Socially Acceptable Bipedal Robot Navigation via Social Zonotope Network Model Predictive Control

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Motivating Social Navigation

- **Problem statement:**
  - Given the dynamics of the **bipedal robot** and a **goal location** find a motion plan that **promotes social acceptability** for the ego-agent in an **environment containing pedestrians** while **ensuring navigation safety**.

Social Navigation Literature

[1] Moder, Martin, and Josef Pauli. RO-MAN (2022)

[2] Schaefer, Simon, et al. ICRA (2021)

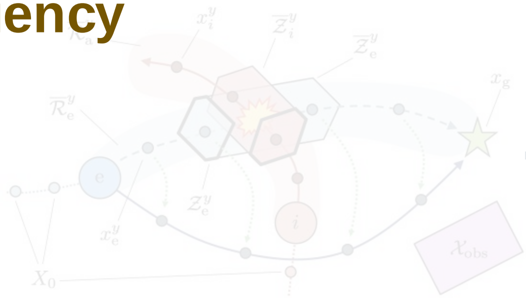
[3] Hong, Yang, et al. TCDS (2023)

Kullback-Leibler di... as interference met... aim to minimize it

...l Autoencoder ...istically

- **Accomplished work:**
  - Learn the socially acceptable path from **real crowd data sets**
  - Learn pedestrians' predictions as **zonotope directly, for computational efficiency**

Assume that minimally-invasive trajectory is the **socially acceptable trajectory**



[4] Paparusso, Luca, et al. ICRA (2024)

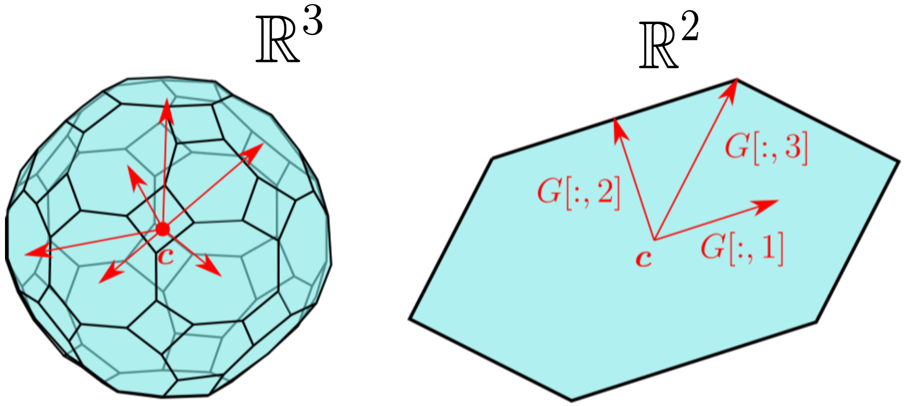
Construct zonotope over obstacles' Gaussian distribution predictions for ego-agent path planning

Zonotopes

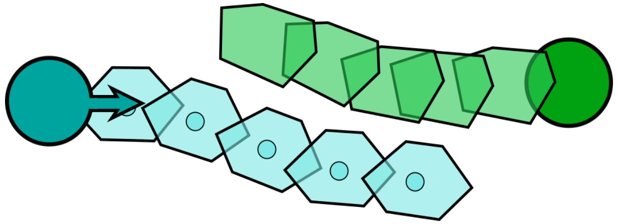
Zonotopes are a convex symmetric polytope

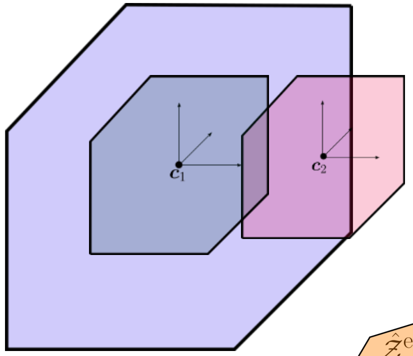
$$\mathcal{Z} = \mathscr{Z}(\boldsymbol{c}, G) = \{c + \beta_1 g_1 + \beta_2 g_2 + \beta_3 g_3 \mid \beta_i \in [-1, 1]\}$$

