Legible Robot Planning for Proactive Human-Robot Interactions

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Abstract and Motivation

As autonomous systems become more prevalent, from autonomous cars to robot caregivers, ensuring safe and efficient human-robot interactions is critical. A common issue that arises from robots operating in unstructured environments can be characterized as the "Frozen Robot Problem," [1] where a robot can not satisfy all its governing constraints in a crowded environment and therefore stands still. The hypothesis is that if robots can behave *legibly* (i.e., effectively convey their intentions) such that interacting humans can better anticipate potential collisions and adjust their behaviors earlier, then robots can more safely and seamlessly coexist with humans in shared spaces. The significance of this research lies in advancing robot adaptation in various navigation tasks, including assistive robotics devices, autonomous vehicles and delivery robots.

Background - How to control a robot

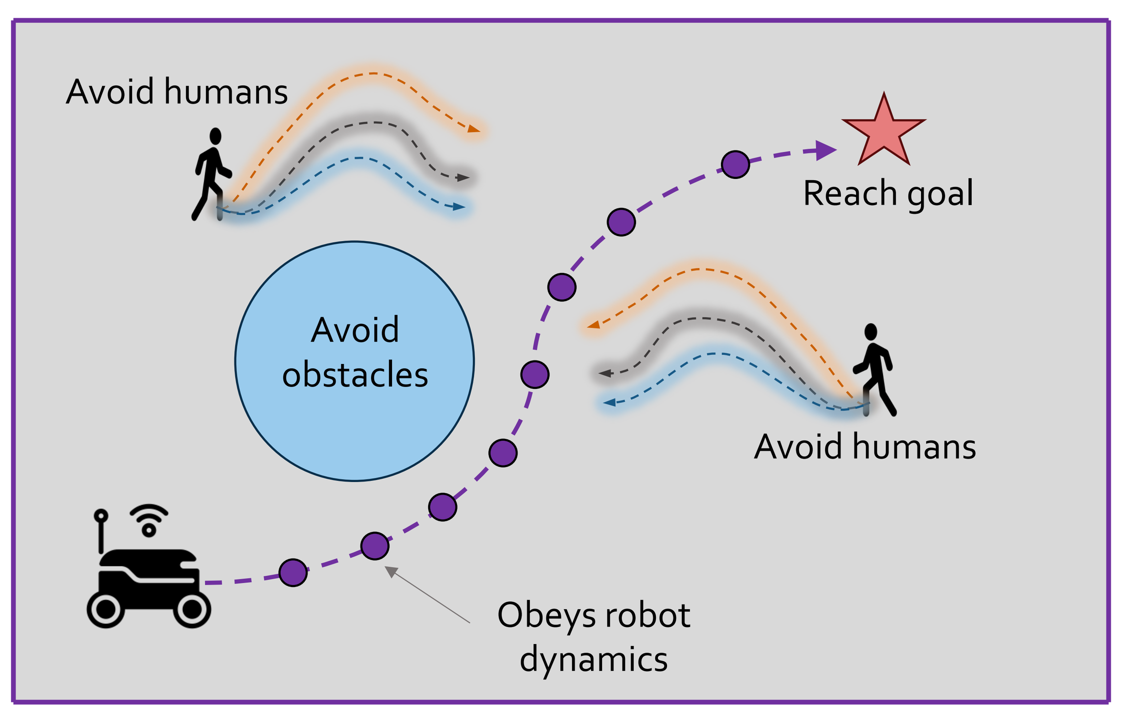


Figure 1: A trajectory planner creates a path using discrete points around obstacles and people. It must also obey dynamics constraints.

