

Proactive Opinion-Driven Robot Navigation around Human Movers

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Abstract—We propose, analyze, and experimentally verify a new proactive approach for robot social navigation driven by the robot’s “opinion” for which way and by how much to pass human movers crossing its path. The robot forms an opinion over time according to nonlinear dynamics that depend on the robot’s observations of human movers and its level of attention to these social cues. For these dynamics, it is guaranteed that when the robot’s attention is greater than a critical value, deadlock in decision making is broken, and the robot rapidly forms a strong opinion, passing each human mover even if the robot has no bias nor evidence for which way to pass. We enable proactive rapid and reliable social navigation by having the robot grow its attention across the critical value when a human mover approaches. With human-robot experiments we demonstrate the flexibility of our approach and validate our analytical results on deadlock-breaking. We also show that a single design parameter can tune the trade-off between efficiency and reliability in human-robot passing. The new approach has the additional advantage that it does not rely on a predictive model of human behavior.

I. INTRODUCTION

Autonomous mobile robots are increasingly being used for tasks in settings such as warehouses and open public spaces where they will encounter human movers. In order to accomplish their tasks in these settings, the robots need to reliably and gracefully navigate around human movers. In this paper, we propose, analyze, and experimentally verify a new approach for the social navigation of a mobile robot. Fig. 1 shows experimental results of a mobile robot navigating around two human movers using the new approach.

We build on the nonlinear opinion dynamics model presented in [1] and propose an approach that allows a robot to rapidly form an *opinion* that represents the strength of its preference for which direction—left or right—it will use to pass each human mover crossing its path. This opinion, in turn, drives the robot’s motion, modifying its nominal path to reliably pass the human. A key to the opinion dynamics is that when the robot’s *attention* to social cues grows above a critical value, the neutral opinion to stay the course is destabilized and the robot rapidly forms a strong and stable opinion for moving in one of the two passing directions. Our approach is therefore to design dynamics for the robot’s

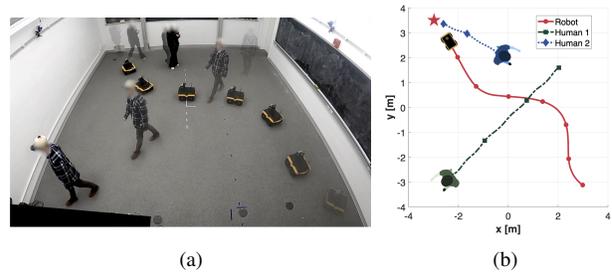


Fig. 1. A robot using opinion-driven navigation to pass two humans. (a) Time-lapse of the experimental trial. (b) The full trajectories of the robot (red line) and two humans (blue and green lines) with temporal markers.

attention that drive it above this critical value when the robot senses a human mover approaching its path. The active control of attention yields a rapid and reliable passing motion in response to an approaching human mover; this renders our approach “proactive” rather than merely “reactive.”

Once the robot passes a human, its opinion with respect to that human is no longer relevant; the opinion quickly returns to its neutral value, allowing the robot to continue towards its destination. Likewise, the robot’s attention also goes to zero, making the robot ready for new potential conflicts with other movers. Figs. 1 and 2 provide experimental results of the robot navigating different encounters when traveling to a goal destination that is diagonally across an open space with two humans moving and pausing in a variety of scenarios.

Opinion dynamics are used to enable decision making in multi-agent systems in a range of tasks [2]–[4]. In the nonlinear opinion dynamics of [1], an agent’s opinion is influenced by the opinions of others when its attention exceeds a critical level. At this point the agents are guaranteed to form strong opinions (e.g., to agree on or coordinate among options), hence avoiding indecision, i.e., deadlock in their decision making. In the robot social navigation problem, we leverage the deadlock breaking guarantees of the coupled attention-opinion dynamics to ensure that, when necessary to avoid an approaching human mover, the robot will rapidly select and move in one of the two passing directions even if there is no indication from the human or the environment that one direction is better than the other, or if the robot’s bias for one direction or the other, if it has one, conflicts with the human’s chosen passing direction.

Of relevance to our work is the literature on robot social navigation (see recent survey articles [5]–[9] and references therein), where a common theme is in investigating the design of navigation algorithms for autonomous robots to safely and comfortably interact with the humans they encounter.

