Opinion-Driven Robot Navigation: Human-Robot Corridor Passing
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Abstract—We propose, analyze, and experimentally verify a new approach for robot social navigation in human-robot corridor passing that is driven by nonlinear opinion dynamics. The robot forms an opinion over time in response to its observations, and its opinion drives its motion control. The algorithm inherits a key feature of the opinion dynamics: deadlock, also known as the “freezing robot” problem, is guaranteed to be broken even if the robot has no bias or evidence for whether it is better off passing on the right or the left. The robot can also overcome a bias that is in conflict with the passage choice the human makes. The approach enables rapid and reliable opinion formation, which makes for rapid and reliable navigation. We verify our analytical results on deadlock breaking and rapid and reliable passage with human-robot experiments. We further verify through experiments that a single design parameter can tune the trade-off between efficiency and reliability in human-robot corridor passing. The new approach has the additional advantage that it does not rely on a predictive model of human behavior.

Index Terms—spatial navigation, robotics, opinion dynamics, decision making, human-robot interaction, socially aware navigation

I. INTRODUCTION

With delivery robots, automated moving carts, and robotic store monitors being employed by businesses today, it is clear that autonomous mobile robots are becoming more commonly used around humans in motion. These kinds of human-robot interactions in dynamic environments require that mobile robots use algorithms that allow them to perform their tasks while safely and gracefully navigating around human movers.

In this paper we propose, analyze, and experimentally verify a new approach for robot navigation around an oncoming human mover (see Figure 1a). The approach guarantees the robot will always break deadlock (i.e., solves the “freezing robot” problem [1]) and choose either to pass the human on the right or on the left, even if the robot has no directional bias and no indication from the human or the environment that one passage is better than the other. In case the robot does have a directional bias, and that bias conflicts with the human’s chosen passing direction, the robot will quickly and reliably move to avoid collision even if the movement is in opposition to its own bias.

Our approach provides a navigation algorithm that relies on a continuous-time nonlinear model of opinion dynamics [2]. The robot forms an opinion using these dynamics, and its time-varying opinion drives its motion control. We leverage a key feature of the nonlinear model: at a critical level of robot “attention”, the opinion dynamics are highly sensitive to observations, and deadlock (indecision) becomes an unstable solution of the dynamics. As a result, deadlock breaks and a strong opinion rapidly and reliably forms. In our algorithm, we have designed the robot’s attention to increase as the robot’s perceived proximity to the oncoming mover increases. We let the critical level of attention be one of the design parameters, which can be used to tune the sensitivity of the robot’s response to its observations.

Of relevance to our work is the literature on robot social navigation (see recent survey articles [3]–[5] 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. Earlier work [6] 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 [7, 8] improve the social force model by incorporating social cues and the improved models are used to design robot navigation algorithms. The work of [9] proposes a constrained optimization approach to design a navigation algorithm that penalizes the robot when its behavior violates conventions observed in human’s navigation. Also, learning-based approaches [10]–[12] leverage the recent advancement in deep reinforcement learning to train mobile robots 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 [13] 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 [12, 14, 15], 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 [16] studies the effect of human-robot communication in social navigation and proposes a IRL-based robot planning framework to generate communication actions that maximize the robot’s transparency and efficiency.

Our work is distinct in that 1) our approach 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. 2) Our robot navigation model is analytically tractable so that we can establish guarantee on deadlock-free navigation. This contrasts the reinforcement learning approaches that are, in general, difficult to analyze, and existing reactive approaches, such as social force models, that do not provide meaningful performance guarantees.

Opinion dynamics have been used to facilitate collective decision-making in robotic teams [17]–[19]. In the present paper, we use opinion dynamics to drive the social navigation of a robot interacting with a human.

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 system theory, we discuss how the model ensures deadlock-free robot navigation. To validate the effectiveness of our approach, we carry out experiments with a human participant and mobile robot, which we report on in Section IV. We conclude the paper with discussion and remarks in Section V.

II. NONLINEAR OPINION DYNAMICS IN SOCIAL NAVIGATION

We study a two-agent social navigation problem where a robot approaches and passes an oncoming human to reach its destination, which is behind the oncoming human as illustrated in Figure 1a. This is representative of problems such as a robot passing a human in a corridor or other narrow passageway [20, 21]. 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 passing but it is not so efficient 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 presented in [2]. We review the model of nonlinear opinion dynamics in Section II-A. We specialize the model to 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. We discuss limitations and possible extensions of the model design in Section II-C.