We can define how an autonomous robot is controlled above by finding a solution to the trajectory optimization problem shown in **Problem 1.**

Problem 1 (An agent's planning problem).

$$\min_{\mathbf{x}^{0:T+1},\mathbf{u}^{0:T}} \sum_{t=0}^{T} J(\mathbf{u}^t,\mathbf{x}^t) + J_{T+1}(\mathbf{x}^{T+1}) \quad \textit{Agent's planning objective} \quad (1a)$$

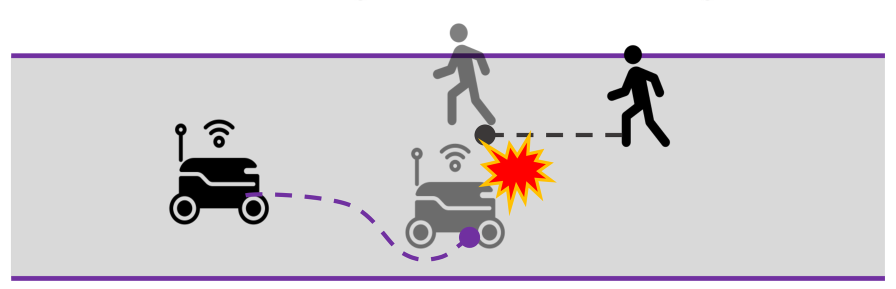
$$\text{s.t.} \quad \mathbf{x}^{t+1} = f(\mathbf{x}^t,\mathbf{u}^t), \quad t = 0,\ldots,T, \quad \textit{Dynamics constraints} \quad (1b)$$

$$\mathbf{x}^t \in \mathcal{X}^t \setminus \mathcal{O}_{\text{static}}, \quad t = 0,\ldots,T+1 \quad \textit{State and static obstacle constraints} \quad (1c)$$

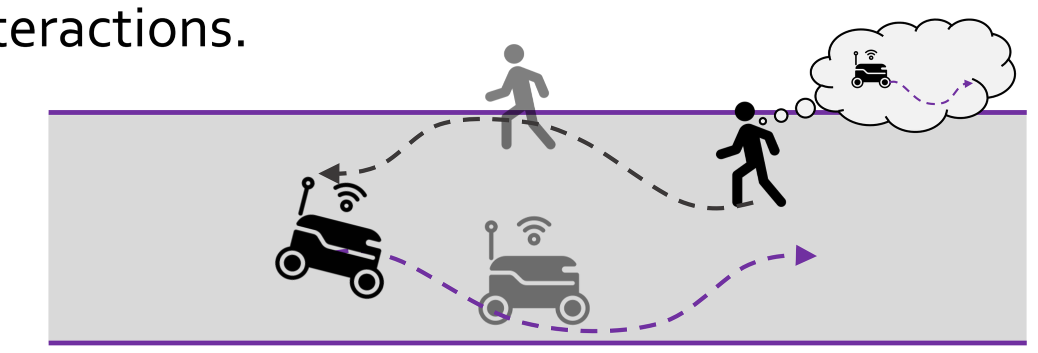
$$\mathbf{u}^t \in \mathcal{U}(\mathbf{x}^t), \quad t = 0,\ldots,T \quad \textit{Control constraints} \quad (1d)$$

Problem Formulation and Proposed Solution

Accounting for human agents: Accounting for how humans will respond to the robot's decisions is challenging to model and incorporate within an optimization problem. It's believed that if a robot moves out of the way early, such as in **Figure 2**, it will be more legible to other agents, resulting in safer interactions.



(a) Reactive planning: Illegible robot behaviors leads to collision-prone and inefficient interactions, such as the robot swerving at the last possible moment, leading to collision/near miss.



(b) Proactive planning: Robot executes legible plans to convey its intent to the human, and both agents coordinate to make space to pass by one another smoothly.

Figure 2: Comparing reactive and proactive safety with a motivating narrow corridor example.

How to promote legibility and proactiveness: We instantiate the formulation shown in **Problem 1** with two novel additions:

Problem 2 (An agent's planning problem with collision avoidance).

$$\min_{\mathbf{x}^{0:T+1},\mathbf{u}^{0:T}} \sum_{t=0}^{T} \boxed{\mu^t} J(\mathbf{u}^t,\mathbf{x}^t,t) + J_{T+1}(\mathbf{x}^{T+1}) \quad \textit{Agent's planning objective} \quad (2a)$$

$$\text{s.t.} \quad \mathbf{x}^{t+1} = f(\mathbf{x}^t,\mathbf{u}^t), \quad t = 0,\ldots,T, \quad \textit{Dynamics constraints} \quad (2b)$$