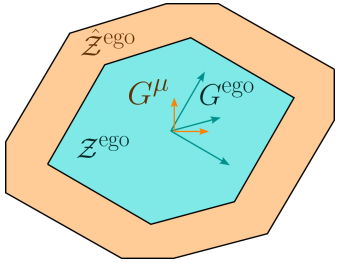
$$G = [\boldsymbol{g}_1, \boldsymbol{g}_2, \ldots, \boldsymbol{g}_n] \in \mathbb{R}^{n \times n_G}$$



- Zonotopes offer efficiencies in:
  - reachability-based planning
  - collision checking [5][6]
  - uncertainty parameterization





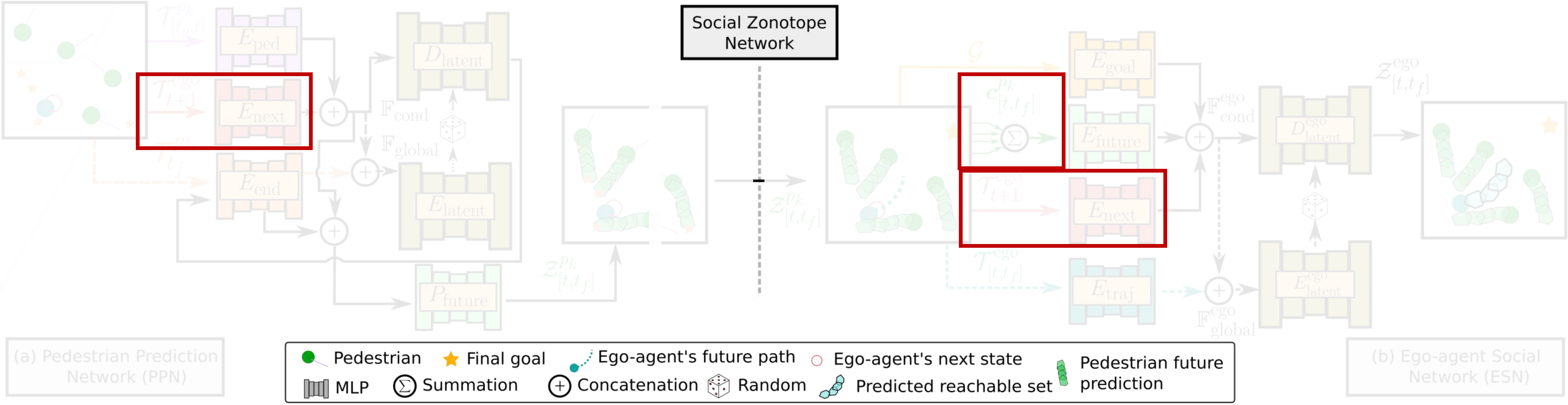


[5] Guibas, Leonidas J, et al. SODA 2003

[6] Althoff, Matthias (2010)

Bipedal Robot Social Navigation Framework

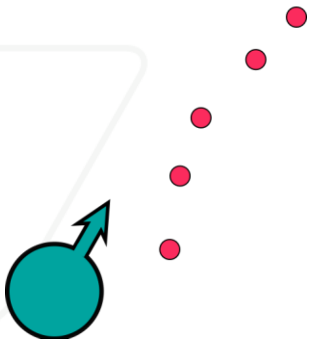
Social Zonotope Network (SZN)



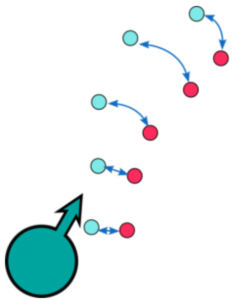
- **Collective effect** of the surrounding pedestrians, while keeping a fixed architecture

- Conditioning the prediction of the pedestrian's future path on ego-agent's next step
  1. Captures the effect of **the ego-agent's control on pedestrians' future path**
  2. Integrates **SZN-MPC decision's variables** into the neural network

