Navigating the Crowd: Non-linear MPC with Social Forces Dynamics for Human-Aware Robot Navigation

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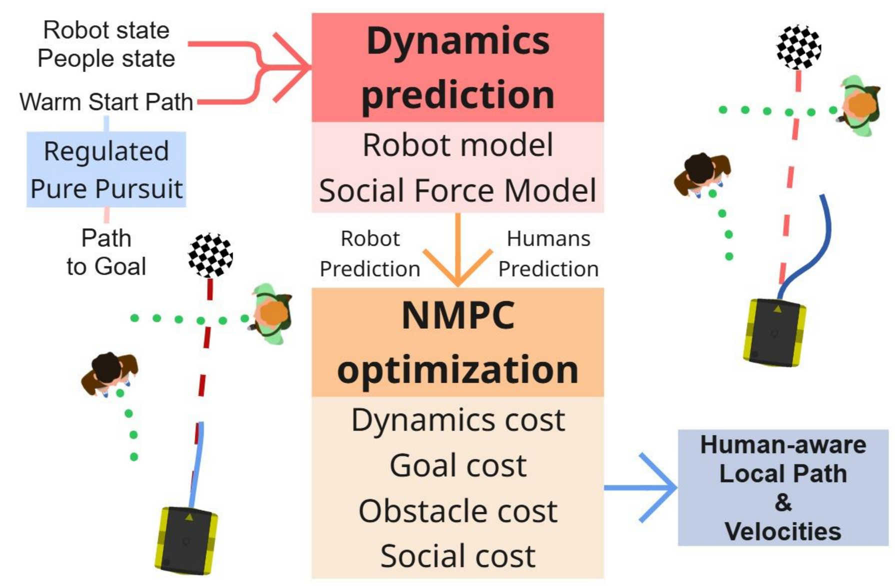
Methodology

- Autonomous robots operating in human-populated environments must plan motions that are not only collision-free, but also socially acceptable. In crowded spaces, safe navigation requires anticipating human motion, preserving comfortable interpersonal distances, and avoiding abrupt or intrusive maneuvers, which are central aspects of **socially-aware navigation evaluation**[1].
- Model Predictive Control provides a structured way to optimize robot motion over a finite horizon while enforcing dynamic, velocity, acceleration, and obstacle-avoidance constraints. However, its effectiveness in social navigation depends on how human motion is predicted during optimization.
- Instead of relying on precomputed human trajectories, **SFM-NMPC** combines an efficient Non-linear MPC that embeds the Social Force Model[2] in the prediction model to jointly propagate robot and human states within the optimization loop.
- SFM-NMPC formulates local planning as a non-linear MPC problem. At every prediction step, the optimized robot state influences the predicted human motion through social interaction forces. This creates a closed-loop prediction model in which the candidate robot trajectory and the agents' future trajectories are **co-evolved** inside the optimization problem.



Optimization Objective

$$J(\chi) = J_{\text{obs}} + J_{\text{goal}} + J_{\text{dyn}} + J_{\text{soc}}$$

- J_{obs}: Penalizes proximity to static obstacles
- J_{goal}: Attracts the robot to its reference path
- J_{dyn}: Encourages smooth and feasible motion
- J_{soc}: Promotes human-aware behavior
  - J_{ρ}: Penalizes intrusions into personal space
  - J_{work}: Penalizes social force exerted on humans
  - $J_{S\theta}$: Encourages nonintrusive headings

Real-time Receding-Horizon Loop

- At every control cycle, SFM-NMPC warm-starts the CERES optimizer, jointly predicts robot and human motion, and applies only the first command before replanning.

