Sampling-based Motion Planning for Guide Robots Considering User Pose Uncertainty

Juan Sebastian Mosquera-Maturana[1][0000−0002−8212−3463], Juan David Hernández[2][0000−0002−9593−6789], and Victor A. Romero-Cano[2][0000−0003−2910−5116]

[1] Faculty of Engineering, Universidad Autónoma de Occidente, Cali, Colombia
smosquera@uao.edu.co

[2] School of Computer Science and Informatics, Cardiff University, Cardiff, United Kingdom
{hernandezvegaj,romerocanov}@cardiff.ac.uk

Abstract. In this paper, we propose a framework to address the problem of guiding a person within a semi-structured environment in a socially acceptable manner that prioritises safety and comfort. We propose an algorithm based on the optimal Rapidly exploring Random Tree (RRT*) algorithm for path planning. Our proposal utilises Dubins curves and takes into account the user during path planning to generate a navigation path that allows the robot to follow a feasible path that can also be navigated by the user. A comparative analysis against standard path planning based on the RRT* algorithm and the Social Force Model validates the efficacy of our proposed algorithm.

Keywords: Social Robot Navigation · Path planning · Social Force Model.

1 Introduction

The use of robots for complementing and enhancing human capabilities is becoming increasingly common. They have been developed and deployed to assist elderly individuals in indoor environments [15], as well as to guide people in settings such as museums or exhibitions [17]. However, for robots to effectively operate in human-populated spaces, they must possess a fundamental characteristic: the ability to navigate the environment in a way that maximises human comfort. A robot's ability to move around people in a socially acceptable manner is crucial in providing comfort and safety to those around it [10]. In [3], the authors define a socially navigating robot as one that respects principles of safety, comfort, legibility, courtesy, social competence, agent understanding, proactivity, and responsiveness to context.

The works in [27, 19] propose methods that tackle the Social Robot Navigation (SRN) problem, however, these methods do not properly distinguish between social agents and other dynamic objects in the environment, and thus omit relevant social aspects for socially acceptable navigation such as comfort zones around people and social norms related to proxemics [4]. Proxemics is the study of how people use and perceive personal space, and it plays a central role in human interactions. Ignoring cultural and individual differences in proxemics could lead to situations where the robot invades personal space, making people feel uncomfortable or intruded upon. By integrating proxemic awareness into their navigation systems, social robots can navigate with greater sensitivity, respecting the varying preferences for interpersonal distances and ensuring a better integration into human environments.

The differentiation between objects and social agents enables robots to take into account social aspects when navigating in environments shared with humans, however, the robot's behaviour and the social aspects to be considered vary depending on the task to be performed. A robot that only needs to navigate through a crowd behaves differently than one that has to make a delivery or one that has to guide people through the environment.

In environments such as airports, shopping malls, universities, or hospitals, robot guides enhance efficiency by enabling individuals to reach their destination, reducing congestion, and improving productivity. By utilising robots to carry out the task of guiding people in these environments, staff, such as nurses in hospitals, can allocate their time to other activities [13]. Our work focuses on guiding an individual ensuring that the generated path is feasible for the robot and comfortable for the user, while maintaining an appropriate proximity between both.

The contributions of this paper are as follows: First, we propose a social robot navigation framework that considers the collision probability of the guided person during path planning. The probability of a collision between the agent and the environment is determined by the uncertainty in the estimation of the agent's position relative to the robot during the planning of a path. Second, we consider the proximity of the user to the robot during path planning by means of a social region around the robot. This enables the robot to remain in close proximity to the user during navigation, thereby preventing the robot from moving forward in space and leaving the user behind when being guided. Finally, we implement a planning algorithm using Dubins curves that generates smooth paths that contribute to socially acceptable navigation.

The rest of this paper is organised as follows: Section II presents related work. Section III provides a definition of the problem and the challenges it presents. Also, this section describes the proposed social robot navigation framework. In section IV, we describe the scenario in which the algorithms were implemented and compared. It also presents the results obtained in the different simulations. Finally, section V discusses the results of each algorithm, a comparison among them, and presents the conclusions of the work done and the challenges to be faced in future developments.