$$\mathbf{x}^t \in \mathcal{X}^t \setminus \mathcal{O}_{\text{static}}, \quad t = 0,\ldots,T+1 \quad \textit{State and static obstacle constraints} \quad (2c)$$

$$\mathbf{u}^t \in \mathcal{U}(\mathbf{x}^t), \quad t = 0,\ldots,T \quad \textit{Control constraints} \quad (2d)$$

$$g(\mathbf{x}^{0:T+1},\mathbf{u}^{0:T},x_{other}^{0:T+1},u_{other}^{0:T}) \leq 0, \quad \textit{Collision avoidance constraint} \quad (2e)$$

$$\boxed{J_{\text{incon}}(\mathbf{x}^{0:T+1},\mathbf{u}^{0:T}) \leq \beta,} \quad \textit{Inconvenience budget} \quad (2f)$$

μ^t: The *markup* term penalizes the planner for making control inputs later in its plan. The hypothesis is that this induces proactive behavior.

$J_{incon}(\boldsymbol{x}^{0:T+1},\boldsymbol{u}^{0:T}) \leq \beta$: The inconvenience constraint limits the deviation allowed for a planner from an ideal, unobstructed path.

Game Theoretic Approach: Iterative Best Response

To account for the interactions and coupling, we implement an Iterative Best Response (IBR) algorithm where one agent solves an ideal path while holding the other agent's path fixed [2]. This process is repeated multiple times until both agents converge to an ideal path.

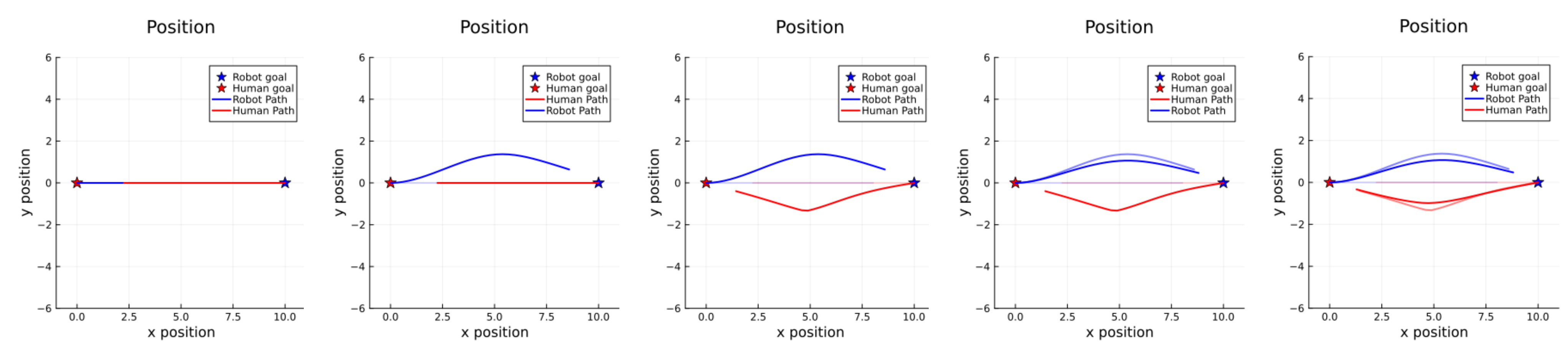


Figure 3: Iterative best response for a single robot planning step. The figure shows the evolution of the agent's trajectory after 5 iterations. The red path is the robot's predicted trajectory of the human based on its planned (blue) path.

Simulation Results and Future Work

To verify the real-time use and effectiveness of the proposed solution, simulations were carried out with multiple different human models, including human-in-the-loop simulations where a real person controlled the simulated human with a controller.