RPP local reference + Warm start: Regulated Pure Pursuit extracts a short reference trajectory from the global path which is combined with the previous control sequence for optimization → **Coupled prediction**: Robot poses and human states are propagated over the horizon → **Optimization**: A non-linear least-squares solver is used to get the optimal trajectory → **Apply first command**: The first velocity command is sent to the robot; the rest is kept as a warm start

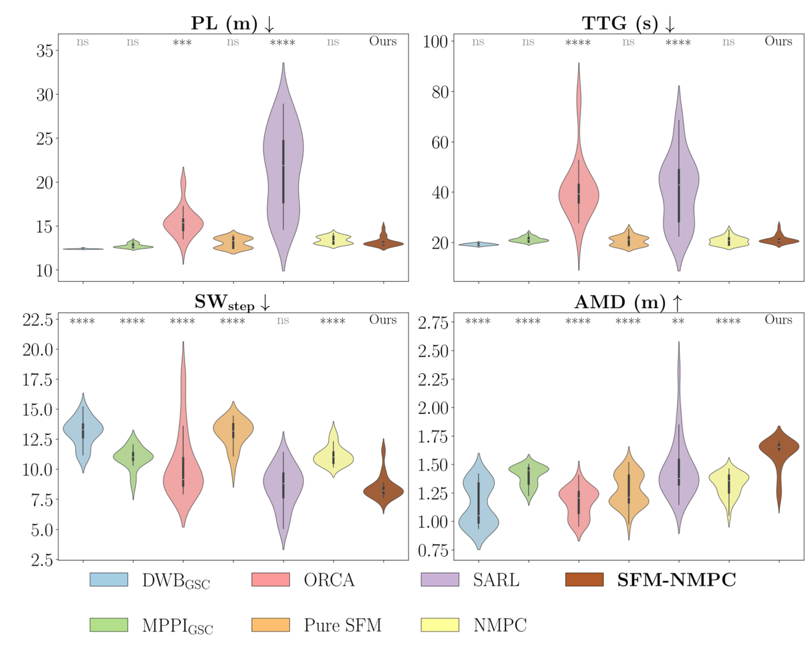
Control Loop run at 20 Hz

Experiments And Results

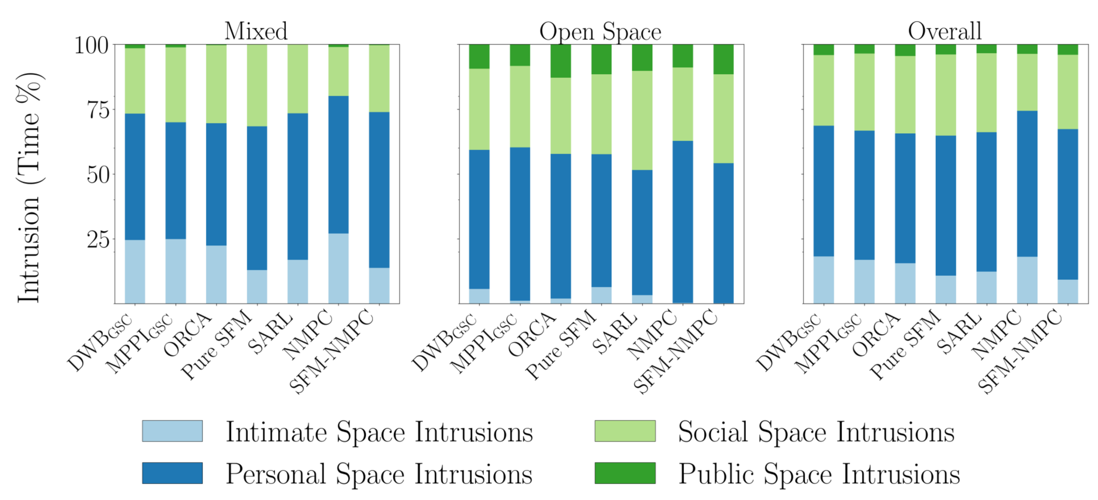
- The framework was evaluated in HuNavSim/Gazebo[3] across two families of simulated environments: an open-space map with crossing, passing, and crowded-navigation scenarios, and a mixed indoor map with corridors, rooms, and narrow passages.
- Performance is evaluated both in terms of **navigation efficiency** and **social compliance**[1].
- The distributional analysis shows that the improvement is not only visible in average values; it shows that SFM-NMPC achieves **socially compliant behavior** while preserving competitive path length and time to goal. SARL achieves good social results only by taking nearly twice the path length.
- Proxemic analysis shows that the method **reduces intimate-space intrusions** and maintains larger interpersonal distances.

