Social Collision Avoidance via Topological Inference

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Abstract

We focus on motion planning for social robot navigation in crowded environments such as pedestrian scenes. Navigating such environments is a difficult task for a robot mainly due to the lack of concrete rules regulating traffic and the lack of explicit communication among agents. Recent works tend to account for these complications by attempting to reproduce selected social conventions or imitate selected patterns of observed human behavior, yielding only domain-specific performance. Our key insight is that crowd navigation exhibits *topological* structure, in the sense that the navigation strategies of rational agents in a shared space are coupled. For instance, in a narrow hallway, two agents must either agree on passing from the left or the right side to avoid collisions. Understanding this structure may enable a robot to make principled decisions even in the absence of detailed models of human navigation. Based on this observation, we design a motion planner that leverages *topological*-level inference rather than detailed trajectory prediction. A physics-inspired metric guides the robot towards actions that comply with the unfolding trajectory topology. Our findings from an online, video-based user study with 180 human subjects illustrate the efficacy of our planner in generating trajectories perceived as intent-expressive by human users. Moreover, evidence extracted from a follow-up in-lab user study with 105 participants suggests that human acceleration is low when navigating in close proximity to an autonomous robot running our planner.

Figure 1: Snapshot from our user study [14] examining the performance of our navigation algorithm in crowded pedestrian spaces.

1 Introduction

As robots start entering human environments to perform a variety of tasks, the need for complying with established social norms and human expectations becomes increasingly important. Within the domain of mobile robotics, this is particularly evident when deploying a robot in a crowded human environment. Due to our limited understanding of the complex mechanisms underlying human navigation [25], roboticists often employ practical engineering approaches such as modeling humans as moving obstacles [20], attempting to reproduce selected social conventions [2, 10, 19, 21] or imitate observed patterns of human behavior [1, 8, 9, 12, 24]. The highly interactive nature of pedestrian environments often *breaks* such approaches yielding notable empirically observed issues such as: (a) the "reciprocal dance" [4], a short deadlock situation in which the human and the robot oscillate around their position as they attempt to agree on a passing side, a phenomenon typically attributed to oversensitivity of the robot's strategy; (b) the "freezing robot problem" [22] in which an overcautious algorithm gets the robot stuck in place by erroneously determining that at its current state there exists no collision-free path to its destination. Observing that human and robot motion in crowded domains is tightly coupled, a number of works have proposed navigation frameworks based on joint behavior prediction models, explicitly reasoning about the effects of the robot's actions on the inference and decision making of human bystanders [2, 9, 11, 22].

Following up on this line of work, our unique insight is that in crowd navigation, the coupling of multi-agent behavior exhibits a *topological* structure. Explicitly incorporating this structure into the robot's decision-making policy has the potential of enabling robust adaptation to the emergence of unexpected human behaviors. Furthermore, understanding and monitoring the multi-agent dynamics gives the robot the opportunity to proactively reinforce the expectations of bystanders about its navigation intentions. Over the past few years, this rationale has resulted in the design of a series of motion planners making use of topological models of multi-agent navigation [13, 15–17] as well as a series of user studies that illustrates the value of topological features for multi-agent and crowd robot navigation [14, 18]. In this short paper, we summarize some of our findings and present directions for future work.

2 The Social Momentum Planning Framework

Consider two agents navigating towards their destinations in a shared workspace. In order to reach their destinations in a collision-free and socially compliant fashion, agents need to negotiate and follow a strategy of collision avoidance (e.g., right or left passing), while respecting the personal space of each other [6]. To quantify how well agents are doing with respect to both of these specifications, we construct an index, defined as an analogy to the physical quantity of Angular Momentum.

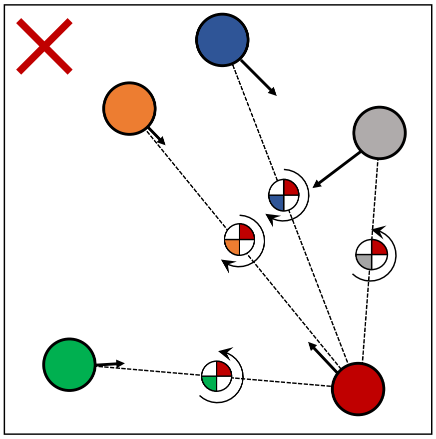


Figure 2: Social Momentum: The planning agent (red color) is moving towards the red target X, while complying with its pairwise momenta with all other agents.

