Towards Socially Competent Navigation of Pedestrian Environments

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Summary

We present a planning framework for producing socially competent robot behaviors in pedestrian environments. The framework is designed according to conclusions of recent psychology studies on action interpretation and sociology studies on human pedestrian behavior. The core of the approach is a novel topological representation of the pedestrian scene, based on braid groups. Thanks to this representation, our online algorithm is able to reason about several topologically distinct scene evolutions, simultaneously predicting future behaviors of other agents and planning the robot's role in the scene. This is especially important in crowded pedestrian scenes of high uncertainty. Preliminary simulation results demonstrate the potential of our approach for application in real world scenarios.

I. Motivation

Pedestrian Environments

- Dynamic.
- No formal rules guiding traffic.
- No explicit communication among humans.

Robotic Navigation

- Typically focusing on geometrically optimal/energy efficient motion generation.
- Typically treating humans as moving obstacles.
- Data-driven approaches focusing on imitating observed human behaviors and human trajectory prediction.

Practical Problems

- Robot motion is hard to read.
- Hinders humans' paths.
- Draws unnecessary attention.
- "Reciprocal dance".
- "Freezing" robot.
- Poor generalization.

Figure 1. An example of *antisocial* robot behavior.

II. Foundations

Human Pedestrian Behavior

The Pedestrian Bargain [1]

1. People must behave like competent pedestrians.
2. People must trust that others behave like competent pedestrians.

The smooth coexistence of pedestrian is based on *trust*.

Human Behavior in the presence of others

Teleological Reasoning [2]

Humans tend to associate an observed action with a potential goal.

Motion Planning in the presence of humans

Incorporating Inference in Motion Planning [3]

Encoding intention into robot motion.

III. Models

A. *Pedestrian Scene Model*

- n agents moving in a common workspace $\mathcal{W}$.
- Starting locations: $\Sigma = \langle s_1, s_2, \ldots, s_n \rangle$, $s_i \in \mathcal{W}$.
- Set of possible destinations $\mathcal{D} \in \mathcal{W}$.
- Intended Destinations: $\Delta = \langle d_1, d_2, \ldots, d_n \rangle$.
- Trajectories: $\zeta = \langle \xi_1, \xi_2, \ldots, \xi_n \rangle$, $\xi_i: I \to \mathbb{R}^2$.
- Topological class of trajectory relationships : τ.
- Pedestrian Scenario: $S = \langle \Sigma, \Delta, \tau \rangle$.

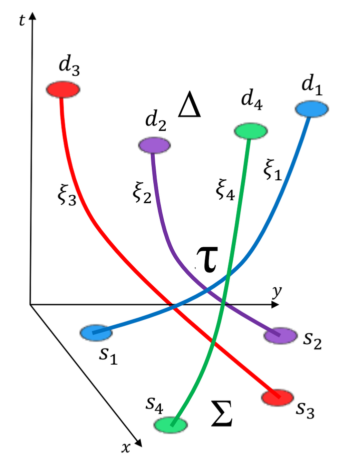


Figure 2. Pedestrian Scene Model.

B. *Representing the Topology of Trajectory Relationships with Braid Groups*

Geometric Braids

A geometric braid on $n \geq 1$ strands is a system of n curves in $\mathbb{R}^3$, called the strands of the braid, such that each strand i connects the point $(i, 0, 0)$ with the point $(p(i), 0, 1)$, where the sequence $p(1), \ldots, p(n)$ is a permutation of the set $\{1, 2, \ldots, n\}$ and intersects each plane {x, y, t'} only once for any $t' \in I$.

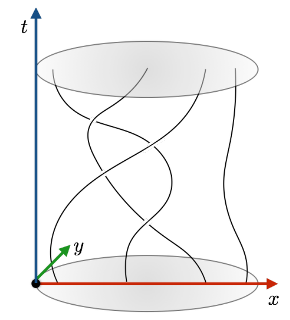


Figure 3. Geometric Braid

Braid Groups

The set of all braids on n strands form a group $\mathcal{B}_n$. The group $\mathcal{B}_n$ is generated from a set of *n-1* elementary braids, symbolized as $\sigma_i, \ldots, \sigma_{n-1}$, called the generators of $\mathcal{B}_n$. A thorough presentation of braid groups can be found in [4].