Zonotope Shaping



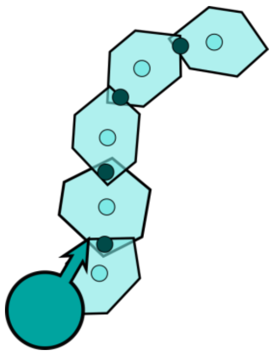
Ground truth tracking



$$\mathcal{L}_{ADE} = \frac{\sum_{i=1}^{t_f-1} \|\mathcal{T}_{\text{mid},i} - \boldsymbol{c}_i\|}{t_f - 1}$$

$$\mathcal{L}_{FDE} = \|\mathcal{T}_{\text{mid},t_f-1} - \boldsymbol{c}_{t_f-1}\|$$

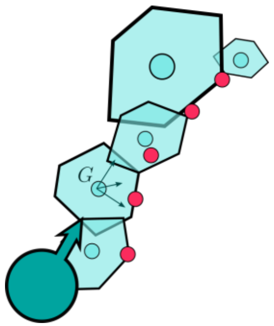
Intersecting zonotopes



$$\mathcal{L}_{\text{prev}} = \sum_{i=0}^{t_f-1} \text{ReLU}(A_i \cdot \boldsymbol{c}^p_{\text{mid},i} - b_i)$$

$$\mathcal{L}_{\text{nxt}} = \sum_{i=0}^{t_f-1} \text{ReLU}(A_i \cdot \boldsymbol{c}^n_{\text{mid},i} - b_i)$$

Size regulation

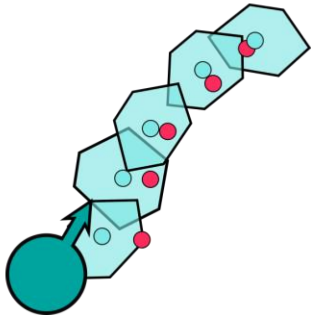


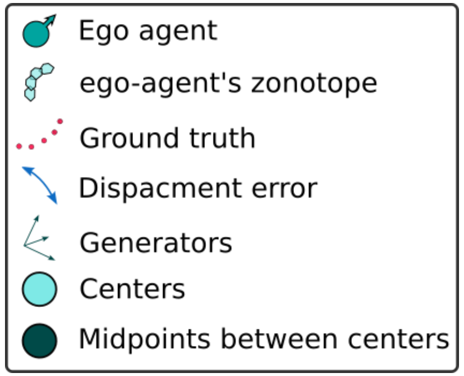
$$\mathcal{L}_G = \|l_G[1] - d_1\| + \|l_G[1:] - d_2\|$$

Digit's physical representation and kinematic limits

Social zonotopes:

$$\mathcal{T}^{\text{ego}}_{[t,t_f]} \in \bigcup_{q=t}^{t_f-1} \mathcal{Z}^{\text{ego}}_q$$





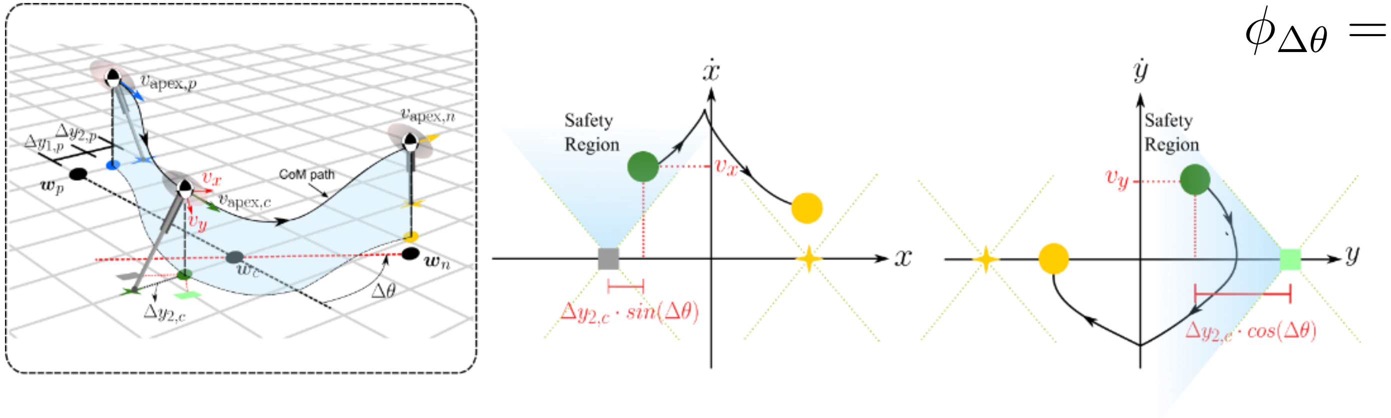
Locomotion-specific Loss Functions

Real-crowd data sets **do not consider** bipedal robot locomotion **capabilities**