A. Nonlinear Opinion Dynamics Model

Consider a system of $N_o$ agents forming opinions about two options\(^1\). Let $z_i \in \mathbb{R}$ define the opinion state of agent $i$ such that it prefers option 1 if $z_i > 0$, it prefers option 2 if $z_i < 0$, and it is indifferent if $z_i = 0$. Strength of preference is $|z_i|$.

The nonlinear opinion dynamics model [2] prescribes how an agent updates its opinion state continuously over time in response to what it can measure about its own state, the state of others, and any internal bias or external stimulus:

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

(1)

where $\dot{z}_i = dz_i(t)/dt$ and $t \in \mathbb{R}_+$ is time.

The opinion state $z_i$ 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 state $z_k$ of every agent $k$ observed by agent $i$ and a bias (or external stimulus) $b_i$. The resistance parameter $d_i > 0$ defines the rate of exponential discount in the accumulation of the social influence. The attention parameter $u_i \geq 0$ is a tuning parameter, 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 $\gamma_i \in \mathbb{R}$ weight how much influence, and in the case of $\gamma_i$ what kind of influence, $z_j$ and the $z_k$ values, respectively, have on agent $i$’s evolving opinion. If $b_i > 0$ (resp. $b_i < 0$), the bias is for option 1 (resp. for option 2). In case of no bias $b_i = 0$.

B. Dynamic Model for Opinion-Driven Robot Navigation

In our navigation problem there are two agents, the robot and the human. We denote the opinion of the robot as $z_r \in \mathbb{R}$. If $z_r > 0$ (resp. $z_r < 0$), the robot prefers to move left

\(^1\)The model of [2] is defined for an arbitrary number $N_o$ of options.
(resp. right). When $z_r = 0$, the robot is indifferent to these options. We do not model the human’s opinion; however, we assume that the robot can measure the heading $\eta_h$ of the human relative to the line between the robot and the human (see Figure 2). We let $\tan \eta_h(t)$ be a proxy for the robot’s observation of the human’s opinion at time $t$, letting the human’s orientation act as a signal of their navigational intent (supported in works such as [22]–[24]).

Using the nonlinear opinion dynamics (1), we propose a dynamic model that provides an algorithm for robot navigation. The model specifies how the robot’s opinion state $z_r$ and attention parameter $u_r$ change in response to its observations of the human ($\eta_h(t)$) and its own state, and how $z_r$ and $u_r$ regulate the robot’s angular velocity as it heads to its goal $\phi_r$.

Before introducing the model, we first define some important variables (see Figure 2). We assume that the robot is moving at a constant speed $V_r$, and we represent the robot’s position and heading angle as $x_r = (x_r, y_r)$ and $\theta_r$, respectively. We denote by $V_h$, $x_h = (x_h, y_h)$ and $\theta_h$ the human’s speed, position and heading angle, respectively. We denote by $\eta_r$ the heading of the robot relative to the line between the robot and the human.

The robot navigation model is described as follows:

\[
\dot{z}_r = -d_z z_r + u_r \tanh (\alpha_r z_r + \gamma_r \tan \eta_h + b_t)
\]
\[
\dot{u}_r = -m_r u_r + \exp (c_r (R_r - ||x_r - x_h||) \cos \eta_r)
\]
\[
\dot{\theta}_r = k_r \sin (\beta_r \tanh z_r + \phi_r)
\]

where $m_r, c_r, k_r > 0$ and $\beta_r \in (0, \frac{\pi}{2}]$ are additional design parameters.

The nonlinear opinion dynamics (2a) govern the robot’s formation of opinion $z_r$ by accumulation of social influence. (2a) is similar to (1) except the human’s opinion state $z_h$ is replaced with $\tan \eta_h$, which we adopt as a proxy for the robot’s perception of the human’s preference on direction.

By (2b), the variable $u_r$ exponentially increases as the robot and human get closer to each other and their distance becomes smaller than the critical value $R_r > 0$, as long as the human has not passed the robot ($\cos \eta_r > 0$). This ensures that the robot becomes increasingly attentive to the human presence when it is near the human. This in turn ensures that the robot will become highly sensitive to what it measures and will rapidly and reliably pass around the human mover.