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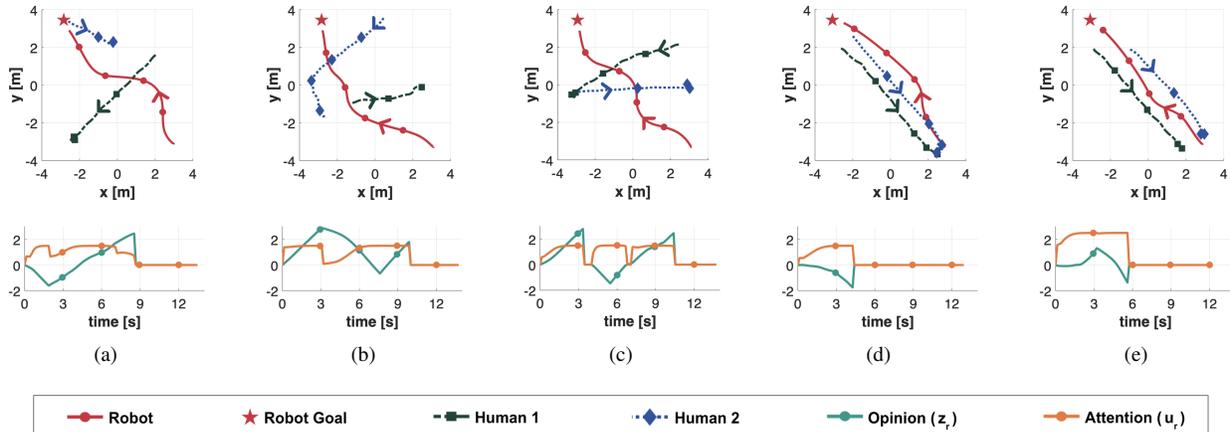


Fig. 2. Multiple experimental trials with two humans and a robot using the new approach. The top row shows the complete trajectories of the robot (red line) and humans (green and blue lines) over the course of a trial as the robot moves toward its goal (red star). Each trajectory is marked with an arrow indicating the mover’s direction. The bottom row shows the robot’s opinion z_r (teal line) and attention u_r (orange line) over the course of the trial above it. Temporal markers (dots) are shown along spatial trajectories, opinion, and attention. See Section IV-A for parameters used.

Earlier work [10] in modeling human navigation behavior proposes a model based on the observation that the motion of pedestrians is subject to *social forces*. More recent works [11], [12] incorporate *social cues* into the social force model and the improved models are used to design robot navigation algorithms. The work of [13] proposes a constrained optimization approach to design a navigation algorithm that penalizes the robot when its behavior violates conventions observed in the human’s navigation. In [9], a reactive control policy is used to follow and maintain the passing sides observed by passing humans through social momentum. References such as [14]–[16] explain learning-based approaches that leverage the recent advancement in deep reinforcement learning to train mobile robots through multiple trial-and-error processes to safely navigate in human-populated areas.

Another important line of research in the social navigation literature is data-driven learning approaches that infer human navigation models from their demonstration data, and use the models to predict human motions and to design robot motion planners. The work of [17] leverages Bayesian learning to construct a motion model and personality characteristics of pedestrians, and use predicted pedestrian trajectories from the model for socially-aware robot navigation. Inverse Reinforcement Learning (IRL)-based approaches, for instance [16], [18], [19], take human demonstration data to estimate a utility function used in human navigation tasks, and use it to generate robot trajectories that imitate the demonstrated human motions. In particular, a recent relevant work [20] studies the effect of human-robot communication in social navigation and proposes an IRL-based robot planning framework to generate communication actions that maximize the robot’s transparency and efficiency.

Our work is distinct in that 1) it is proactive rather than reactive, 2) it does not require constructing a predictive model of human navigation as in IRL-based approaches, rather it only needs the robot to observe the position and

moving direction of the human, and 3) our robot navigation model is analytically tractable so that we can establish a guarantee on deadlock-free decision making in the robot-human navigation. This contrasts with the reinforcement learning approaches, which are in general difficult to analyze, and existing reactive approaches, such as social force models, which do not provide the same deadlock-free guarantee.

In Section II, we introduce the nonlinear opinion dynamics and propose a new model for robot navigation in a human-robot navigation setting. In Section III, using tools from nonlinear dynamical systems theory, we discuss how the model ensures rapid deadlock-free robot navigation. To demonstrate and test the flexibility of our approach, we carry out experiments with two human participants and a mobile robot in a range of scenarios, which we report on in Section IV-A. We examine and validate the effectiveness of rapid deadlock-free navigation with further experiments in Section IV-B. We conclude with a discussion in Section V.