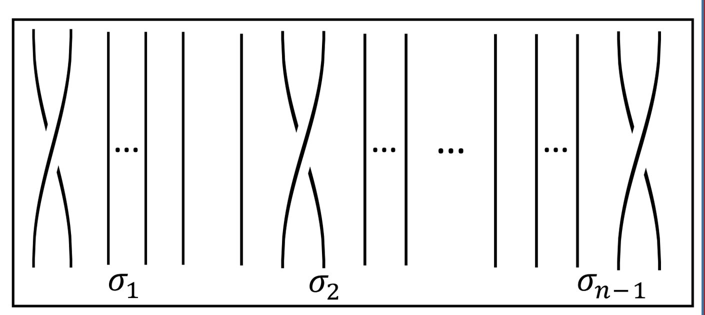
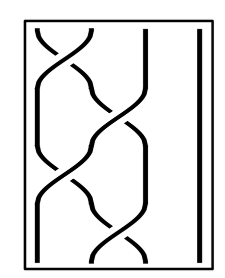


Figure 4. The Braid Group $\mathcal{B}_n$.

Braid Representations

A Braid can be schematically represented with a *braid diagram,* a projection of a geometric braid to $\mathbb{R}\times\{0\}\times I$, including indications of the generators that composed it. A braid can also be algebraically represented as a *braid word*, a string of symbols, arranged in increasing order with *t*.



$\sigma_2\sigma_1\sigma_2\sigma_1$

Figure 5. Braid diagram and Braid word.

Topology of Trajectory Relationships as a Braid

Given a collection of agents' trajectories ζ in a space time representation and a selected projection plane, we derive a braid that describes the topological relationships among all agents by labeling trajectory crossings with elements of the corresponding braid group and arranging them in temporal order.

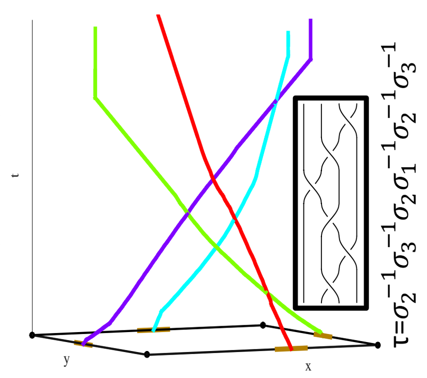


Figure 5. A trajectory collection and its corresponding braid characterization

C. *Modeling Pedestrians' Inference Mechanism*

As pedestrians move in the workspace, they make inferences regarding the evolution of the scene, reasoning about the future behaviors of other agents before planning their own paths. We model their inference mechanism as a distribution over pedestrian scenarios, given a set of observed, partial trajectories ζ', i.e., P(S|ζ'), which we decompose into 1) a prediction of destinations P(Δ|ζ') and 2) a prediction of the trajectory collection topology P(τ|Δ,ζ'):

P(S|ζ')= P(Δ|ζ') P(τ|Δ,ζ').

D. Incorporating Pedestrians' Inference into Robot Motion

To incorporate our pedestrian inference model in the motion planning process, we employ the *predictability* and *legibility* metrics proposed by Dragan and Srinivasa [3].

Intuitively, *predictable* is the motion that an observer expects from an agent whose goal is known, whereas *legible* is the motion that allows an observer to quickly, confidently and accurately predict the agent's goal. In our framework, a trajectory collection represents the action and a pedestrian scenario S represents the goal.

$$Predictability(\zeta, S) = \exp(-C(\zeta, S))$$

$$Legibility(\zeta, S) = \frac{\int_0^T P(S|\zeta) f(t) dt}{\int_0^T f(t) dt}, with\ f(t) = T - t$$

$C: \mathcal{Z} \to \mathbb{R}$ is a cost function representing the *joint comfort* of all pedestrians in the scene and T is the time length of the trajectory.