Assuming unit masses for the two agents, the angular momentum of their system with respect to its center of mass C is defined as:

$$L^{AB} = r_A^C \times v_A + r_B^C \times v_B \tag{1}$$

where

$$r_A^C = q_A - r_C, \qquad r_B^C = q_B - r_C \tag{2}$$

are agents' positions, defined with respect to their center of mass

$$r_C = (q_A + q_B)/2. \tag{3}$$

For a system of agents navigating on the horizontal plane, the angular momentum is a vector perpendicular to the workspace, pointing along the positive direction of the z-axis for counterclockwise agent rotations and along the negative direction of the z-axis for clockwise rotations, thus encoding the right and left passings respectively. Its magnitude depends on the distance between the agents and also on the angle of their velocities, with larger distances and antiparallel velocities scoring higher. Thus, we observe that the angular momentum may be used: (a) as a tool to monitor an emerging avoidance protocol (right/left passing); (b) as a tool to generate easily interpretable avoidance maneuvers in compliance with the preferences of the other agent and in consistency with previous behaviors of the agents.

In a crowded workspace, an agent interacts with multiple others at the same time, in the sense that every action taken broadcasts signals of intentions or preferences over avoidance strategies. We express this observation through the *Social Momentum* index $\mathcal{L}$, defined for agent i as a real function $\mathcal{L} : \mathcal{A} \to \mathbb{R}$ over the agent's action space $\mathcal{A}$:

$$\mathcal{L}(a) = \begin{cases} \sum_{j \neq i} w_j ||\hat{L}^{ij}(a)||, & \text{if } sign\left((L^{ij})^T \hat{L}^{ij}(a)\right) > 0 \;\forall j \in N_i \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where $\hat{L}^{ij}(a)$ denotes the expected pairwise momentum between agents i and j, upon agent i taking an action in consideration, $a \in \mathcal{A}$ and agent j moving with its current velocity, L^{ij} is their current momentum and $w_j \in \mathbb{R}$ is a weight, computed as a function of the inverse of the distance between agents i and j. The quantity $sign\left((L^{ij})^T \hat{L}^{ij}(a)\right)$ indicates whether the expected evolution of the pairwise momentum between agents i and j is in compliance with their current momentum L^{ij}. A positive sign corresponds to an action that preserves the current momentum sign and thus the currently preferred pairwise avoidance protocol. A negative sign indicates inversion of the established pairwise avoidance protocol, which is undesired. For this reason, an action that results to inversion of a pairwise momentum is assigned a score of zero. Overall, higher $\mathcal{L}$ values indicate higher certainty over the emerging pairwise avoidance protocols between the agent others. The proposed index enables an agent to monitor the compliance among the intended navigation strategies of multiple agents and select actions that amplify it. These actions are naturally intent-expressive, simplifying inference and decision making for other agents.

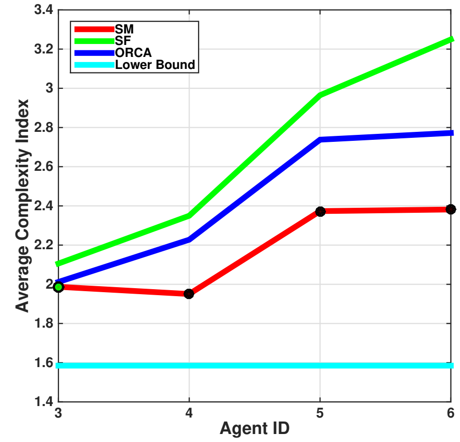


Figure 3: Average *Topological Complexity* of trajectories generated by executing 200 scenarios with 3, 4, 5 and 6 agents with the *Social Momentum* (SM), *Social Force* (SF) and *Optimal Reciprocal Collision Avoidance* (ORCA) models. A theoretical lower bound baseline is also included for reference. Datapoints marked black correspond to significantly lower average *Complexity* of SM than both SF and ORCA, whereas the datapoint marked green indicates significantly lower average *Complexity* of SM than SF, according to paired Student's T-test.