Locomotion safety loss: ROM-based loss on step length, velocity and heading change

$\rho(s_t, \phi)$ quantifies **the degree of satisfaction or violation** of the specification ϕ given a specific signal s_t

$$\rho(s_t, \phi) = \begin{cases} \geq 0 & s_t \text{ satisfies } \phi \\ < 0 & s_t \text{ violates } \phi \end{cases}$$



- **Locomotion velocity specification:**

$$\phi_{\text{sag}} = \Box_{[t+1,t_f]}(s^{v_{\text{sag}}}_{[t+1,t_f]} \leq v_{\max} \wedge s^{v_{\text{sag}}}_{[t+1,t_f]} \geq v_{\min})$$

$$\phi_{\text{lat}} = \Box_{[t+1,t_f]}(s^{v_{\text{lat}}}_{[t+1,t_f]} \leq v_{\text{lat}} \wedge s^{v_{\text{lat}}}_{[t+1,t_f]} \geq -v_{\text{lat}})$$

$$\phi_{\text{vel}} = \phi_{\text{sag}} \wedge \phi_{\text{lat}}$$

$$\mathcal{L}_{\phi_{\text{vel}}} = \underbrace{\text{ReLU}(-\rho((s^{v_{\text{sag}}}, s^{v_{\text{lat}}}), \phi_{\text{vel}}))}_{\textit{velocity violation}}$$