2 Related work

Several authors have proposed algorithms that distinguish between objects and social agents, such as people, as seen in [2, 18, 20, 25]. The work in [20] considers the difference between social agents and dynamic objects in a dynamic scenario, enabling robot navigation in uncontrolled human-populated environments. However, these algorithms typically operate on static environment representations, where all elements and agents in the environment, except for the robot, are assumed to be instantaneously static.

In general, a robot can guide people in two ways: it can either remain stationary and provide indications, or it can navigate the environment along with the user while heading to the target position. The first approach involves the robot remaining immobile in a specific place where it gives indications to the person to be guided such as the works in [26, 23]. This approach implies proper communication between the robot and the user, as well as a perfect understanding of the robot's indications by the user, in order to be able to follow them to reach the destination. Similarly, as the robot remains stationary, it cannot detect changes in the environment that may require a different path to be taken. In the second approach, the robot moves along with the user while guiding him to the destination [6]. In this case, it is necessary that the user follows the robot during the navigation, otherwise, the robot will fail in its task of guiding the user by reaching the destination without him.

Typically, guide robots have not incorporated considerations for the individuals they are guiding during path planning; instead, they react to them once navigation commences. For instance, in [17], researchers addressed the challenge of guiding visitors in a museum by deploying a guide robot. The robot follows a predefined path with stops at various stations, providing information at each stop until the end of the tour. Users can customise their tour by selecting specific stations of interest. In another study by [1], researchers utilised a robot to guide shoppers in a mall. Notably, their work included considering people's poses for obstacle avoidance. Similarly, in [7], the authors implemented the service robot SPENCER [24] to guide travellers in an airport, taking into account the social interactions of the individuals.

The Social Force Model (SFM), firstly proposed in [5], is widely used for solving local motion generation problems in social robot navigation [21]. SFM is a reactive algorithm that inherits the limitations of potential field-based algorithms, such as the local minima problem. The local minima problem in social robot navigation refers to a situation where a robot becomes trapped in a region of its environment where the cost of moving in any direction appears higher than the current position. In other words, the robot perceives its immediate surroundings in such a way that it seems more beneficial to stay in its current location rather than attempting to navigate to a different location.

To avoid the local minima problem of reactive motion planning methods, one option is to plan paths that take into account the environment in which the robot is located [20]. Planning methods that avoid collisions while considering the collision probability based on the robot's dynamics have improved navigation in dynamic or unknown environments [16]. However, navigating an environment without considering the user during path planning can lead to situations where the robot reaches the target position while the user may stop or lose sight of the robot. In this paper, we propose a planning framework that takes into account the collision probability of the user and their pose, allowing the robot to navigate the environment while guiding a person. Our approach aims to estimate the path with the least probability of collision for both the robot and the user. Our proposal is based on the asymptotically optimal Rapidly-exploring Random Tree (RRT*) [8, 9] path planning algorithm. The RRT* algorithm has been modified to take into account the user to be guided. Based on the user's pose relative to the robot, we consider the probability of collision of the user with obstacles and his distance to the robot.

3 Social navigation framework for a guide robot

The configuration space $\mathcal{C}$ consists of the space occupied by obstacles $\mathcal{C}_{obs}$ and the free obstacle space $\mathcal{C}_{free}$ [12]. Path planning in robotics tries to find the path that connects an initial configuration q_{start} with a final configuration q_{goal} belonging to $\mathcal{C}_{free}$.

$$P^*(q_{start}, q_{goal}) = \underset{P \in C_{free}}{\arg\min} \quad F(P(q_{start}, q_{goal})) \tag{1}$$

The task of guiding a person in a semi-structured environment requires path planning to consider, among other social constraints, the relative position between the user (guided person) and the robot. Considering the social cues during path planning is possible by representing them with a function $G(u_{sc})$, where u_{sc} represents these social cues and the social path planning problem is then:

$$P^*(q_{start}, q_{goal}) = \underset{P \in C_{free}}{\arg\min} \quad F(P(q_{start}, q_{goal})) + G(u_{sc}) \tag{2}$$

This section presents a framework for addressing the problem of social robot navigation, specifically designed for guiding people. The framework, depicted in Fig. 1, is comprised of three components: world representation, user-aware path planning, and motion control.