Map	Method	SR (%) ↑	PL (m) ↓	TTG (s) ↓	SW_{step} ↓	AMD (m) ↑
Mixed	DWB_{GSC}	42.00	9.04	14.27	16.02	0.99
	MPPI_{GSC}	91.00	9.28	16.56	13.48	1.00
	ORCA	16.00	**5.99**	**10.45**	19.90	0.98
	Pure SFM	31.00	17.34	31.43	13.80	**1.02**
	SARL	46.00	7.98	11.91	17.19	0.93
	NMPC	81.00	9.26	16.50	13.27	0.88
	SFM–NMPC	**97.00**	9.96	18.70	**11.96**	0.99
Open Space	DWB_{GSC}	**100.00**	**10.36**	**15.83**	9.96	1.60
	MPPI_{GSC}	99.00	10.56	17.57	9.83	1.52
	ORCA	81.00	11.71	26.39	9.10	1.63
	Pure SFM	**100.00**	11.00	17.47	9.73	1.71
	SARL	96.00	15.94	29.47	**8.04**	1.70
	NMPC	**100.00**	10.88	16.73	10.27	1.53
	SFM–NMPC	**100.00**	11.13	18.17	8.17	**1.73**
Overall	DWB_{GSC}	70.00	**9.54**	**14.86**	14.00	1.19
	MPPI_{GSC}	94.00	9.71	16.90	12.26	1.17
	ORCA	38.00	10.28	22.41	16.30	1.20
	Pure SFM	54.00	14.62	25.45	12.44	**1.25**
	SARL	62.00	11.96	20.69	14.14	1.18
	NMPC	87.00	9.87	16.59	12.27	1.10
	SFM–NMPC	**98.00**	10.35	18.52	**10.70**	1.24

SR: success rate; PL: path length; TTG: time to goal; SW_{step}: social work per step; AMD: average minimum distance.