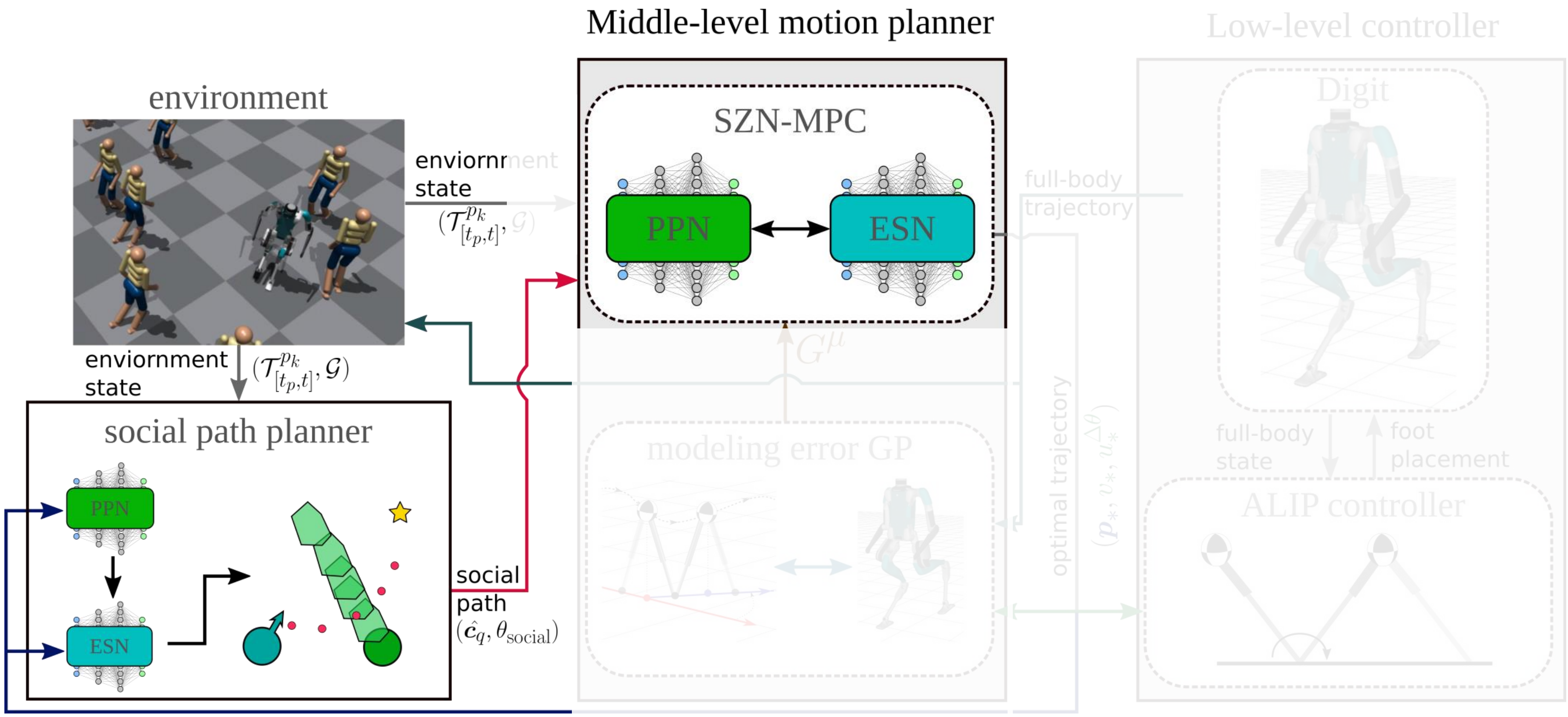
- **Heading change specification:**

$$\phi_{\Delta\theta} = \Box_{[t+1,t_f]}(s^{\Delta\theta}_{[t+1,t_f]} < \Delta\theta_{\max} \wedge s^{\Delta\theta}_{[t+1,t_f]} > -\Delta\theta_{\max})$$

$$\mathcal{L}_{\phi_{\Delta\theta}} = \underbrace{\text{ReLU}(-\rho(s^{\Delta\theta}, \phi_{\Delta\theta}))}_{\textit{heading change violation}}$$

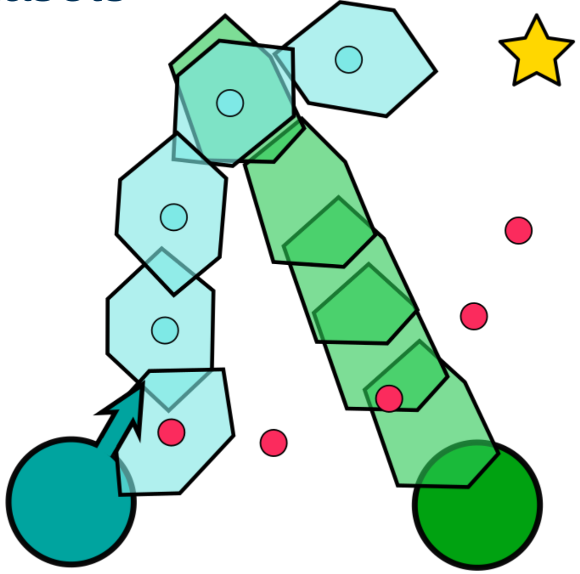
[7] Leung, Karen, et al. IJRR (2021)