Based on this index, we design a policy for the generation of socially compliant robot motion:

$$a^* = \underset{a \in \mathcal{A}}{\operatorname{argmax}} \{\lambda \mathcal{E}(a) + (1 - \lambda)\mathcal{L}(a)\}, \tag{5}$$

where $\lambda \in \mathbb{R}$ is a parameter accounting for proper scaling and weighting of the two quantities. We model the progress function $\mathcal{E} : \mathcal{A} \to \mathbb{R}$ to be the inverse of the length of the unobstructed line to destination. The action space $\mathcal{A}$ comprises a presampled set of actions of finite duration that are executable by the agent.

2.1 Simulation Study

Our first step towards validating our policy was a simulated evaluation in which we investigated whether the behaviors generated with Social Momentum (SM) are indeed socially compliant. To this end, we employed a measure of Complexity of multi-agent behavior, the *Topological Complexity* Index [3]. This notion of complexity quantifies the intensity of agents' mixing patterns –the more direct the encounters among agents are, the higher the topological complexity of their trajectories is. Considering a circular workspace with a diameter of $5m$, and agents represented as discs of diameter

$0.6m$, we generated a set of challenging scenarios involving groups of homogeneous agents navigating towards antipodal sides of a circular workspace. We compared the performance of SM against the *Social Force* (SF) model [7] and the *Optimal Reciprocal Collision Avoidance* (ORCA) framework [23] in 4 classes of scenarios, involving respectively 3, 4, 5, and 6 agents (200 scenarios per class).

Fig. 3 depicts the average *Topological Complexity* (TC) for each planner and class of scenarios considered. TC of executions generated by SF and ORCA appears to be consistently rising with the number of agents. In contrast, SM exhibits a slower rise; the transitions between 3 and 4 agents and between 5 and 6 agents are done with almost constant complexity, with the only rise taking place in the transition between 3 and 4 agents. Overall, SM achieves consistently lower topological entanglement with statistical significance, except from the case of 3 agents, where the scenarios are not geometrically challenging to yield significantly diverse behaviors. Despite this result, the theoretical Lower Bound consistently outperforms all planners, providing an illustrative demonstration of their suboptimality in terms of *topological efficiency* which reflects the price of no explicit communication in multi-agent planning. Note that the constant *Complexity Index* value of 1.5850 that the Lower Bound achieves is an artifact of the symmetry of the considered scenarios (agents traveling to antipodal points in the workspace).

2.2 Online Study

As a next step, we sought to ground the simulation results to real-world implications. To this end, we conducted an online, video-based user study, in which we asked participants to watch a series of videos of simulated executions of scenarios involving 5 agents navigating a circular workspace (shown from a top view). For each video, users were asked to predict the way two agents were going to avoid each other (right or left side). Speed and correctness (the basis of the legibility definition) were incentivized through a scoring system that awarded points for quick and accurate answers and deducted points for wrong or slow responses (Fig. 4 depicts the study interface). The study used a total of 15 videos, with duration ranging from 6.3 to 15.7 seconds, corresponding to scenarios of varying complexity, measured using the *Topological Complexity* index [3]. More than 180 users, recruited from the social media platforms of Reddit and Facebook, contributed a total of 2704 video views and clicks.

Fig. 5 depicts our findings from analyzing the collected dataset. The blue trend shows the relation between the *Complexity Index* and the median time of correctly predicting the side on which one agent will pass another. We fit a linear model to the data using iteratively reweighted least squares, shown in Fig. 5 as a blue line with a 95% confidence interval. The effect of the *Complexity Index* on click time is positive, with a slope of 0.0236, and significant (Student's t-test, $t = 5.60, p < 0.001$). In other words, as the topological entanglement intensifies, users take more time to accurately predict the side of passing, i.e., more complex scenarios are less legible.

