# Social Navigation for Tour-guide Robot

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***Abstract*— We propose a force-based model for social navigation of a tour-guide robot. Social forces due to various factors like obstacles, user position and heading, have been accounted for in the model. We hypothesize that each one of these forces makes the robot more sociable to the user and we design an experimental setup for evaluation. In the proposed experiment, the participant follows an autonomous robot to a destination in a known map, while undertaking a few simple sub-tasks in the middle, which serve as distractions. Each participant will complete several rounds of the experiment, each using a different force or a shortest-path A*-search baseline. Using per-round subjective indicators, we propose to study the effect of our force model on perceived naturalness, perceived safety, and perceived intelligence, complemented by objective measures of how well the robot stays visible to, and at a social distance from, the follower.**

## I. Introduction

In this work, we present a social force model for a tour-guide robot and propose experiments to study its effect on human's perception about the robot. As the globe is becoming more connected, cities around the world are attracting more tourists every year. As a result, more people are exploring public spaces like museums, parks and shopping malls. Often, these huge public spaces are clumsy and time consuming to navigate through, especially for elderly people. This motivates the development of a tour-guide robot, which helps the tourists in navigating to their destinations, thus, making the tour more fulfilling and productive.

To be a successful tour-guide robot, it needs to properly follow the expectations of tourists, thus adding social constraints on robot's behavior. For example, it is reasonable for a tourist to expect that the robot moves at a safe speed, so that they can follow it without rushing through the scene. Thus, traditional shortest path planning approaches need to be adapted in this scenario to account for social constraints imposed by the user. In this work, we are interested in evaluating the benefits of following social constraints from a human's perspective.

The main focus of social navigation research in the past years has been to help the robot stay farther away from humans in crowded environments; however, there is little work in the case when the robot has to guide a human to a destination. In scenarios, where the robot has to simply reach a destination, the humans are treated as obstacles and thus, there is a penalty associated with coming too close to the humans. In contrast, a tour-guide robot needs to stay close to the tourist, so that they do not get lost in the crowd. Furthermore, it should move in a manner that makes it easier for the tourist to follow. These challenges motivate our social force model where the robot is acting as the leader and is tasked to guide the tourist to their destination, in a friendly manner. Fig. 1 shows schematic of a social tour-guide robot, helping out a user to navigate safely to the goal location, while following social constraints.

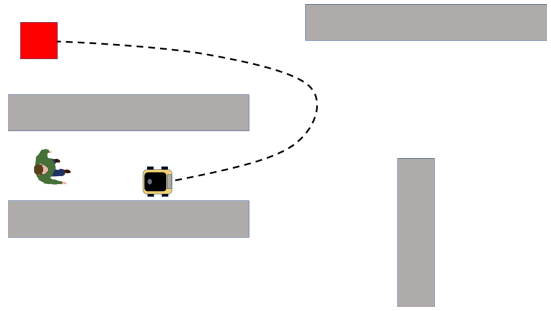


Fig. 1. Schematic of a tour-guide robot helping user to navigate to goal, shown in red.

The contributions of this paper are: (1) a social force model for a tour-guide robot that extends the model of Zhang et al. [7] with a force based on the user's field of view; (2) an evaluation protocol for this model, comprising hypotheses, a modified Godspeed questionnaire, objective measures of visibility and distance keeping, a statistical analysis plan, and a power analysis, with virtual and in-person variants; and (3) a pilot session of the virtual variant and the practical lessons it raised. Running the full study to test the hypotheses is left to future work.

## II. Related Work

### A. Robot Navigation in Presence of Humans

Social constraints first entered into navigation with a promise of keeping safe distance between the robot and humans [1]–[3]. Bellarbi et al. [1] established social rules that allow the robot to navigate smoothly and socially in indoor environments. Ramon-Vigo et al. [2] leveraged inverse reinforcement learning to transfer skills of human navigation behavior to a robot. Perez-Higueras et al. [3] take a cost-based optimization route where a social cost map is learned from expert demonstrations. However, these works do not address the challenges that arise when the robot is leading a human, which is necessary for a tour-guide robot.