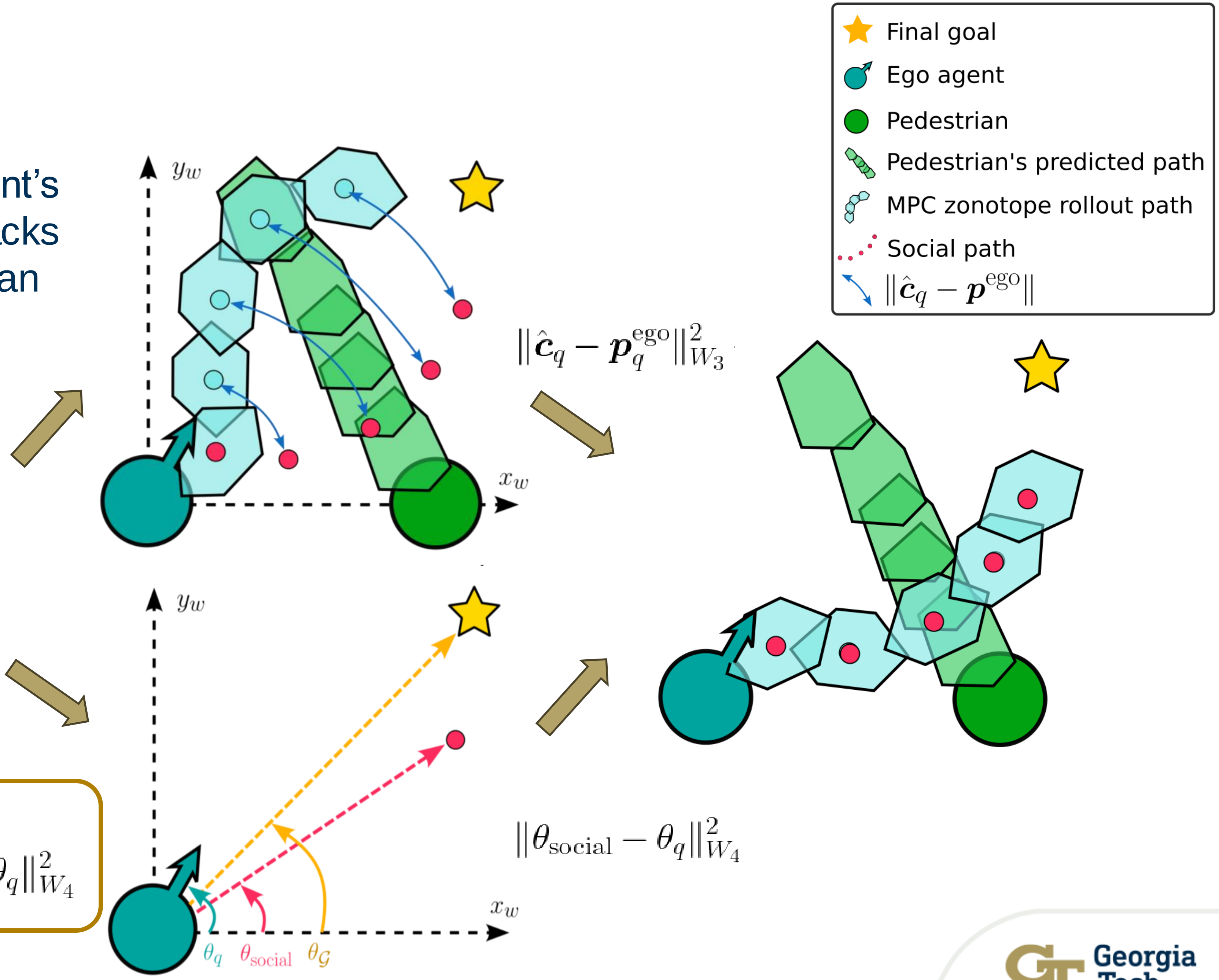
Social Path Planner



Social Path Planner

Social Acceptability: the ego-agent's path is **socially acceptable** if it tracks the **learned social path** from human crowd datasets





- Running cost in the MPC

$$J_{\text{social}}(\boldsymbol{x}_q) = \|\hat{\boldsymbol{c}}_q - \boldsymbol{p}_q^{\text{ego}}\|_{W_3}^2 + \|\theta_{\text{social}} - \theta_q\|_{W_4}^2$$

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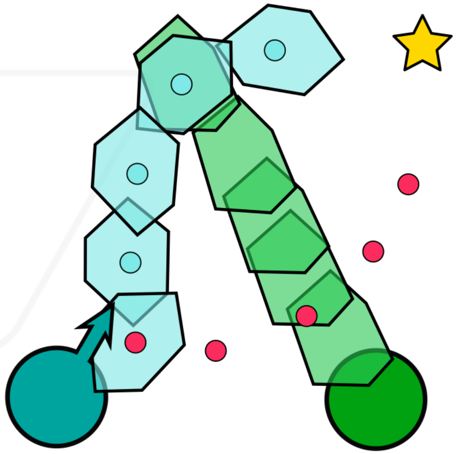
SZN-MPC

