting people and environmental features using the methods described in the next subsection. A training set of 20 recordings were collected for each of the three scenarios. The model used relative distances as the key feature to classify actions.

A model for each social scenario was constructed using a Gaussian Mixture Model (GMM). A GMM was chosen over other methods described in Section II because it can handle models that are not unimodal. Appropriateness can then be determined using Gaussian Discriminant Analysis (GDA). A given position's conformity to a given model can be derived from the Mahalanobis distance of a candidate point w to a given component k of the model:

$$\delta_M(w,k|\phi) = \frac{(w-\mu_{\phi(k)})^T \sum_{\phi(k)}^{-1}(w-\mu_{\phi(k)})}{2} \quad (1)$$

This term is the standardized distance from an individual component of the GMM, taking into account the variance of that component. This value can then be used to calculate the probability that w is part of this model:

$$p(w,k|\phi) = \frac{1}{(2\pi)^{n/2}|\sum_{\phi(k)}|^{1/2}} e^{-\delta_M(w,k|\phi)} \quad (2)$$

The probability that w conforms to a given model ϕ is the sum of the probabilities that it conforms to each of the k components of that model:

$$p^{'}(w|\phi) = \sum_k p(w,k|\phi) \quad (3)$$

This score of appropriateness of a potential path given the scenario can then be used by the modified trajectory planner. This can be used to choose trajectories based on their social appropriateness score. To evaluate the navigation behavior, the model was demonstrated using the simulated PR2 and a standardized navigation planner.

C. Socially Aware Navigation Planner

The socially-aware navigation (SAN) planner consists of three major components: the feature extractor node, the GMM-based model of social behavior, and the trajectory planner. The trajectory planner module is a modification of *nav_core* package of the ROS, which operates by enumerating all possible trajectories, scoring them for the amount each trajectory moves toward the goal, and the deviation of each trajectory from a globally-planned path [8]. While this does effectively navigate in complex and dynamic environments, no social information is considered. We have modified this planner to utilize conformity to a social model in addition to these more utilitarian metrics.

The above navigation planner solves two problems to operate in an uncertain environment. First, by using an *a priori* map of the environment, a *global* path plan is derived (usually by using wavefront planning to find a shortest possible path from point A to point B). However, while this plan will be the optimal solution, following it exactly will not account for dynamic obstacles in the scene. In this case, a *local* path planner utilizes egocentric sensor data from the robot (augmented by known obstacles from the *a priori* map of the environment). This local planner works by determining all possible future trajectory points. Our modification to this local planner also scores the trajectories for social appropriateness, thus making the planner socially-aware.

This local planner works by weighing candidate trajectories (v_x, v_y, v_θ) for progress toward the goal and adherence to the global plan. v_x and v_y are translational velocities along the robot's x and y axes respectively (non-holonomic robots have a v_y of zero), and v_θ represents the rotational velocity. In order to make the *nav_stack* planner more socially-appropriate, we have modified this local planner to weigh trajectories based not only on the above metrics of path adherence and goal-directedness, but also adherence to models of human-human social interaction (see GDA approach in the previous section). The GMM based model from the prior section is used to score the appropriateness of the possible trajectories and the trajectory with the highest score is chosen as the navigation behavior for a particular scenario.

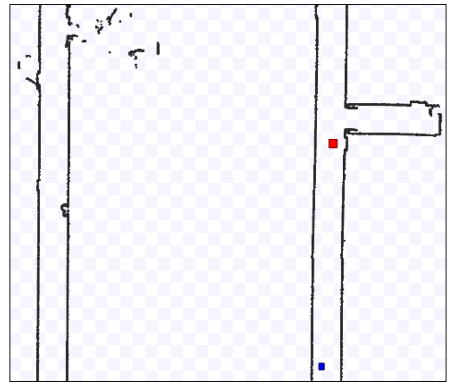

Fig. 1. Simulated environment showing both human agent (blue) and a PR2 robot (red) performing a spatial interaction in a hallway scenario.

This alternative weighting should favor more socially appropriate trajectories, potentially picking longer paths or less efficient paths, because they are more socially-appropriate. The endpoints of a given trajectory are analyzed for their social appropriateness. The planner then executes the given trajectory. The modified planner will execute simultaneously socially appropriate and goal-directed behavior until the robot achieves its navigation objective. Thus, the modified trajectory planner plays a crucial role in driving the robot towards the goal in a socially appropriate way.

IV. Evaluation

The performance of the planner can be evaluated in two ways. First, the performance of the planner itself can be evaluated [6]. Second, the social effect such a planner has on interaction partners can be assessed [4]. For this paper, we have limited our evaluation to the performance of the system in simulation with a planned real-world follow-up to be presented in a later paper.

We evaluated the system by assessing the differences in task performance (in this case time to complete a navigation action) between the traditional and the SAN planner. With respect to the SAN planner, we wished to know if the SAN planner adhered to the social model better than the traditional planner. Seven different metrics have been defined to evaluate the performance of the system:

- m1: Robot task efficiency, time taken by the robot to navigate from point A to point B.
- m2: Human task efficiency, Human task efficiency is equally important as robot task efficiency and is often neglected. So, we will not only calculate robot task efficiency but also human task efficiency which is the

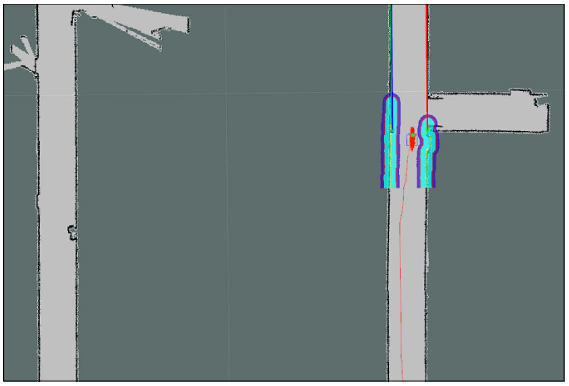

Fig. 2. Rviz screen capture showing robot navigation in the simulated environment and the detected hallways represented by line markers.

time taken for the human participant to navigate from point B to point A.