II. NONLINEAR OPINION DYNAMICS IN SOCIAL NAVIGATION

We study a robot navigation problem where a robot approaches and passes human movers while traveling to its destination (see examples in Figs. 1 and 2). In this context, we want to enable the robot to repeatedly overcome human movers in a rapid and reliable fashion. We are also interested in tackling challenging scenarios such as the human-corridor passing problem [21]–[23] that may result in deadlock if, for example, both the robot and the human have conflicting passing biases. In these situations, a key objective is to ensure that the robot moves reliably around the human regardless of the human’s awareness of the robot. It is also desirable that the robot moves efficiently around the human. However, reliability and efficiency are in tension: giving the human a lot of space may create reliably successful but inefficient passing whereas giving the human only a little space is efficient but creates less reliably successful passing.

To address these competing objectives, we propose a new dynamic model for robot navigation based on the nonlinear opinion dynamics of [1]. We review these dynamics in Section II-A. We specialize the dynamics to proactive opinion-driven robotic navigation in Section II-B and show how a single design parameter can be used to control the reliability-efficiency trade-off. In Section III, we provide analysis that shows how deadlock breaking is guaranteed.

A. Nonlinear Opinion Dynamics Model

Consider a system of N_a agents forming opinions about two options. Let $z_i \in \mathbb{R}$ be the opinion of agent i , which represents the strength of its preference for option 1 if $z_i > 0$ and for option 2 if $z_i < 0$. It is indifferent, i.e., neutral, if $z_i = 0$. Strength of preference is $|z_i|$. The nonlinear opinion dynamics model, described below, explains how each agent i updates its opinion z_i continuously over time in response to its own opinion, the opinions of others z_k , and any internal bias or external stimulus b_i . Letting $\dot{z}_i = dz_i/dt$,

$$\dot{z}_i = -d_i z_i + u_i \tanh \left(\alpha_i z_i + \gamma_i \sum_{k \neq i}^{N_a} a_{ik} z_k + b_i \right). \quad (1)$$

The opinion z_i can be interpreted as the discounted accumulation of *social influence* weighted by the parameter $u_i \geq 0$. The social influence is defined as the hyperbolic tangent function of the weighted sum of the opinion z_k of every agent k observed by agent i and a bias/stimulus b_i . The *resistance parameter* $d_i > 0$ defines the rate of exponential discount in the accumulation of the social influence. The *attention* $u_i \geq 0$ is a tuning variable, which can be adjusted to reflect the agent's (changing) effort to pay attention to the social influence. The parameter $a_{ik} = 1$ if agent i can observe agent k ; otherwise, $a_{ik} = 0$. The parameters $\alpha_i > 0$ and $\gamma_i \in \mathbb{R}$ are weights defining how much influence z_i and z_k , respectively, have on agent i 's opinion update. If $b_i > 0$ (resp. $b_i < 0$), the bias is for option 1 (resp. for option 2). In case of no bias, we set $b_i = 0$.

B. Dynamic Model for Opinion-Driven Robot Navigation

Building on (1), we propose a robot navigation model that forms an opinion to drive the robot's motor control in an uncrowded and uncluttered environment with human movers. We assume that the robot moves at a constant speed V_r , but can regulate its angular velocity. We represent the robot's position and heading angle as $\mathbf{x}_r = (x_r, y_r)$ and θ_r , respectively. For each human j that the robot can detect, we denote their speed V_{h_j} , position $\mathbf{x}_{h_j} = (x_{h_j}, y_{h_j})$, and heading angle θ_{h_j} . Let η_{r_j} be the heading of the robot relative to the line between the robot and the human j . Let η_{h_j} be the heading of human j relative to the line between the robot and the human. See Fig. 3 for illustration of notation.

The robot focuses on the human mover j that minimizes χ_j/κ_j where $\chi_j = \|\mathbf{x}_r - \mathbf{x}_{h_j}\|$, $\kappa_j = \cos \eta_{h_j}$, and $\eta_{h_j} \in (-\frac{\pi}{2}, \frac{\pi}{2})$. This is the human who is most rapidly approaching the robot. We use $\mathbf{x}_h(t)$, $\eta_h(t)$, $\chi(t)$, and $\kappa(t)$, i.e., without index j , to refer to whichever human is the one most rapidly approaching the robot at time t .

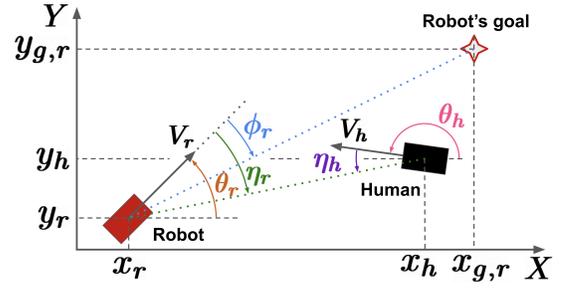


Fig. 3. An illustration of notation for human-robot passing.