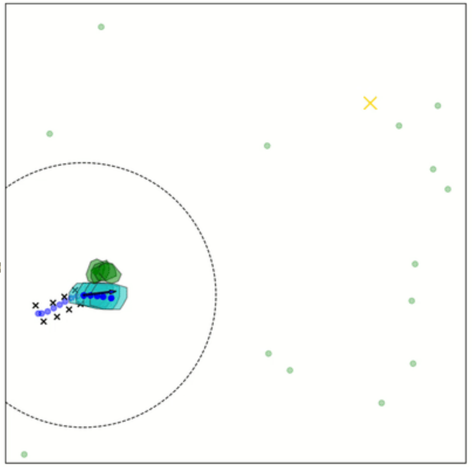


$$\min_{X,U} \sum_{q=0}^{N-1} \Delta \boldsymbol{u}_q^2 + J(\boldsymbol{x}, \boldsymbol{u}) + J_{\text{social}}(\boldsymbol{x}_q, \boldsymbol{u}_q)$$

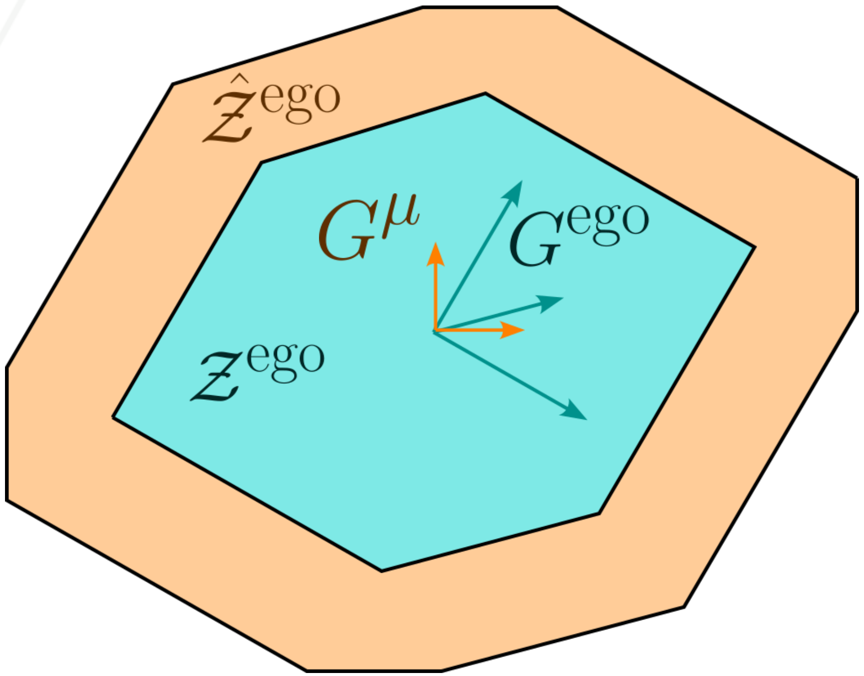
$$\begin{aligned} \text{s.t.} \quad & \boldsymbol{x}_{q+1} = \Phi(\boldsymbol{x}_q, \boldsymbol{u}_q) \\ & \boldsymbol{x}_0 = \boldsymbol{x}_{\text{init}}, \ (\boldsymbol{x}_q, \boldsymbol{u}_q) \in \mathcal{XU}_q \\ & \boldsymbol{x}_{q+1} \in \mathcal{Z}_{q+1}^{\text{ego}}(\Delta \boldsymbol{p}_q^{\text{ego}}, E_q) \\ & \mathcal{Z}_{q+1}^{\text{ego}}(\Delta \boldsymbol{p}_q^{\text{ego}}, E_q) \bigcap \mathcal{Z}_{q+1}^{p_{k_q}}(\Delta \boldsymbol{p}_q^{\text{ego}}) = \emptyset, \ \forall \, k_q \end{aligned}$$

min $\sum$ Control effort + Distance to goal
+ Social path deviation

s.t. Dynamics constraint
Ego-agent's CoM is inside social zonotope
Ego-agent's zonotope does not intersect
with pedestrians' zonotope