Equations (2a) and (2b) enable the robot to form a strong, non-neutral, opinion on the direction it will move to pass the oncoming human mover – see Section III for a rigorous analysis of deadlock breaking in the case that the human is either unaware of the robot or ignores the robot and heads straight for the robot. Unlike other approaches that require a longer-term prediction of human trajectories, such as [12, 14]–[16], our model only needs the instantaneous observations of $\eta_h$, which is an important advantage of our approach.

By (2c), the robot’s heading angle is regulated by its own opinion state $z_r$ and its orientation to its goal $\phi_r$. To understand the role of design parameter $\beta_r \in (0, \frac{\pi}{2}]$, note that when $z_r$ is sufficiently large so that $\tanh z_r \approx 1$, (2c) steers the robot’s heading angle an additional $\beta_r$ radians in the counterclockwise direction from the orientation to the goal location. Hence, we can tune $\beta_r$ 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. As a result, the parameter $\beta_r$ can be used to tune the reliability-efficiency trade-off as we show through the human-robot experiments described in Section IV.

For all simulations and experiments in this paper, we let $\alpha_r = 0.1, \gamma_r = 3, m_r = c_r = 1$ and $k_r = 1$.

C. Discussions on Model Design

We discuss some restrictions of the current version of our approach and potential remedies to overcome the limitations, which we plan to pursue as future directions. Since the model only controls the robot’s heading angle while keeping the moving speed constant, (2c) can be thought of as reactive robot control. Such methods have been shown effective when the robot is navigating in rather simple environments, for instance, areas without many obstacles. However, the controller may maneuver the robot to a local minimum especially when the environment is cluttered and prevent the robot from reaching its goal. In addition, our problem formulation focuses on a two-agent (human and robot) two-option (move left or right) navigation scenario. Such formulation and our solution to it may not be directly applicable when we want to develop a robot navigation algorithm that allows the robot to stop and wait for the human to go first, or there is a group of humans passing by the robot.

As a future direction, we plan to integrate a path planning approach, such as the rapidly-exploring random tree (RRT), to prevent the robot from entering a local minimum, and improve the robot control by regulating not only its angular velocity but also its moving speed. The improvement on the controller will allow the robot to stop when needed. In addition, we plan to explore computational tools to automate finding viable options for effective navigation in human-populated areas. A recent work in multi-agent learning [25] demonstrated the use of machine learning methods to find effective options in multi-agent strategic interactions.

Fig. 2: An illustration of human-robot corridor passing in the 2D plane and key variables describing geometric relations between the two agents.
settings, (2a) simplifies to

\[ z_r = 0 \]

The neutral (deadlock) state \( z_r = 0 \) is always an equilibrium solution of (3). 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 Figure 3a 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 state equation (3) around the equilibrium state \( z_r = 0 \) and examine the eigenvalue \( \lambda = -d_r + \alpha_r u_r \) of the resulting linearization. This is important because the sign of \( \lambda \) governs the stability of the equilibrium state \( z_r = 0 \). When \( \lambda < 0 \), \( z_r = 0 \), and thus deadlock, is stable, but when \( \lambda > 0 \), \( z_r = 0 \), and thus deadlock, is unstable.

The value of \( u \) corresponding to \( \lambda = 0 \), computed as \( u^*_\lambda = d_r/\alpha_r \), is thus the critical attention value. When the robot pays less attention \( (u_r < u^*_\lambda) \), \( \lambda < 0 \) and the robot remains in deadlock, attempting to go straight to its goal location. However, when the robot pays more attention \( (u_r > u^*_\lambda) \), \( \lambda > 0 \) and deadlock becomes unstable. For \( u_r > u^*_\lambda \) it can be shown that there are two additional symmetric equilibrium states \( z^+ = -z^- > 0 \) that are both stable. These solutions correspond to a preference \( \gamma_r > 0 \) for going left \( (z_r = z^+ > 0) \), or the positive blue curve in Figure 3a, and a preference \( \gamma_r < 0 \) for going right \( (z_r = z^- < 0) \), shown as the negative blue curve in Figure 3a. Note that the strength of preferences increases with increasing \( u_r > u^*_\lambda \). 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 Figure 3b. This implies that the robot prefers one side over the other when it passes the unaware human mover. In particular, it can be shown that the robot prefers to move left \( (\gamma_r \tan(\eta_h) + b_r > 0) \), and right \( (\gamma_r \tan(\eta_h) + b_r < 0) \). Also, as we can observe from the diagram in Figure 3b, 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 Figure 3c. 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 Figure 3a. 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 the positive blue curve in Figure 3b.