We define $z_r > 0$ (resp. $z_r < 0$) as the robot's strength of preference for moving left (resp. right). When $z_r = 0$, the robot's opinion is neutral, i.e., it is indifferent to these options. Our approach does not require any knowledge of a human model; however, we assume that the robot can measure η_h and use it as a proxy for the robot's perception of the human's opinion on direction as $\hat{z}_h = \tan \eta_h$ ¹. This is unlike other approaches that require a longer-term prediction of human trajectories, such as [16], [18]–[20].

Our proactive opinion-driven robot navigation model specifies (a) how the robot's opinion z_r changes in response to its attention u_r , its current opinion, its estimate \hat{z}_h of the opinion of the focal human mover, and possibly a bias b_r ; (b) how the robot's attention u_r changes in response to κ and χ ; and (c) how the robot's heading θ_r changes as a function of its opinion z_r and the direction ϕ_r to its goal:

$$\dot{z}_r = -d_r z_r + u_r \tanh (\alpha_r z_r + \gamma_r \hat{z}_h + b_r), \quad (2a)$$

$$\tau_u \dot{u}_r = -u_r + g(\kappa, \chi; R_r), \quad (2b)$$

$$\dot{\theta}_r = k_r \sin (\beta_r \tanh z_r + \phi_r), \quad (2c)$$

where $d_r, \alpha_r, \gamma_r, \tau_u, R_r, k_r > 0$ and $\beta_r \in (0, \frac{\pi}{2}]$ are design parameters. Note that (2a) is similar to (1) except the human's opinion z_h is replaced with the proxy $\hat{z}_h = \tan \eta_h$.

We design the attention dynamics (2b) so u_r grows quickly when a human mover gets close. Unless otherwise noted, we let $\tau_u \rightarrow 0$ and define g using a Hill function to get

$$u_r = g(\kappa, \chi; R_r) = \underline{u} + (\bar{u} - \underline{u}) \left(\frac{(R_r \kappa)^n}{(R_r \kappa)^n + \chi^n} \right), \quad (3)$$

where $0 \leq \underline{u} < \bar{u}$ and $n > 0$. The variable u_r increases from \underline{u} as the robot and human move closer towards collision, based on a critical distance parameter $R_r > 0$, and saturates at the value \bar{u} . This drives u_r above a critical value that destabilizes the neutral opinion $z_r = 0$, allowing the robot to rapidly form a strong opinion when a human mover approaches, and thus rapidly pass the human on one side or the other. In this sense our approach is proactive. See Section III for a rigorous analysis of the deadlock breaking.

To understand the role of design parameter $\beta_r \in (0, \frac{\pi}{2}]$, note that when z_r is sufficiently large so that $\tanh z_r \approx 1$ (resp. -1), (2c) steers the robot's heading angle an additional β_r radians in the counterclockwise (resp. clockwise)

¹We resort to [24]–[26] for the basis for estimating the human's navigation intent using their orientation.

direction from the orientation to the goal location. Hence, we can tune β_r to prescribe how much the robot's heading angle should deviate from its direct path to its goal when it detects the human and forms a strong opinion on its passing direction. In this way the parameter β_r can be used to tune the reliability-efficiency trade-off as we show through the deadlock breaking human-robot experiments described in Section IV-B.

Our approach can be extended to incorporate path planning, e.g., to avoid driving the robot to a local minimum in the case of a cluttered environment. For example, this would be possible using a path planning approach such as the rapidly-exploring random tree (RRT) in place of (2c), with opinion z_r as an input. This would regulate not only the robot's angular velocity but also its moving speed.

III. GUARANTEE ON DEADLOCK-FREE NAVIGATION

A key contribution of our work is in guaranteeing deadlock-free navigation. We establish such a performance guarantee by analyzing the robot navigation model (2). In particular, we discuss how the robot can rapidly and reliably form a strong opinion to select one of the two options—move left ($z_r > 0$) or right ($z_r < 0$)—and avoid colliding with a human, even when the human maintains a path straight for the robot and the robot has no bias ($b_r = 0$) on which way to pass. To establish this, we use tools from nonlinear dynamical systems theory [27] to show that there is a deadlock-breaking *pitchfork bifurcation* in (2) when the robot's attention u_r reaches a critical level u_r^* (as it nears the human), corresponding to the destabilizing of the deadlock solution and the emergence of bi-stable solutions for moving left and for moving right.

We examine the challenging case in which the human does not react to the robot's movement. We validate our analysis through human-robot experiments in Section IV-B.