3.1 World Representation

The obstacles in the environment are represented as bounding boxes using the pedsim_ros library and information from a lidar sensor. The information about the objects allows the configuration space to be established. The mean pose and dimensions of each box are employed to calculate its covariance matrix.

To consider the user to be guided as a social agent during path planning, we model their pose as a Gaussian random variable and estimate it relative to our guide robot for each of the possible configurations that the robot can take in the free configuration space. This estimation is done assuming that the social

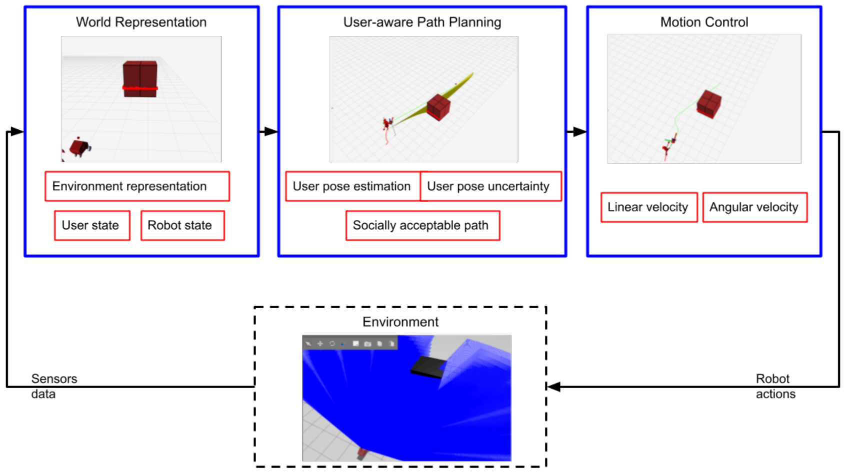


Fig. 1: Proposed framework for addressing the social robot navigation problem. The framework obtains data from sensors, performs a world representation, plans a path considering the user, and generates control actions to follow the planned path.

agent follows the guide robot according to the model proposed by [11] for a follow-the-leader configuration. According to this model, the guided user's pose $x(t)$ evolves according to:

$$x(t+1) = x(t) + v(t)cos(\psi(t)) \tag{3}$$

$$y(t+1) = y(t) + v(t)sin(\psi(t)) \tag{4}$$

where $\psi(t)$ is the anticlockwise heading relative to the robot frame's x - axis, and $x(t)$, $y(t)$ are the user positions in Cartesian coordinates.

Predicting the pose where the agent could be at each configuration that the robot can take during navigation requires a sequential increase in uncertainty. The user pose uncertainty increases as the tree is extended to connect the initial and final configurations, but it reduces every time the robot measures the user pose.

3.2 User-aware Path Planning

We propose an algorithm based on the optimal Rapidly Exploring Random Tree (RRT*) for path planning. The cost function of our extended RRT* algorithm includes a factor that considers the current and predicted user's motion. The algorithm has an online execution, so it is designed to obtain new paths from the current pose of the robot to reach the target configuration as shown in Alg. [1]. Path planning is conducted in a manner analogous to the RRT* algorithm.

Distinct configurations are generated within the free configuration space, and a tree is extended by connecting the different configurations. During the expansion of the tree, in addition to collision checking, our algorithm seeks to minimise the probability of collision of the agent with the obstacles by incorporating this probability into the cost function of the algorithm.

Algorithm 1 socialPathPlanning

Input: q_{start}: Start configuration
q_{goal}: Goal configuration
Output: P: asymptotically optimal path
begin:
planner ← RRT*(DubinsStateSpace)
$last\_best\_known\_solution \leftarrow \{\}$
$q_{new\_start} \leftarrow q_{start}$
while not *end_condition* **do**
    world_model ←reqUpdatedWorldRepresentation()
    planner.updateWorldRepresentation(world_representation)
    planner.optimalObjective(cost_function)
    planner.startFrom(*last_best_known_solution*)
    planner.solve(q_{new_start} , q_{goal})
    if *solutionnotfound* **then**
        $P \leftarrow$ planner.getPartialSolution()
    else
        last_best_known_solution ← planner.getSolution()
        $P \leftarrow last\_best\_known\_solution$
    end if
end while
return P

The proposed path planning algorithm accepts as inputs the start and goal configurations. The algorithm initiates by establishing the Dubins-type state space, initialising a variable to store the most recent optimal solution, and defining the start configuration to be utilised by the algorithm. A cycle to search the asymptotically optimal path begins. At each cycle iteration, the representation of the semi-structured environment is updated, the cost function is established, and the optimal solution previously identified is designated as the base path for planning. A solution is sought that accounts for both the goal configuration and the start configuration, which corresponds to the robot's current position. Upon the identification of a solution, it is registered as the most recent optimal solution and as the asymptotically optimal path. If no optimal solution can be found, a partial or approximate solution will be returned, which does not guarantee that the goal configuration can be reached.