IV. Algorithm Design

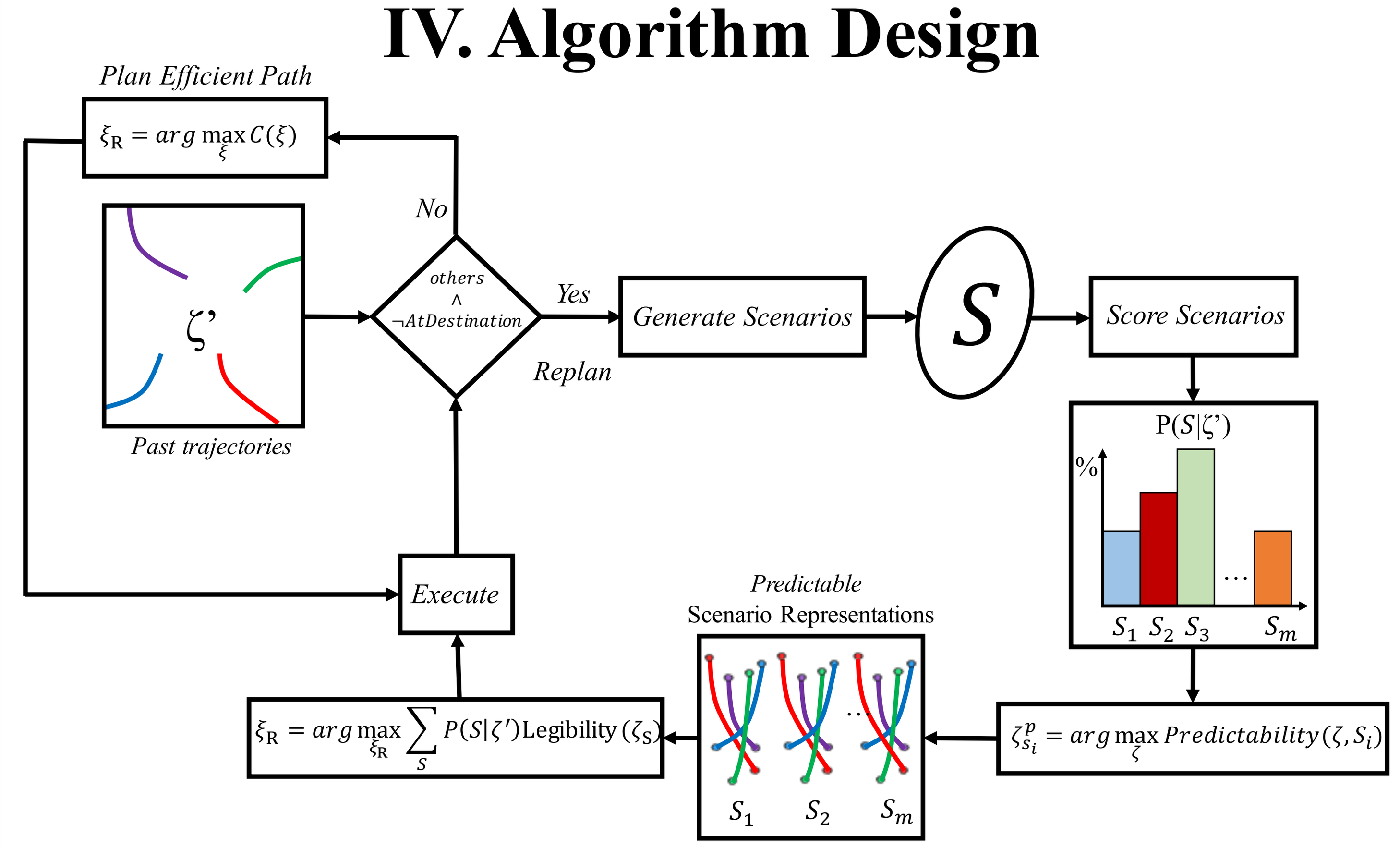


Figure 6. Flowchart, demonstrating our online navigation algorithm.

V. Simulation Results

We present preliminary simulation results, demonstrating the potential of our algorithm for application on robots operating in pedestrian environments. Three scenarios are presented, involving respectively 2, 4 and 8 agents, running online a separate instance of our algorithm. Fig. 7 depicts the swept volumes of the agents, along with the emerged *braids* of the execution.

Implementation details:

- The distributions P(Δ|ζ') and P(τ|Δ,ζ') were analytically approximated, both favoring low energy scenarios and penalizing costly ones, under the assumption of rational action.
- The cost C was defined as a weighted sum of functionals accounting for smoothness, clearance from other agents and clearance from workspace bounds.
- Legibility was approached as a clearance functional, favoring trajectory modifications that take place early.
- At every time step, each agent complies with the scenario that appears to be the most likely.

The trajectory optimization computations were implemented using CHOMP [5] and the braid visualizations with Braidlab [6].