Suppose the robot is unbiased ($b_r = 0$) and approaches a human who is walking straight towards it ($\eta_h = 0$). In this setting, (2a) simplifies to

$$\dot{z}_r = -d_r z_r + u_r \tanh(\alpha_r z_r). \quad (4)$$

The neutral (deadlock) opinion $z_r = 0$ is always an equilibrium solution of (4). However, we show that while for small values of attention u_r deadlock is a stable solution, for larger values of u_r it becomes unstable and two symmetric bi-stable solutions emerge corresponding to a strong opinion, one for going left and one for going right. This transition, illustrated in Fig. 4a as a plot of equilibrium values of z_r as a function of u_r , is called a *pitchfork bifurcation*.

To analyze the deadlock-breaking bifurcation, we linearize the nonlinear opinion equation (4) around the equilibrium $z_r = 0$ and examine the eigenvalue $\lambda = -d_r + \alpha_r u_r$ of the resulting linearization. The sign of λ governs the stability of the equilibrium $z_r = 0$. When $\lambda < 0$ (resp. $\lambda > 0$), then $z_r = 0$, and thus deadlock, is stable (resp. unstable).

The value of u_r corresponding to $\lambda = 0$, computed as $u_r^* = d_r/\alpha_r$, is thus the critical attention value. When the robot pays less attention ($u_r < u_r^*$), then $\lambda < 0$ and the

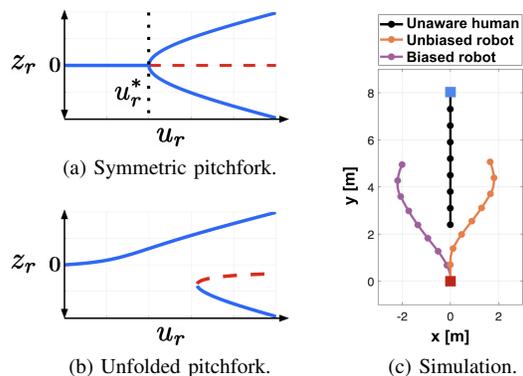


Fig. 4. Analysis of deadlock breaking in the robot's opinion dynamics when the human moves straight towards the robot. (a) When the robot is unbiased ($b_r = 0$), deadlock is broken as u_r increases above critical value u_r^* , where two stable (blue solid) symmetric opinionated solutions emerge and deadlock becomes unstable (red dashed). (b) When the robot is biased ($b_r = 0.5$), the bifurcation “unfolds” where deadlock breaks but the likelihood of converging on one opinionated solution is greater than on the other. (c) Simulations of social navigation dynamics. Initial conditions for the robot and human indicated with red and blue boxes. Parameters of (2): $d_r = \alpha_r = 0.1$, $\gamma_r = 3$, $\tau_u = 1$, $g(\kappa, \chi; R_r) = \exp(\kappa(R_r - \chi))$ with $R_r = 16$, $k_r = 1$, and $\beta_r = \pi/4$.

robot remains in deadlock, attempting to go straight to its goal location. However, when the robot pays more attention ($u_r > u_r^*$), $\lambda > 0$ and deadlock becomes unstable. For $u_r > u_r^*$ it can be shown that there are two additional symmetric equilibria $z_r^{\text{eq}1} = -z_r^{\text{eq}2} > 0$ that are both stable. These solutions correspond to a preference for going left ($z_r = z_r^{\text{eq}1} > 0$), shown as the positive curve in blue in Fig. 4a, and a preference for going right ($z_r = z_r^{\text{eq}2} < 0$), shown as the negative curve in blue in Fig. 4a. Note that the strength of preferences increases with increasing $u_r > u_r^*$. Because deadlock is unstable, the robot's opinion will necessarily converge on one or the other opinionated solution. Which one it chooses will depend on initial conditions and noise.

When the robot is biased ($b_r \neq 0$) or the human is approaching the robot obliquely ($\eta_h \neq 0$), the pitchfork bifurcation *unfolds*, as illustrated in Fig. 4b. This implies that the robot prefers one side over the other when it passes the human mover. In particular, it can be shown that the robot prefers to move left if $\gamma_r \tan \eta_h + b_r > 0$, and right if $\gamma_r \tan \eta_h + b_r < 0$. Also, as we can observe from the diagram in Fig. 4b, where the robot has a bias $b_r > 0$ for moving left, when u_r becomes sufficiently large, even though the robot favors left, if the robot is already moving right, it continues to move to this side. The analogous holds if $b_r < 0$.