- m3: Combined task efficiency, time taken by both robot and human to navigate from point A to point B, point B to point A respectively.
- m4: Distance covered by the robot to reach its goal location which is point B.
- m5: Distance covered by the human participant to reach his goal location which is point A.
- m6: The minimum distance the robot kept with the human participant during the course of its interaction with the human. Maintaining social distance while interacting with human is an important factor in human-robot interaction studies [5].
- m7: The average probability that a trajectory is appropriate for a given situation.

A. Mobile Robot Simulator

To conduct the experiment and validate the architecture, we used a simulated PR2. The validity of the planner's operation under predictable conditions can be observed through testing in a simulated environment. The simulated environment made it possible to incorporate mobile obstacles as well as immobile obstacles into the system. Figures 1 and 2 show the screen shots of the simulator and visualization of the simulated environment respectively. In the simulated environment, there were two robots, red and blue. The red robot utilized the SAN trajectory planner and the blue robot was programmed to act according to human-human interaction norms for a given social scenario as was recorded earlier. The simulated robot used data from a laser scanner for feature detection, localization, and obstacle avoidance. Since the simulated PR2 utilized identical sensing to the actual PR2, the navigation module of the simulated robot is compatible with the real PR2.

Navigation planning began when the robot was given a navigation goal, and a social scenario to adhere to. The SAN planner then autonomously detected the features of the scene, such as hallway position, and partner distance in the current simulator scene as described in section III-A.

V. Results

We conducted ten trials for each of the three scenarios using the traditional navigation planner and ten trials with the SAN planner in the simulated environment. We then compared the results from each planner using the metrics mentioned in Section IV to evaluate the performance of the system. The results from the tests are shown in Table I.

Planner	Metric	Scenario I	Scenario II	Scenario III
SAN Planner	m1 (in sec)	49.4	100.18	43.67
	m2 (in sec)	49.5	49.79	42.28
	m3 (in sec)	98.96	149.99	86.02
	m4 (in m)	10.77	10.92	10.40
	m5 (in m)	8.86	9.76	10.49
	m6 (in m)	6.38	8.09	7.43
	m7	0.31	0.96	0.86
Traditional Planner	m1 (in sec)	50.12	45.17	42.28
	m2 (in sec)	50.4	41.6	45.78
	m3 (in sec)	100.53	86.81	92.63
	m4 (in m)	10.84	10.67	10.75
	m5 (in m)	8.91	9.80	11.39
	m6 (in m)	6.02	8.80	8.37
	m7	0.26	0.92	0.81

TABLE I
TABLE SHOWING A COMPARISON OF THE OBSERVED RESULTS FOR THE VALIDATION METRICS IN SAN PLANNER AND TRADITIONAL PLANNER

Predictably, and most importantly, the data for metric 7 (m7) shows that for each of the three scenarios, the robot adhered more to the norms of human-human interaction with the SAN planner than with the traditional planner. For scenarios, I (meeting) and II (passing), the planner was more efficient. This make sense, since the robot was actively weighting its behavior to conform to the social model. Additionally, the lower times for metric m1 demonstrate that the robot reaches its goal faster using the SAN planner, travelling a shorter distance (m4). This makes sense, since the robot uses the information from the social model that inherently predicts where the person will be over time, where the traditional planner does not. These results demonstrate that the SAN planner acts in a more socially appropriate way when compared to the traditional planner in meeting and passing scenarios without being significantly different for another performance metrics.

VI. Discussion

The results demonstrate that a traditional planner can be modified to achieve socially-aware navigation behavior utilizing a GMM model based on feature list extracted from human-human interaction data. As can be seen in Table I, the SAN planner could distinguish between the scenarios. The probabilities were much higher in SAN planner when compared with traditional planner. Also, the robot came closer to the person during interaction using the SAN planner. This means that the robot may be able to (within social norms) move more closely to a person than traditional robot safety absolutes dictate, if the social scenario permits.

One limitation of the evaluation presented in this paper is that it only operated in a simulated environment with a simulated person. The individual components of the system have been validated in real-world settings. However, future work will examine a real-world system's operation with people in each social scenario. This evaluation will also ask the interacting participants to rate the robot's behavior related to several social factors [4]. This should inform on the perception of the social performance of the system as well.

Another limitation of this work is that it relies on an *a priori* definition of the social scenario. While this is limiting, we have demonstrated in earlier work that we can use these social models to recognize a navigation social scenario with high accuracy [10]. Future work will integrate these components for a richer autonomous system.

VII. Conclusion

In this paper, we presented a socially-aware navigation planner that enables an autonomous robot to navigate along with humans in a socially appropriate manner. The *nav_core* package of Robot Operating System (ROS) has been modified to include the social model as a weighting factor for trajectory planning. Gaussian Mixture Models (GMM), based on interpersonal distance, have been employed to differentiate human actions related to their navigation behavior. This model selected the most appropriate trajectory that can be executed by the robot based on the observed social scenario.

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