Processing data from exteroceptive sensors, it is possible to determine the position and speed of agents present in the environment shared with the robot. In this work, we obtain the agent pose and speed directly from the pedsim_ros library. The dynamic state of the user being guided is represented with respect to the robot's local frame.

Path planning attempts to connect different waypoints between the start and goal configurations. The waypoints are generated in the configuration space by checking that they are in collision free space. During path generation, each waypoint represents a possible configuration to be taken by the robot.

Using the estimated position and the uncertainty generated by the estimation procedure, the probability of collision of the agent with obstacles in the environment is estimated. Building a planning cost function that includes the guided agent's collision probability effectively allows our planning framework to generate paths that avoid the user and the robot collision with the environment. In this framework, we implement our social factor $G(u_{sc})$, introduced in the problem formulation above, as the following cost function based on the Mahalanobis distance:

$$G(u_{sc}) = \sqrt{(x_{user} - x_{obs})^T \Sigma^{-1} (x_{user} - x_{obs})} \tag{5}$$

In this context, the variable x_{user} represents the user pose, while x_{obs} denotes the obstacle pose. The symbol Σ denotes the covariance matrix of both poses. The user-estimated pose covariance matrix is a diagonal matrix with each value representing the uncertainty in the pose estimation.

3.3 Motion Control Approach

Our motion control module attempts to follow the path planned based on a differential robot kinematics model, obtaining maximum linear and angular speeds from a path parametrisation based on Dubins curves. Path generation using Dubins curves was performed using the state space class of the Open Motion Planning Library [22]. The library allows the generation of paths in SE(2) with a geometric planner that interpolates the different configurations, thus enabling the movements "go straight," "turn left," and "turn right".

The robot's position and orientation are updated continuously via odometry data and the planned path, which is provided as a sequence of waypoints. The robot navigates by moving iteratively towards the next waypoint in the path. The linear and angular velocities are set according to the distance from the current position to the waypoint and the bearing and heading angles.

The motion control algorithm ensures that the robot is oriented towards the waypoint by calculating the bearing angle. The current heading angle is obtained from odometry. The robot adjusts its velocities in consideration of the predefined thresholds in order to minimise oscillations and guarantee socially acceptable and safe movements.

4 Simulations and Results

The methodology employed in this study involves working within a simulation environment that enables the generation of scenarios incorporating obstacles and the addition of individuals whose movement is governed by the social forces model. Furthermore, the environment allows for the simulation of mobile robots and the examination of the interactions between all elements within the environment.

For this work, a modified version of the pedsim_ros packages was implemented. The modification enables the simulated robot to exert an attractive force on an agent, emulating the function of being followed by the agent. The simulation of the environment was done using these packages and Gazebo ignition. Pedsim_ros allows to emulate the behaviour of the agents considering the obstacles. Gazebo ignition as a simulation environment allows to emulate sensors, actuators, as well as the environment and different physical variables. The simulation was conducted using a setup composed of an Intel Core i5-7200 CPU with a Intel HD Graphics 620 GPU and 8 GB RAM.

The proposed framework, has been evaluated against both the unmodified RRT* algorithm and the widely employed Social Force Model. The comparison was performed in three different scenarios involving the robot and an agent to be guided. In the first scenario, there is only one stated obstacle. The robot and the social agent are placed in front of the obstacle at a certain distance as seen in fig. 2. In this scenario the robot has to navigate from its starting position, which was randomly chosen within the blue zone in fig. 2 to a position behind the obstacle, also randomly chosen in the green zone depicted in fig. 2.