Few researchers have studied the problem of human interaction with guide robots [4], [5]. Shen et al. [4] explored the

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"object approaching" behavior for guide robots in a museum. Azenkot et al. [5] introduced multiple modes of guidance for blind people. However, these works focused on human-robot communication, and social navigation constraints were ignored.

### B. Social Force Model

Researchers first proposed to add pseudo forces onto the robot to mimic socially acceptable behavior [6], [7]. One of the earliest works on social forces is by Helbing et al. [6] where the authors added social forces owing to the presence of humans and intermediate goals in the environment. Zhang et al. [7] incorporate attractive and repulsive forces for the robot to address two social constraints: speed control to stay close to the user and maintaining safe distance from obstacles in the environment. However, they fail to evaluate the effect of those forces through human experiments and surveys.

Repiso et al. [8] extended the social force model so that a robot accompanies a person side-by-side, approaches a second person, and positions itself to interact with both. They introduced forces that maintain an adaptive side-by-side formation and a safe distance from the accompanied person, learned the force parameters from simulations and from trajectories of people walking in pairs. Our work differs in three respects. First, our robot leads the user to a destination that the robot knows, rather than walking beside a person who chooses the destination. Second, their model considers the field of view only in how strongly surrounding pedestrians influence the robot-person pair, through an anisotropic weight on the interaction forces, whereas we add a force that pulls the robot towards the user's heading direction to keep it within the user's field of view. Third, our proposed study is designed to isolate the effect of each individual force against a baseline, whereas they evaluated the complete model.

Our work extends the existing social force model for tour-guide robot, developed by Zhang et al. [7], by adding additional force due to the limited field of view of the human. In addition to adapting the speed and maintaining safe distance from obstacles, we add attractive force in order to impel the robot to stay close to the heading direction of the user. Furthermore, to establish the utility of the force model, we plan to evaluate the effect of each force on the user through rigorous human-participant studies.

## III. System

To behave socially, we believe that a tour-guide robot should adapt to the motion of the user, so that it can suit their desires and needs. We leverage potential fields for achieving this adaptive control for the robot. In this work, we propose to generate adaptive potential fields due to static and dynamic obstacles, the tourist and intermediate goal points. The robot tends to move in the direction of lower potential, thus producing the required adaptive behavior.

### A. Potential Field

We apply two types of potential fields: attractive and repulsive. These fields get updated online based upon the configuration of the world and forces are generated accordingly to control the robot.

*1) Sub-goal Attractive Potential:* To force the robot to move towards a nearby goal point, similar to previous work by Zhang et al. [7], we apply an attractive potential from it. Often this goal is not the final destination for the robot, rather an intermediate subgoal on the path to the final destination. This is to avoid the robot getting stuck in deadlock situations. The attractive potential $P_{ag}$ is given by:

$$P_{ag} = \frac{K_{ag}}{2} \times d_g^2 \tag{1}$$

Where $K_{ag}$ is a constant coefficient and $d_g$ is the distance of the robot from the goal. Fig. 2 shows the sub-goal and the corresponding attractive potential field for a model environment. This causes an attractive force $F_{ag}$ to act on the robot which is given by:

$$F_{ag} = -K_{ag} \times d_g \tag{2}$$

The proportional force allows the robot to drive faster towards the goal, when it is far away from the goal.

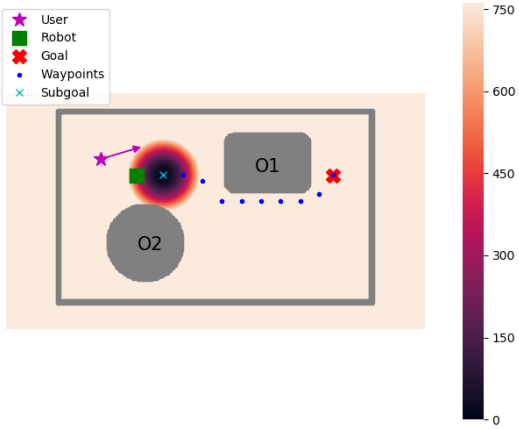



Fig. 2. Potential field generated from closest waypoint to the robot.