We further illustrate the deadlock-breaking behavior with simulations in Fig. 4c. The human (trajectory in black) heads straight for the robot. In the unbiased case ($b_r = 0$), the robot (trajectory in orange) moves straight just briefly before arbitrarily choosing to go right to pass around the human. This corresponds to behavior indicated by the negative blue curve in Fig. 4a. In the biased case ($b_r > 0$), the robot (trajectory in purple) follows its bias and moves left, departing even sooner than it did in the unbiased case. This corresponds to

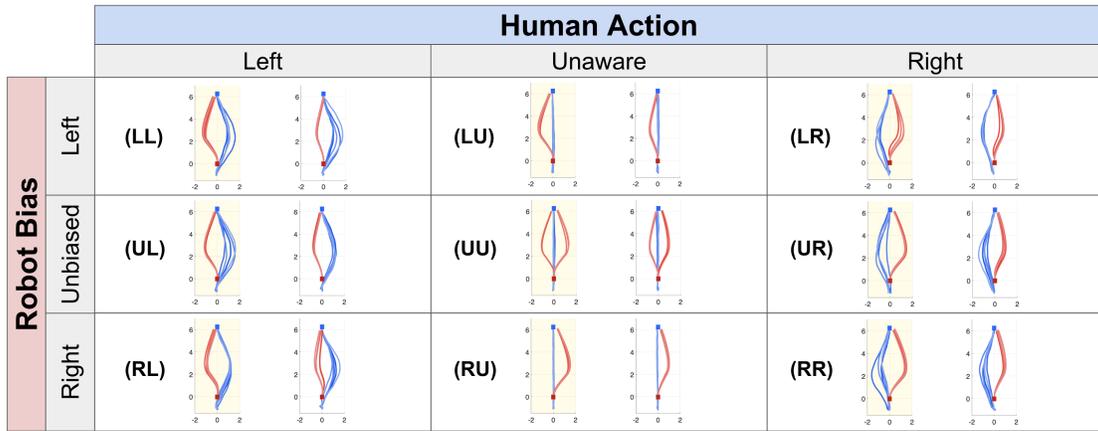


Fig. 5. The trajectory data for five runs each of the nine trial configurations for the case $\beta_r = \pi/4$ (shaded yellow) and for the case $\beta_r = \pi/6$ (unshaded). Axes correspond to the xy -plane in meters. The robot paths are shown in red with a red box at the robot's starting position at about (0m, 0m). The human paths are shown in blue with a blue box at the human's starting position at about (0m, 6.1m). In trial configuration labels, L=left, U=unaware/unbiased, and R=right. Shorthand labels (eg. LL, LU) can be read as (robot bias, human action).

the positive blue curve in Fig. 4b.

IV. EXPERIMENTS

We conducted two laboratory studies with human participants and one wheeled robot, a Clearpath Jackal UGV, moving in the $8\text{m} \times 8\text{m}$ uncluttered space shown in Fig. 1(a). We used a Vicon motion capture system to track the position and orientation of the robot and human movers who wore hats with a set of Vicon markers. The robot used the Vicon data to track the human movers. Our experimental goals are threefold: 1) to demonstrate the flexibility of the approach in that the robot can navigate a space while reliably interacting with multiple human movers in its path over a range of scenarios; 2) to validate the analysis of our algorithm, which shows that the robot is guaranteed to break deadlock, gracefully moving around an oncoming human mover even if the human is unaware of (or ignores) the robot and even if the robot has a bias that conflicts with the passing direction used by the human mover; and 3) to test our hypothesis that the trade-off between more efficient but less reliable passing and less efficient but more reliable passing can be controlled by the single parameter β_r in the robot's algorithm (2).

A. Validation of Flexibility of the Approach

1) *Experimental Setup*: We ran a range of experimental trials each with a different scenario involving the robot and two human participants. In each trial, the robot and each of the humans were assigned a starting and goal location, which were selected to make the robot and human paths intersect. Human participants could walk along any path at any speed between their starting and goal locations.

In each trial, the robot was programmed to move at a constant speed of $V_r = 0.75\text{m/s}$ towards its goal location while adjusting to human movement according to the navigation model (2) with attention dynamics specified by (3). At any given time, the robot considers only the closest nearby human (according to the measure χ/κ) seen within a distance of 20m and an angular range of $(-\frac{\pi}{3}, \frac{\pi}{3})$ with

respect to the robot's heading. If no humans are detected, the robot's attention and opinion are reset to their neutral value, $u_r = z_r = 0$. Results from five representative trials are shown in Fig. 2. The parameters for (2) were $d_r = \alpha_r = 0.1$, $\gamma_r = 4$, $k_r = 1.5$, and $\beta_r = \pi/4$. The parameters for (3) were $\underline{u} = 0$ and $R_r = n = 7$. For trials in Fig. 2a-2d, $\bar{u} = 1.5$ and for the trial in Fig. 2e, $\bar{u} = 2.5$.