### III. Guarantee on Deadlock-Free Navigation

A key contribution of our work is in guaranteeing deadlock-free navigation. We establish such 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 \((x < 0)\) or right \((x > 0)\) – 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 [26] to show that there is a deadlock-breaking pitchfork bifurcation in (2), when the robot’s attention \( u_r \) reaches a critical level \( u^*_\lambda \) (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 case where the human is unaware of the robot’s presence and does not react to the robot’s movement and the robot is either unbiased or biased. We validate our analysis through human-robot experiments in Section IV.

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

\[ \dot{z}_r = -d_r z_r + u_r \tanh(\alpha_r z_r) \]  

\[ z_r = 0 \]
Fig. 4: 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 $(0,0)$ m. The human paths are shown in blue with a blue box at the human’s starting position at about $(0,6.1)$ m. In trial configuration labels, L=left, U=unaware/unbiased, and R=right.

A. Experimental Setup

All walking trials took place in a laboratory space equipped with a Vicon motion capture system. The participant wore a hat tagged with a set of Vicon markers to capture their position and heading angle as they walked. Similarly, the robot’s position and heading angle were recorded using the Vicon system.

Fixed pairs of starting and goal locations were assigned to the robot and human participant. The human participants were 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 toward one another (see Figure 1b for an illustration).

In each experiment, the robot was programmed to move at a constant speed $V_r = 0.7m/s$ toward its goal location while reacting to the human movement according to the navigation model (2). The parameters of (2) were selected as $d_r = 0.5$, $\alpha_r = 0.1$, $\gamma_r = 3$, $m_r = c_r = 1$, $R = 11$, and $b_r = 1$.

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 as $V_h = 1.09 \pm 0.03m/s$) 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.

B. Results

Figure 4 shows the results of all 90 experimental trials with the 9 different trial configurations organized on a 3x3 grid. All five trials for a given configuration and value of $\beta_r$ are plotted on the same graph. Plots of trials where $\beta_r = \pi/4$ are shaded in yellow and plots where $\beta_r = \pi/6$ are unshaded.

It can be observed in Figure 4 that the robot navigated each trial configuration in experiment with similar path structure, regardless of the value of $\beta_r$. In scenarios where the robot’s bias was in conflict with the action taken by the human, e.g. the robot had a bias to its left while the human walked towards their right, the robot was able to quickly adapt so that it passed the human in a cooperative fashion, i.e., matching the human 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 second row of Figure 4 shows the experimental results for the unbiased robot. Here it can be seen that in every case, the robot 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 not only started directly facing the robot but also continued walking straight ahead, (middle of the grid), as in Figure 3a and the simulation of Figure 3c, 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.

The results of Figure 4 also provide evidence that a smaller $\beta_r$ (unshaded plots) lead to more efficient passing around the human as compared to a larger $\beta_r$ (shaded plots).

Further evidence of the role of $\beta_r$ in tuning efficiency is provided in Figure 5, which shows that the percent increase in length of the robot’s path for the experiments 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 experiments with larger $\beta_r$ the robot exhibited consistently higher maximum curvature along its path. Trials conducted with $\beta_r = \pi/4$ showed an increase of approximately 22.37% ± 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 $\beta_r$ is less efficient.

Figure 5 shows that the smallest percent increase in robot path length for the increase in $\beta_r$ 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 $\beta_r$ cases closer to the experimental space’s centerline than observed in other trial configurations.

Figure 6 provides evidence that $\beta_r$ tunes reliability and together with the results of Figure 5 that $\beta_r$ 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 $\beta_r$ values is shown in Figure 6. 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 $\beta_r = \pi/6$ experiments. This suggests that this case is the most challenging for the robot independent of $\beta_r$. Still, the general decrease of the minimum distance between the robot and human that comes from a decrease in parameter $\beta_r$ 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

In this work, we present a new approach to social robot navigation wherein a nonlinear opinion dynamics model is leveraged to enable a robot to rapidly and reliably pass an approaching human mover in a corridor, 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 human or the environment that one passing direction is better than the other. 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 $\beta_r$ tunes the efficiency-reliability trade-off in the passing problem. Future directions include extending the new approach to robot navigation in the passing problem to more human movers and/or more robots. We also plan to investigate making design parameters that tune important trade-offs, like $\beta_r$, adaptive to changing environments and social context.

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