*2) Obstacle Repulsive Potential:* To avoid collision with static and dynamic obstacles in the map, repulsive potential is developed around them in the same way as in prior work by Zhang et al. [7]. The repulsive potential $P_{ro}$ is given by:

$$P_{ro} = \frac{K_{ro}}{(d_r - d_o)} \text{ if } d_r > d_o; \quad P_{ro} = \infty, \text{ otherwise.} \tag{3}$$

$K_{ro}$ is a constant coefficient, $d_r$ is the distance of the closest point on the obstacle to the robot and $d_o$ is a parameter defining the minimum distance that the robot can approach the obstacle, without hitting it. Fig. 3 shows the obstacles $(O1, O2)$ in a model environment and their corresponding repulsive potential fields. This causes a force $F_{ro}$ to act on the robot which is given by:

$$F_{ro} = \frac{K_{ro}}{(d_r - d_o)^2} \text{ if } d_r > d_o; \quad F_{ro} = \infty, \text{ otherwise.} \tag{4}$$

In general, the path of the robot does not intersect with any obstacle. However, having the repulsive force puts an

additional guarantee to drive the robot away, in case it comes closer to the obstacles. In addition, the inverse quadratic relationship ensures that the robot's path is unaffected by the repulsive force, if it is sufficiently far away from any obstacles.

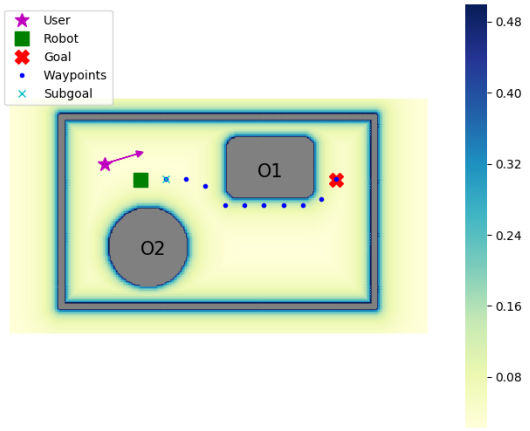



Fig. 3. Potential field generated from the obstacles.

*3) Attractive-Repulsive Potential due to User:* For adapting the robot to the motion of the user, similar to the prior work by Zhang et al. [7], we apply a special potential field that has both, attractive and repulsive, properties in it. The potential field $P_{ar}$ is given by:

$$P_{ar} = \frac{K_{ar}}{2} \times (d_s - d_u)^2 \tag{5}$$

Where $K_{ar}$ is a constant coefficient, $d_s$ is a parameter that can be viewed as the social distance and $d_u$ is the distance of the robot from the user. Fig. 4 shows a user in a model environment and their corresponding potential field $P_{ar}$. This leads to a force $F_{ar}$ on the robot which is given by:

$$F_{ar} = K_{ar} \times (d_s - d_u) \tag{6}$$

If the robot gets too far ahead of the user, the attractive force slows it down. The repulsive force gets activated, when the robot comes too close to the user, thus driving it away from the user. As a result, this combination of attractive-repulsive potential fields from the user helps the robot to maintain a desirable relative distance from the user.