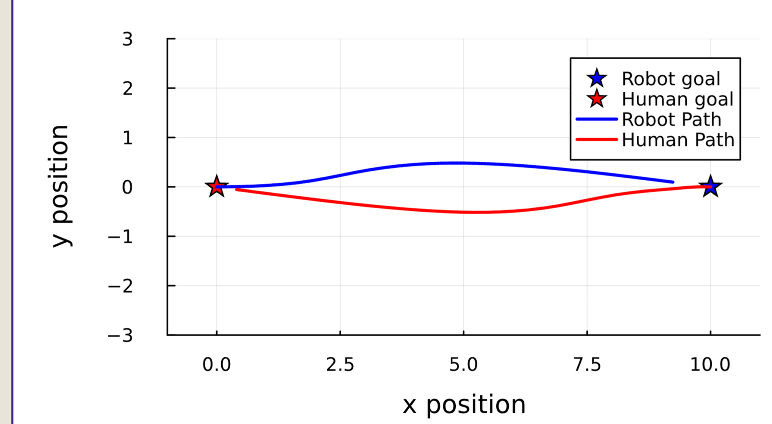
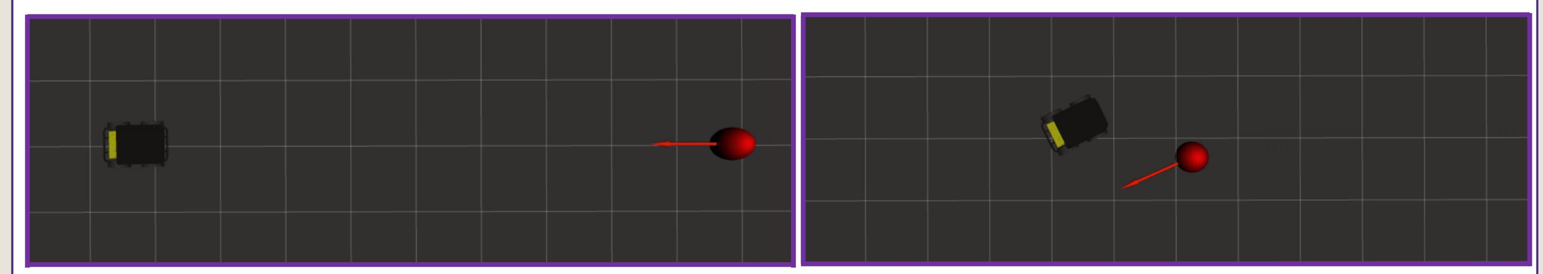


Figure 4: Shows the simulated path that a robot and human follow when both agents are using the formulation described in **Problem 2**.



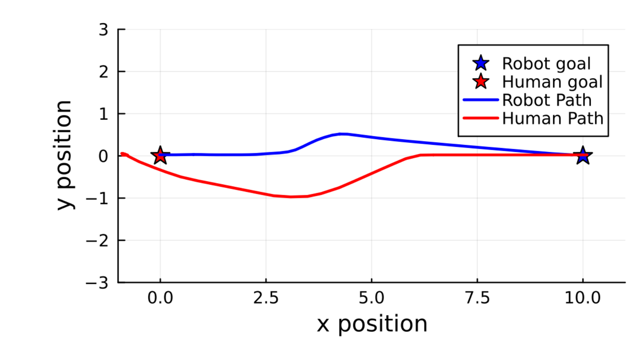


Figure 5: Human in the loop simulation showing the real-world capabilities of the robot (yellow/black) interacting with a simulated human (red) controlled using an Xbox controller.

Future Work: As shown above, the planning algorithm works for interactions with one other agent. Future work includes (i) expanding the algorithm to account for multiple agents, using techniques to simplify agents classified as non interacting, (ii) complete real-world studies in structured and unstructured scenarios and, (iii) improve human prediction models using machine learning methods [3].

Acknowledgements

We'd like to thank the UW + Amazon Science Hub for their support and Nia Jetter for her feedback on this work.

Citations

[1] P. Trautman and A. Krause. Unfreezing the robot: Navigation in dense, interacting crowds. In IEEE/RSJ Int. Conf. on Intelligent Robots & Systems, 2010.

[2] M. Wang, Z. Wang, J. Talbot, J. Christian Gerdes, and M. Schwager. Game-theoretic planning for self-driving cars in multivehicle competitive scenarios. IEEE Transactions on Robotics, 37(4):1313–1325, 2021.

[3] E. Schmerling, K. Leung, W. Vollprecht, and M. Pavone. Multimodal probabilistic model-based planning for human-robot interaction. In Proc. IEEE Conf. on Robotics and Automation, 2018.