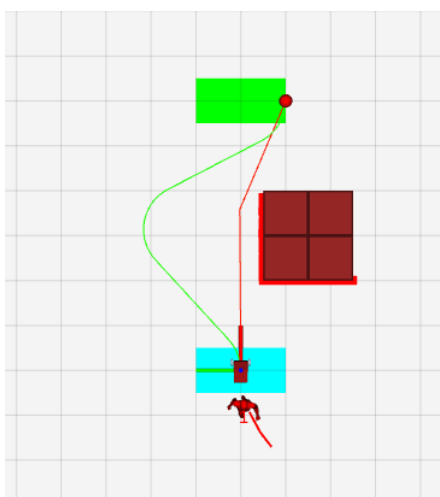


Fig. 2: Test scenario 1. A simulated environment with only one static object. The blue and green squares represent the zone where a random start and destination configuration is chosen to plan a path. The red line is the path planned by the RRT* algorithm, and the green line is the path planned by our proposal.

In the second scenario, five static objects are placed in the environment (see fig. 3). The robot must navigate through the obstacles from the start position to a target position. This scenario emulates environments where multiple obstacles, such as tables in a cafeteria, are encountered.

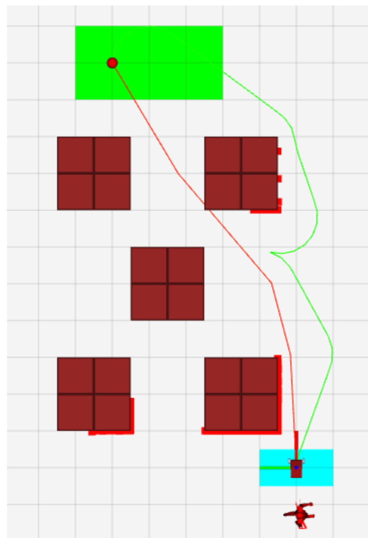


Fig. 3: Test scenario 2. A simulated environment with several obstacles. This type of environment represents social scenarios such as a cafeteria. As in scenario 1, blue and green squares represent zones where a random start and destination configuration is chosen to plan a path. The red line is the path planned by the RRT* algorithm, and the green line is the path planned by our proposal.

To validate the performance of our proposal against the other methods, we analyse success rate and path smoothness over many trials. A trial was considered successful if the robot navigated from the start position to the goal position while maintaining a proximity to the user and avoiding obstacles. The path smoothness metric was obtained by analysing the total bending energy of the path traversed by the robot during each simulation. A smoothness value close to zero indicates a smoother path. Achieving socially acceptable navigation depends heavily on the smoothness of both planned and executed paths [14]. The results of the simulations on scenarios 1 and 2 can be found in tables 1 and 2 respectively.

In the third scenario, there are two static objects placed one in front of the other as seen in fig. 4. In this scenario the robot has to navigate the environment to a goal position behind the obstacles. The two obstacles formed a corridor and the distance between them is reduced until a narrow corridor where the robot and the agent cannot pass side by side is created. Metrics obtained from simulations in this scenario can be seen in table 3.

Table 1: Metrics from the scenario 1.

	Success rate	Smoothness
SFM	0.85	0.12
RRT*	0.89	0.049
our proposal	0.96	0.037

Table 2: Metrics from the scenario 2.

	Success rate	Smoothness
SFM	0.74	0.23
RRT*	0.76	0.091
our proposal	0.85	0.067

The success rate for the SFM and RRT* methods are slower than our proposal because a success trial imply to reach the destination point maintaining close to the user. In cases where the robot and the user can't travel together trough the narrow corridor, SFM and RRT* can provide a motion planning to pass in the middle of the obstacles leaving the user behind. Meanwhile, our proposal takes into account the collision probability and plan a path to avoid the corridor as can be seen in fig. 5. This results in a robot behaviour that prioritises user safety and comfort.