*4) Attractive Potential due to User's Field of View:* To keep the robot in the field of view of the user, we add an attractive potential that pulls the robot towards the heading direction of the user, as depicted in Fig. 5. The potential field $P_{fov}$ is given by:

$$P_{fov} = \frac{K_{fov}}{2} \times d_l^2, \text{ if } \theta < \theta_o. \tag{7}$$

Where $K_{fov}$ is a constant coefficient, $d_l$ is the distance of the robot from the user's heading direction, $\theta$ is orientation of the vector from user to robot, and $\theta_o$ is half of the maximum field of view. Fig. 6 depicts the field of view of a user and the corresponding potential associated with it for a model

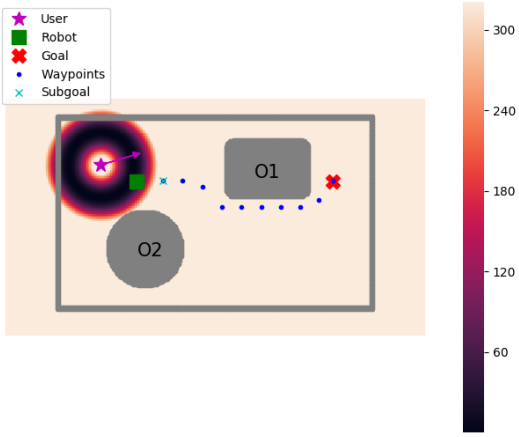



Fig. 4. Potential field generated from the User.

environment. The force $F_{fov}$ acting on the robot is:

$$F_{fov} = -K_{fov} \times d_l, \text{ if } \theta < \theta_o; \; F_{fov} = F_{\max}, \text{ otherwise.} \tag{8}$$

The force due to the field of view constraint makes it easier for the user to keep track of the robot by driving the robot towards the heading direction of the user.

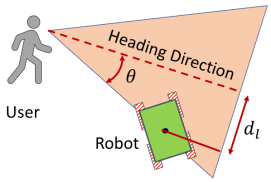



Fig. 5. Field of view of a user.

## B. Global Planner

Apart from the local forces experienced by the robot, we utilize A* algorithm [9] to generate the global path from robot's current location to the goal location. Typically, it is desirable to guide the user to the destination in a minimum

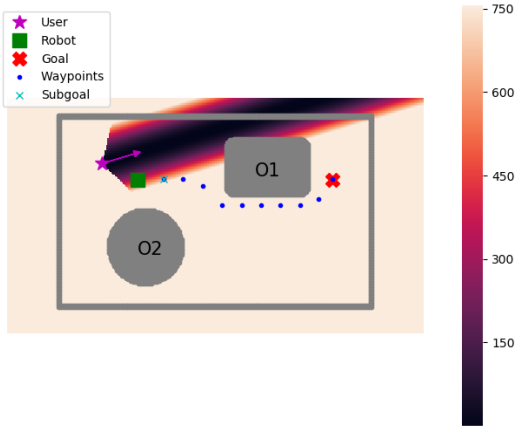



Fig. 6. Potential field generated from user's field of view.

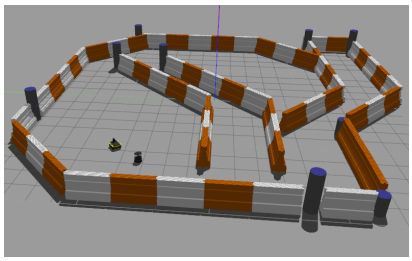


Fig. 7. Gazebo environment for conducting virtual experiments, with Jackal robot and Turtlebot3 in it.

amount of time. Accordingly, the A* algorithm produces a series of contiguous points corresponding to the shortest path in the discrete map. These points are treated as subgoals for the robot, eventually leading to the final destination.

### C. Implementation

We design our system in a manner so that we can conduct our study in-person or virtually. There are slight differences in the experimental procedure depending on which method is used.

*1) Simulation Environment:* For the virtual study, we implemented our system in Gazebo and ROS kinetic. We use a ClearPath Jackal robot as the leader robot. The Jackal is equipped with RGBD sensors and a 16-scan lidar. We modified ROS packages from ClearPath to create a Gazebo world map and leverage the basic navigation stack. These packages were also modified to include a Turtlebot3 robot which is used as an avatar for the human follower. Fig. 7 shows the simulation environment with the robots in it. The open source Turtlebot3 navigation stack is used. The Turtlebot3 is equipped with an RGB camera and all other sensors are deactivated. Global position and orientation of both the Jackal and Turtlebot3 are tracked using the Gazebo's state messages. Additionally, during the virtual study we use zoom to give participants control of our keyboard and access to our display. Participants control the Turtlebot3 through a keyboard using the open source `teleop_twist_keyboard` package. They are shown the RGB video feed from the front camera of Turtlebot3 using `rviz` as seen in Fig. 8. Participants are not allowed to see the overhead Gazebo map during the study. The social forces and A* algorithms are both implemented in Python language.