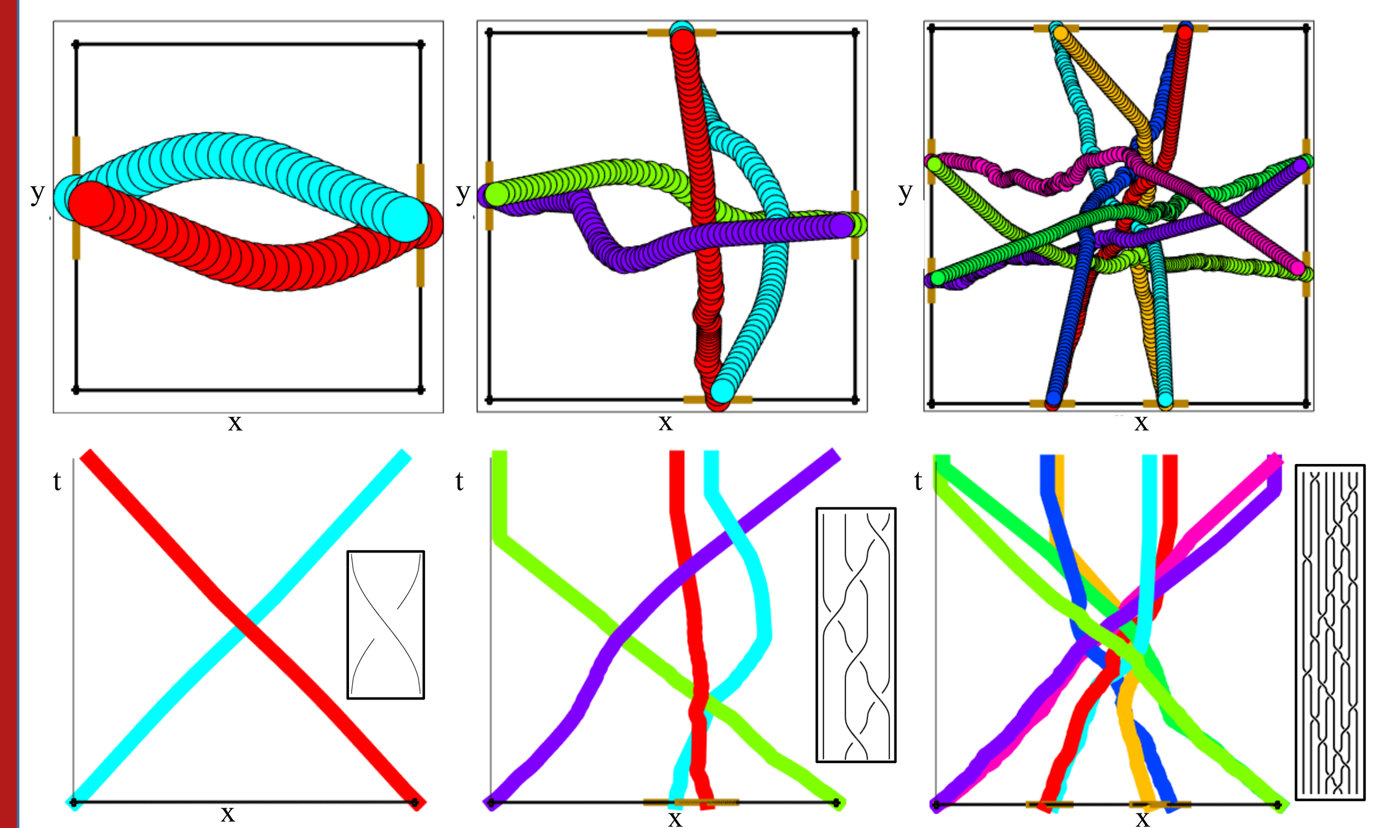


Figure 7. Online Execution: Swept Volumes, Trajectory Projections and Corresponding braid diagrams.

VI. Future Work

- Collect trajectory data from human pedestrians.
- Learn a model of P(τ|Δ,ζ').
- Improve the algorithm design in terms of computational efficiency.
- Optimize the code for real time execution.
- Validate the algorithm in real world experiments with our social robot platform (Fig. 8).
- Perform a user study to get feedback from humans.

Figure 8. Our social robot platform: A Beam (Suitable Technologies, Inc.), equipped with the Occam Omni Stereo rgbd camera (Occam Vision Group).

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