2) *Results*: Fig. 2 shows the resulting trajectories and the robot's opinion z_r and attention u_r over the full length of each trial. Temporal markers (dots) are included along the humans' trajectories and the robot's opinion and attention profiles. The top row shows how the robot navigates towards its goal while gracefully modifying its trajectory when encountering humans along its path. The bottom row shows how the robot's attention rises and falls in response to its proximity to a human. When the robot sees a human moving towards its left (resp. right), the opinion becomes negative (resp. positive) and the robot can be observed turning to its right (resp. left). When the robot sees no human to navigate around, its opinion is neutral and its go-to-goal behavior moves the robot towards its goal.

We observe in Fig. 2a-2c that the robot's opinion switches sign throughout each trial and that this is reflected in the robot's trajectory, which switches between turns to the left and turns to the right when it passes the human movers. The robot's attention rises and falls as the different participants are seen, maneuvered around, and passed by the robots. In Fig. 2d and 2e, the two human participants approach the robot side-by-side. However, the response of the robot is different in the two cases because the distance between the two participants is different. In Fig. 2d, the participants are close together and the robot passes to the right of both, whereas in Fig. 2e, the participants are further apart, and the robot navigates between them. This is a consequence of the proxy $\tan \eta_h$ that has the same sign for each human mover in the first case but different signs in the second case.

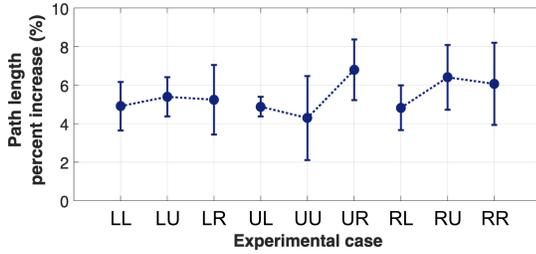


Fig. 6. Percent increase of the robot’s path length for $\beta_r = \pi/4$ compared to $\beta_r = \pi/6$ for each of the nine configurations. Dotted lines link results associated with the same robot bias. L/U/R labels as in Fig. 5.

B. Validation of the Deadlock Breaking

1) *Experimental Setup*: Fixed pairs of starting and goal locations were assigned to the robot and a human participant. The human participant was asked to walk from (0m, 6.1m) to (0m, -1m), and the robot was programmed to navigate from (0m, 0m) to (0m, 6.1m). These locations were selected to make the robot and human move head-on toward one another.

The robot was programmed to move at a constant speed $V_r = 0.7\text{m/s}$ toward its goal location, modifying its trajectory when encountering movers according to the navigation model (2) with parameters $d_r = 0.5$, $\alpha_r = 0.1$, $\gamma_r = 3$, $\tau_u = k_r = 1$, and $g(\kappa, \chi; R_r) = \exp(\kappa(R_r - \chi))$ with $R_r = 11$. We designed three cases corresponding to three different values of the robot’s bias b_r : 1) unbiased ($b_r = 0$), 2) biased to its left ($b_r = 0.5$), and 3) biased to its right ($b_r = -0.5$).

The participant was instructed to walk at their normal pace (their speed was recorded to be $V_h = 1.09 \pm 0.03\text{m/s}$) towards their goal location according to one of three prompts: 1) go straight, 2) bear to the left, and 3) bear to the right.

We crossed the three cases for the robot and the three prompts for the human participant for a total of nine different trial configurations. We ran each of these nine different trial configurations five times for a total of 45 trials. Each of the 45 trials was run with $\beta_r = \pi/4$ and $\beta_r = \pi/6$ in (2) for a total of 90 trials.

2) *Results*: Fig. 5 shows the resultant trajectories of the 90 trials organized by configuration on a 3×3 grid. For a given configuration and value of β_r all five trials are plotted on the same graph. Trials where $\beta_r = \pi/4$ are shaded in yellow and trials where $\beta_r = \pi/6$ are unshaded. It can be observed that the robot navigated each trial configuration with similar path structure, regardless of the value of β_r .

In all the scenarios where the robot was unbiased (second row of Fig. 5), it successfully broke deadlock, verifying the guarantee of deadlock-free navigation provided by the model (2) and justified in the analysis of Section III. In the trials when the human started directly facing the robot and continued walking straight ahead (UU), as in the simulation Fig. 4c, the robot quickly formed a strong opinion for one or the other direction. The robot chose to go left with about the same frequency that it chose to go right.