The green trend shows the relation between the *Complexity Index* and the time of passing between the two agents. We fit a linear model to the data, shown as the green line with a 95% confidence interval. The trend is positive (slope of 0.0833) and nearly significant ($t = 1.93$, $p = 0.0538$). Increased *Complexity* correlates positively

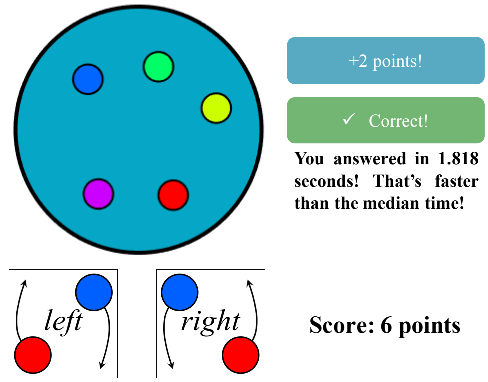


Figure 4: Study interface: A video of a scenario execution is shown and users predict how the red agent is going to avoid the blue agent by pressing the corresponding button at the bottom. The display of user's score and performance statistics aim to to incentivize fast and accurate responses.

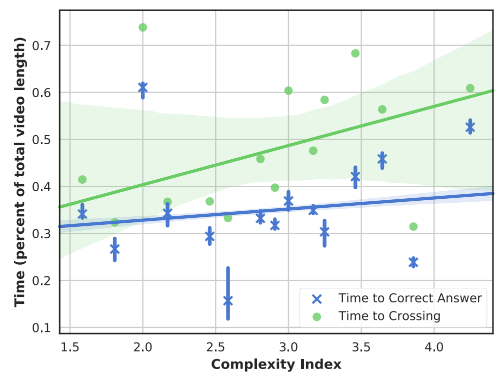


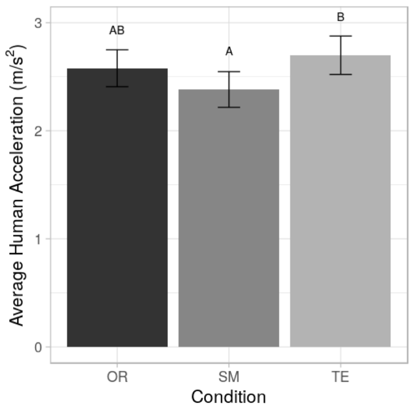
Figure 5: Relation between the *Complexity Index* and (a) time until two specific agents pass each other (green points/line) and (b) median time until users give a correct prediction of the passing (blue crosses/line). Times are normalized to the total length of the relevant video.

with increased time of passing, and thus with longer, less efficient interactions.

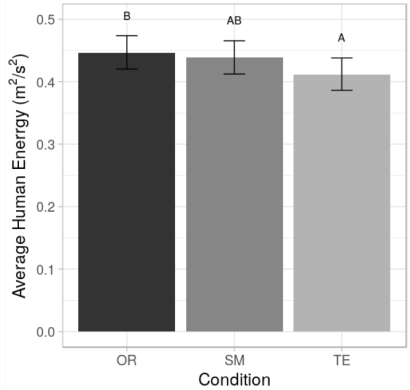
This study illustrates the implications of our simulated study for the application of SM as an algorithm for navigation in crowded real-world environments. SM yields executions of significantly lower complexity than the baselines considered. Further, we showed that low Topological Complexity is correlated with high legibility in multi-agent scenarios. Therefore, SM has the potential of yielding legible robot behaviors in crowded environments.

3 Lab Study

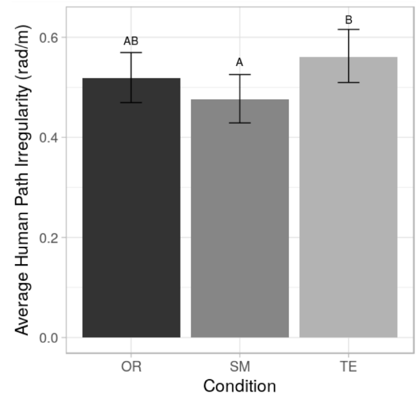
Our next step was to study the implications of our online study for robot navigation in crowded real-world environments. To this end, we conducted a lab study, specifically designed to enforce a setting of coincidental, implicit, nonverbal encounters between the robot (a Beam Pro, depicted in Fig. 1) and a group of three human participants. The study took place in a rectangular workspace with an area of $16m^2$ which yielded a moderately crowded scene. Under a fictional factory-setting scenario, the participants and the robot were assigned a set of fictional maintenance tasks that motivated their continuous movements across all sides of the workspace. With



(a) Acceleration per segment.