*2) Real-world Implementation:* For the in-person study, the implementation is similar. However, we remove the Turtlebot3 as the person can follow the robot themselves. One major change is the need for a lidar detector for pedestrians and a Kalman filter tracker to infer the participant's position and orientation. The position and orientation of the jackal is tracked using ClearPath's own navigation stack. The Jackal's navigation stack includes a map making package which is used to globally locate stationary obstacles in the study environment. All other aspects of the implementation are shared between the two studies.

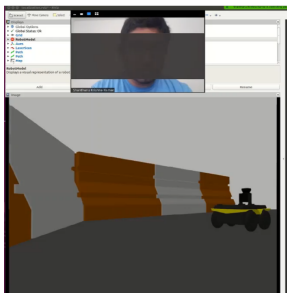


Fig. 8. Zoom study setup. Participant is given access to the computer running ROS, through zoom. Using the keyboard and images from Turtlebot3, they follow the Jackal robot to the goal.

## IV. Evaluation Method

This section describes the protocol for the full study, which has not yet been conducted. So far, only a pilot session of the virtual setup has been run (Sec. V).

### A. Hypotheses

The purpose of this study is to measure the influence of each social force on the following constructs: perceived naturalness, perceived safety, and perceived intelligence when compared to an A*-search baseline model. Therefore, for each social force "x" we propose the following hypotheses:

**H1**: A robot that uses social force x is perceived as more intelligent than the baseline.

**H2**: A robot that uses social force x is perceived as safer than the baseline.

**H3**: A robot that uses social force x is perceived as more natural than the baseline.

### B. Procedure

For the study we intend to ask participants to follow the Jackal robot to four goal positions in the map. In each sequence, the robot will navigate to a goal point using one of the following algorithms: baseline, obstacle force ($F_{ro}$), Field of view force ($F_{fov}$), and proximity force ($F_{ar}$). We refer navigation to one goal as a *following* sequence. For each *following* sequence, participants and the robots will be placed at a predefined start position. The robot will then be commanded to navigate to one of the pre-selected goal points. The goal point and social force algorithm used during the following sequence will be randomly assigned to avoid ordering effects. During a *following* sequence, the participant will be given a subtask of completing math problems to simulate distractions in the environment. At the end of the following sequence the participants and robot will be reset to the start position.

To measure the impact of the social forces on the constructs of perceived naturalness, perceived safety, and perceived intelligence, after each following sequence the participants will complete a customized Godspeed Questionnaire [11]. The Godspeed questionnaire is a well-used metric in Human robot interaction studies and examines if participants associate the following factors with the robot: anthropomorphism, animacy, likability, perceived intelligence and

TABLE I
MODIFIED GODSPEED SURVEY QUESTIONS AND ASSOCIATED CONSTRUCTS.

| Survey Questions (1-5 scale) | Construct |
|---|---|
| Machinelike/Humanlike | Perceived Naturalness |
| Fake/natural | Perceived Naturalness |
| Moving rigidly/moving elegantly | Perceived Naturalness |
| Incompetent/competent | Perceived Intelligence |
| Ignorant/Knowledgeable | Perceived Intelligence |
| Irresponsible/Responsible | Perceived Intelligence |
| Unintelligent/Intelligent | Perceived Intelligence |
| Foolish/Sensible | Perceived Intelligence |
| Anxious/Relaxed | Perceived Safety |
| Agitated/Calm | Perceived Safety |
| Quiescent/Surprised | Perceived Safety |