Having a bias allows the robot to rapidly form an initial opinion and break deadlock (turn left if $b_r > 0$ or right if $b_r < 0$). In the scenarios where the robot’s bias was in

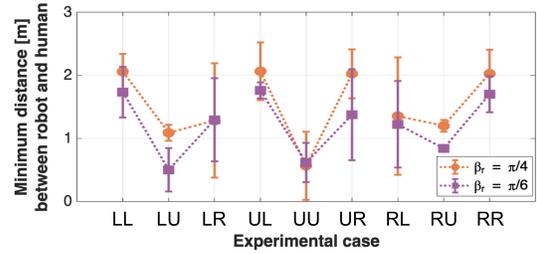


Fig. 7. Average minimum distance between the robot and human for each of the nine configurations. Dotted lines link results associated with the same β_r value (orange line for $\beta_r = \pi/4$, purple line for $\beta_r = \pi/6$) and robot bias. L/U/R labels as in Fig. 5.

conflict with the action taken by the human ((LR) and (RL) in Fig. 5), the robot initially moved according to its bias but quickly adapted to the social cues given by the human and passed them in a cooperative fashion, i.e., matching the human movement and in opposition to its bias. This demonstration of flexibility provides evidence that the robot can reliably adjust its opinion to fit the social context in which it interacts with the human.

The results of Fig. 5 also provide evidence that a smaller β_r (unshaded plots) leads to more efficient (less time to goal) passing around the human as compared to a larger β_r (shaded plots). Fig. 6 provides further evidence of the role of β_r in tuning efficiency as the percent increase in length of the robot’s path for the trials when $\beta_r = \pi/4$ as compared to the case in which $\beta_r = \pi/6$ was uniformly positive, at least 4% on average. Additionally, for each configuration, in trials with larger β_r the robot exhibited consistently higher maximum curvature along its path. Trials conducted with $\beta_r = \pi/4$ showed an increase of approximately $22.37\% \pm 6.71\%$ of the maximum curvature of the robot’s trajectory as compared to the case $\beta_r = \pi/6$. This confirms that a robot with a larger β_r is less efficient.

Notably, Fig. 6 shows that the smallest percent increase in robot path length for the increase in β_r is in the UU case, when the robot was unbiased and the human unaware of the robot. This is consistent with the result that in this trial configuration, the robot took the most time to form a non-neutral opinion and turn to pass the human, which kept its paths in both β_r cases closer to the trial space’s centerline than observed in other trial configurations.

Fig. 7 provides evidence that β_r tunes reliability and, together with the results of Fig. 6, that β_r tunes the efficiency-reliability trade-off, as hypothesized. The difference in the minimum distance recorded between the robot and human as they passed one another in each trial configuration for the different β_r values is shown in Fig. 7. The robot consistently came closer to the human along their paths for $\beta_r = \pi/6$ as compared to $\beta_r = \pi/4$.

For each set of three configurations grouped by the robot’s bias, the robot came closest to the human whenever the human was unaware of the robot (i.e. LU, UU, RU). In the other configurations, the robot was able to cooperate with the human to form its opinion and pass the human like the human

passed the robot. Without this cooperation, when the robot was the only participant in the passing, the passing distance was consistently smaller. The minimum distance in the case of the unbiased robot and unaware human was similar for the $\beta_r = \pi/4$ and $\beta_r = \pi/6$ trials. This suggests that this case is the most challenging for the robot independent of β_r . Still, the general decrease of the minimum distance between the robot and human that comes from a decrease in parameter β_r across all other configurations suggests that there is some design threshold where, once passed, the robot could not reliably navigate its way out of collision. Even if the robot's algorithm is such that it can reliably form non-neutral opinions to break deadlock, the design parameters within the model must be sufficiently tuned for use in a real world dynamic context.

V. DISCUSSION AND FINAL REMARKS

We present a new proactive approach to social robot navigation that leverages a nonlinear opinion dynamics model to enable a robot to rapidly and reliably pass approaching human movers, without requiring a model of human behavior. We show analytically and verify with human-robot experiments that this new navigation algorithm is guaranteed to break deadlock, even when the robot has no bias or evidence from the humans or the environment that one passing direction is better than the other. The experiments verify the flexibility of the approach with the robot reliably modifying its trajectory when encountering two human movers in its path. The experiments also verify that a robot with a bias for passing in one direction can still reliably pass the human mover even if the human chooses to pass in the direction that conflicts with the robot's bias. We show further how design parameters in the robot navigation algorithm can tune the robot's behavior, and verify in the experiments that parameter β_r tunes the efficiency-reliability trade-off in the passing problem. Future directions include extending the new approach to multi-robot social navigation in more complex scenarios, e.g., with more human movers and more cluttered environments. We also plan to investigate an extension that allows for increased sensitivity to changes in context and tuning important trade-offs like efficiency versus reliability.

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