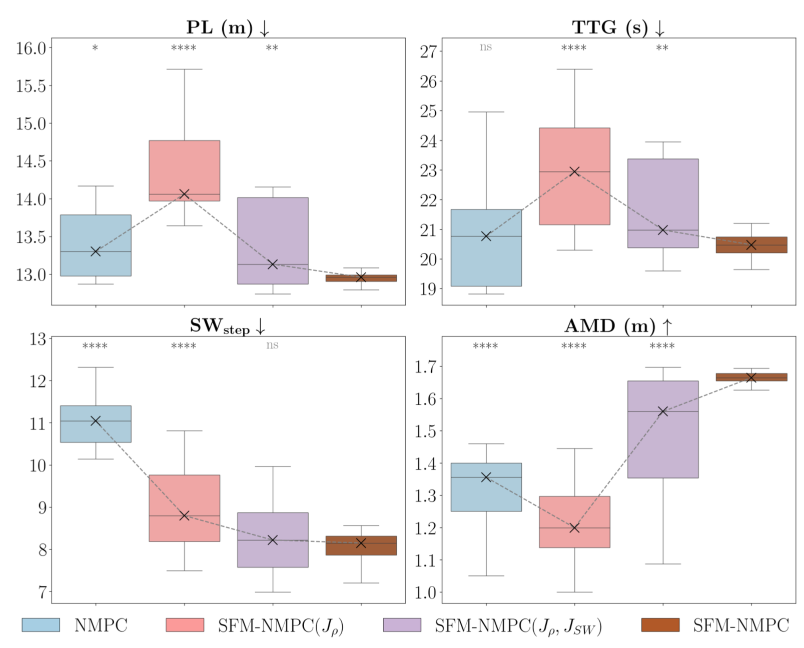


Results on Open Scenario

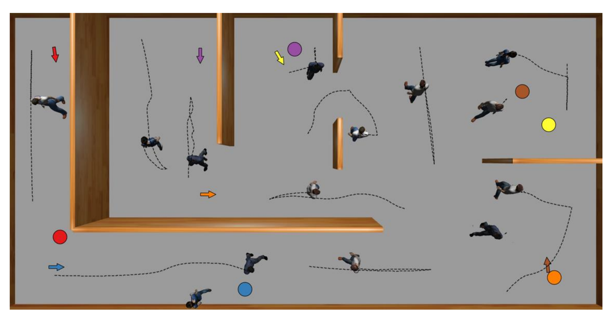


Ablation Study

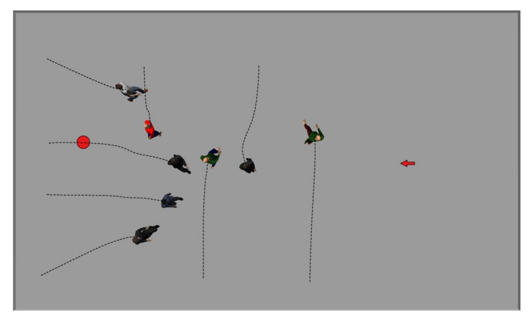
- The ablation study clarifies how each component contributes to the final behavior. A basic NMPC already provides efficient navigation, but produces stronger social disturbance.
- Adding the proxemic and social-work terms **progressively improves social behavior**, while the heading social cost produces the largest gain in robustness and predictive interaction quality, leading to **shorter paths and arrival times**.



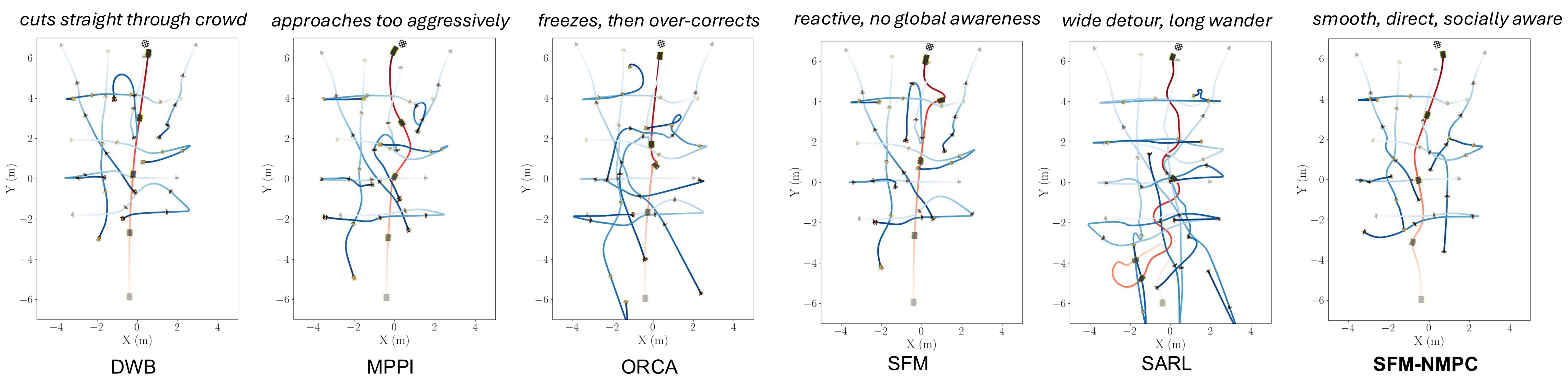
Ablation Results on Open Scenario



Mixed Scenario



Open Scenario



Conclusion And Future Work

- SFM-NMPC integrates Social Force Model dynamics directly into a non-linear MPC planner, enabling the robot and surrounding pedestrians to be **predicted jointly** during optimization.
- The resulting controller remains interpretable and real-time, while **improving social compliance** across crowded simulated environments.
- Future work will focus on **real-robot validation** under perception uncertainty and on extending the framework toward **richer forms of** human-robot **co-adaptation**.

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2. D. Helbing and P. Molnár, "Social force model for pedestrian dynamics," Phys. Rev. E, 1995.
3. N. Pérez-Higueras et al., "HuNavSim: A ROS 2 human navigation simulator for benchmarking human-aware robot navigation," RA-L, 2023.

Scan this code for the github repo

Scan this code for the paper