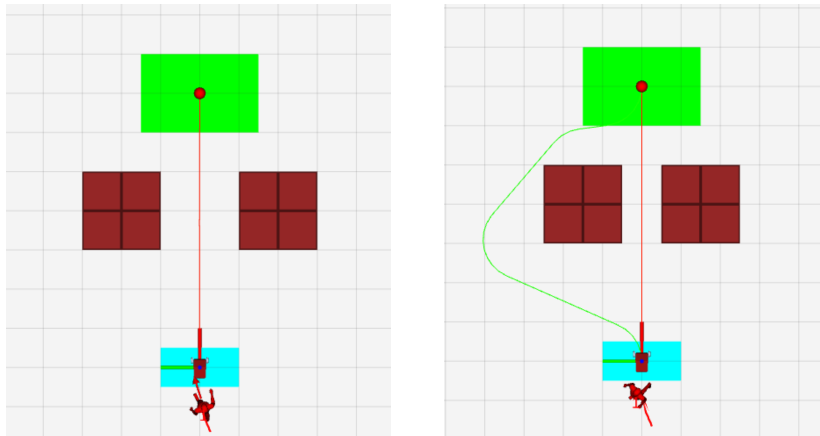
5 Conclusions and Future Work

This paper presents a path planning framework for a guide robot that considers estimates of the relative user's pose and its corresponding uncertainty. Our framework enables mobile robots to guide users through an environment in a free-collision and comfortable manner. We present modifications to the RRT* sampling-based algorithm that aim to contribute to the generation of socially acceptable paths for the task of guiding people, taking into account the possibility of collisions of the user with the environment.

The use of Dubins curves for path planning allows the generation of smoother paths compared to the SFM and RRT* algorithms. This is supported by the observation that the average smoothness in the three scenarios is lower when using our proposal. Following a smoother path while navigating may enhance the user's perception of the path as a natural path.

The proposed algorithm, compared to the classical SFM and RRT*, allows planning and executing paths that take into account the user to be guided. The consideration of the user during the planning and execution of the path leads to a successful navigation in which the robot prioritises the task of guiding over that of navigating the space, i.e. the robot tries to complete the navigation with the user and not individually as in classical robot navigation.

As future work, we intend to validate the proposed methodology in scenarios of higher structural complexity, as well as those scenarios with other social agents



(a) Initial corridor.

(b) Narrow corridor.

Fig. 4: Test scenario 3. A simulated corridor environment. This scenario presents two obstacles that create a corridor for the robot and the user to navigate through. The distance between the obstacles is decreased over different trials, resulting in a narrow corridor that the robot and the user cannot pass through side by side. As in the others scenarios, blue and green squares represent zones where a random start and destination configuration is chosen to plan a path. The red line is the path planned by the RRT* algorithm, and the green line is the path planned by our proposal.

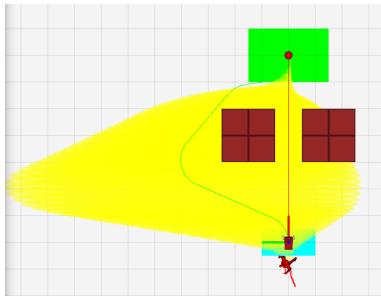
Table 3: Metrics from the scenario 3.

	Success rate	Smoothness
SFM	0.4	0.15
RRT*	0.5	0.071
our proposal	0.8	0.041

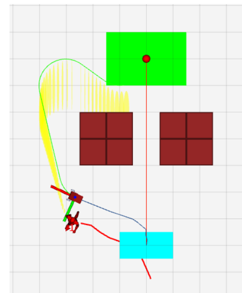
involved in both low and high densities. In order to account for the presence of other social agents, their poses and velocities relative to the robot, as well as their state of motion, i.e., whether they are moving or stationary, must be considered. Moreover, individuals and groups of varying sizes and compositions, with their respective personal or social areas, should also be considered.

The environment abstraction in this work enables our algorithm to navigate in a safe and socially acceptable manner. However, discriminating between different elements in the environment using metric-semantic maps will allow for better performance in social robot navigation. In situations where the terrain presents concrete roads with grass or sand around them, the socially accepted path is usually the road, even if crossing the grass offers a shorter path.

To validate the results obtained in the simulations and to obtain user feedback, real-world experiments should be conducted using case studies.



(a) Paths planned.



(b) Uncertainty.

Fig. 5: Paths planned for scenario 3 in a trial. A path planning result for a trial to navigate from the robot position to the target position (red circle). The red line is the path planned by the RRT* algorithm, and the green line is the path planned by our proposal. The yellow ellipses represent the uncertainty in the user pose estimation for each waypoint in the planned path. Note that user pose uncertainty reduces at every time step after the robot updates its believe about the user's pose

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