(b) Energy per segment.



(c) Path Irregularity per segment.

Figure 6: Expected means and confidence intervals for human trajectory quality criteria. Quantities labeled with distinct letters (A, B) are significantly different (Tukey's HSD test, $p < 0.05$).

this design, we elicited a high frequency of close but comfortable encounters between the robot and participants. In order to motivate natural walking behaviors, we did not disclose the true purpose of the study. Participants' cognitive load from following the scenario and executing tasks also contributed to this goal. Finally, we considered three conditions and kept the total duration of the study under thirty minutes to minimize fatigue effects. The outlined design was specifically chosen to resemble the typical interaction among walking pedestrians in public spaces [26].

Each group of human subjects participated in three experimental trials. Each trial is executed under a different condition, corresponding to a distinct navigation algorithm run by the robot. As baselines to *Social Momentum* (SM) [18]), we consider *Optimal Reciprocal Collision Avoidance* (ORCA) [23], and teleoperation strategy (TE), in which a member of the research team controls the robot in a Wizard-of-Oz fashion. These conditions were selected due to the diversity of decision making principles that they represent, i.e., ORCA is designed to be optimal, SM is inherently intention-aware; TE is designed to appear humanlike. During each trial, we tracked and recorded the human and robot trajectories through an overhead motion capture system.

We conducted 35 experiment sessions, in which a total of 105 (59 female, 45 male, 1 unidentified) human subjects (age $M = 21.45$, $SD = 3.19$), recruited from the student population of Cornell University were exposed to all conditions in groups of 3 (within-subjects design). Focusing on dynamic interactions of close proximity (minimum distance $d < 1m$) between the robot and participants, we split the human trajectory dataset into a set of 1566 segments. We characterized the trajectory dataset using a set of trajectory quality measures, including: (1) the average *Acceleration* per segment; (2) the average *Energy* per segment, where energy is defined as the integral of the squared velocity of an agent throughout its trajectory; (3) the *Path Irregularity* per segment, measuring the total amount of unnecessary rotation (angle between an agent's heading and direction to goal) that an agent exhibits per unit path length [5].

We modeled the dependency of the human trajectory quality measures to the condition with linear mixed-effects models, accounting also for random effects of session, trial and helmet per trial. Fig. 6 depicts the expected means and confidence intervals for the human trajectory quality measures. We observe that humans exposed to the SM condition followed smoother trajectories, of lower acceleration (Fig. 6a; one-way ANOVA: $F(2, 250.4) = 3.888$, $p = 0.0217$) and path irregularity (Fig. 6c); one-way ANOVA: $F(2, 249.4) = 3.286$, $p = 0.0390$) than humans exposed to either ORCA or TE, which confirms. This was in line with our expectations: SM's intention-aware navigation strategy adapts the robot's behavior to the preferences of humans, thus facilitating human inference and decision making. Further, it was observed that humans spend the least energy when exposed to TE. We attribute this finding to the perceived humanlikeness of the motion generated by a teleoperated robot: the embodiment of human decision making on a robot platform features humanlike traits that potentially enable a higher level of human comfort. Finally, humans spend the most energy around OR (see Fig. 6b), which confirms. This could be perceived as an result of ORCA's more predictable motion (minimal divergence from desired direction). Higher predictability potentially results in higher confidence for participants, which allows them to move faster and thus spend more energy.

4 Discussion

While our experiments illustrated the value of topological features for social robot navigation, we have not yet validated our approach outside of the lab. Our lab experiments were designed to reinforce incidental, off-task human-robot encounters, however the complexity of real-world environments would be significantly higher. Future work involves planning a field study in a crowded environment such as an academic building.

Furthermore, while our quality measures are physically motivated, they have not been benchmarked. It is still unclear what are the right metrics and experiments with which we should measure the performance of social robot navigation frameworks. Further research should specifically investigate the test methods, variables, experiments and metrics for benchmarking social robot navigation research.

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