perceived safety. Instead of using all factors within the questionnaire we chose to only use characteristics under perceived intelligence and perceived safety. Additionally, we use the three motion-related items of the anthropomorphism scale (Machinelike/Humanlike, Fake/Natural, and Moving rigidly/Moving elegantly) to measure the perceived naturalness of the robot's motion. We include this construct because we expect a guide robot whose motion appears natural to be easier for the follower to read and anticipate. However, these items capture how the motion appears rather than how easy the robot is to follow, so we complement them with the objective measures described below. The survey questions and associated constructs can be seen in Table I. This survey is based on a 1 to 5 Likert scale. We will compare the ratings for each social force against the baseline. We will use a one-tailed paired t-test to test the null hypothesis for **H1**, **H2**, and **H3**. If the resultant p-value for a hypothesis is less than 0.05, we will reject the null hypothesis and accept the alternative hypothesis. We will also compute Cronbach's alpha for each construct; a value above 0.7 will be taken to indicate internal consistency.

In addition to the questionnaire, we will log the poses of the robot and the participant during each *following* sequence and compute two objective measures: (i) the fraction of time the robot lies outside the participant's field of view, i.e., $\theta > \theta_o$, and (ii) the mean absolute deviation of the robot-participant distance $d_u$ from the social distance $d_s$. These measures quantify how well the robot stays visible to, and at the intended distance from, the follower. They serve as manipulation checks for $F_{fov}$ and $F_{ar}$, respectively, and will be reported for each condition alongside the baseline rather than tested as hypotheses. In the virtual study, the poses are obtained from Gazebo's state messages. In the in-person study, they come from the lidar-based tracker, whose estimate of body orientation serves as an approximation of the participant's viewing direction.

### C. Participants

We plan to recruit participants from Cornell University for the study. Each participant will receive a $10 Amazon gift coupon after completing the experiment. To determine the number of participants, we conducted a power analysis test. For this analysis, we need to set the power, significance level, and effect size. To avoid a type-2 error most literature picks a value of 0.8 or above for the power. In our case we chose a value of 0.95. We choose the commonly used significance level of $0.05$. The effect size is a measure of the difference between two groups. This can usually be found through a pilot study or through literature review of similar studies. Based on Cohen's recommendation [10], we have chosen a medium effect size of 0.5, which yields a participant count of 45 for the planned study.

## V. DISCUSSION

Through our simulations, we observed that the behavior of the Jackal can vary greatly based on the selected parameters for each force. For example, the jackal can get stuck in a local minimum if the goal and obstacle forces cancel each other. Additionally, if the repulsive force from the person is too strong then the robot can miss goal locations or crash into an obstacle. For this reason, these parameters had to be carefully tuned to avoid such pathological behavior. An extension of this work could be to learn these parameters through reinforcement learning through observations of human controlled robots.

Our virtual setup makes it possible to run studies when participants cannot come to the laboratory, but it has caveats. To check the feasibility of the protocol, we ran a pilot session of the virtual study with one participant; its responses were not used to test **H1**–**H3**. The pilot surfaced two issues. The participant found the Turtlebot3 avatar hard to control because the keyboard teleoperation is discrete, and the narrow field of view of the Turtlebot3 camera made them feel restricted. Both issues could affect survey responses in the virtual study independently of the social forces being tested. We therefore consider the in-person study better suited for a faithful evaluation of the force model.

## VI. CONCLUSION

In this work, we presented a social force-based model for a tour-guide robot that accounts for obstacles, social spacing, and the field of view of the human follower, and implemented it in simulation. We also designed a human-participant study, with virtual and in-person variants, to measure the influence of each social force on perceived naturalness, perceived safety, and perceived intelligence, together with objective measures of visibility and distance keeping. A pilot session of the virtual variant showed that difficulty teleoperating the Turtlebot3 avatar could confound participants' ratings. Future work will therefore run the full study in person, with 45 participants as determined by our power analysis, to test **H1**–**H3**.

## ACKNOWLEDGMENT

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