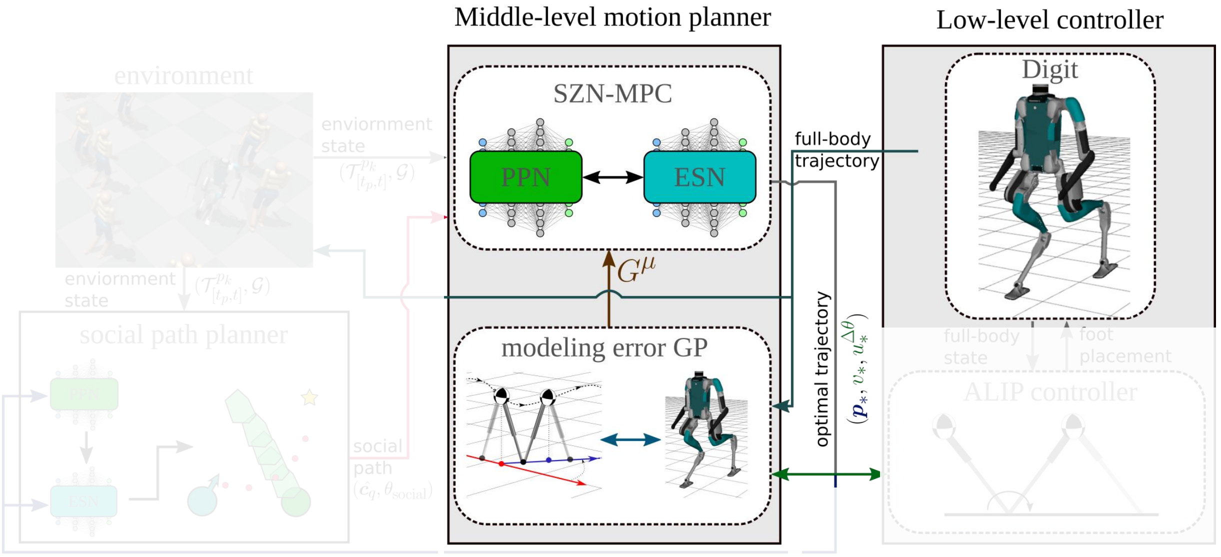


Uncertainty Quantification



$$G^{\mu} = \begin{pmatrix} \mu_x & 0 \\ 0 & \mu_y \end{pmatrix}$$

$$\hat{\mathcal{Z}}^{\text{ego}} = \mathscr{Z}(\boldsymbol{c}^{\text{ego}}, [G^{\text{ego}}\ G^{\mu}])$$



- Introduce a GP that takes as an input:
  - Digit's current velocity
  - SZN-MPC optimal solution
- Outputs the **expected mean deviation**

$$\boldsymbol{\mu} = (\mu_x, \mu_y)$$

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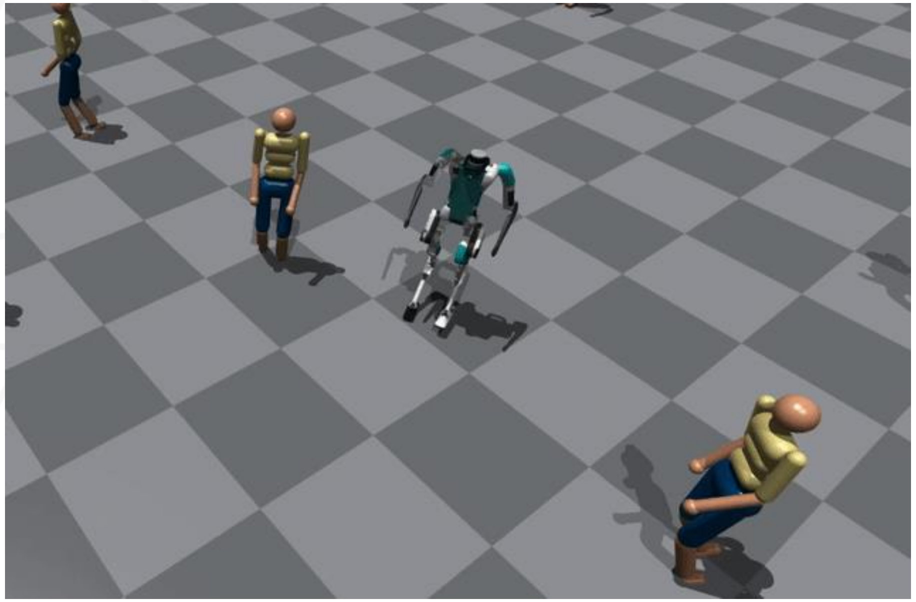
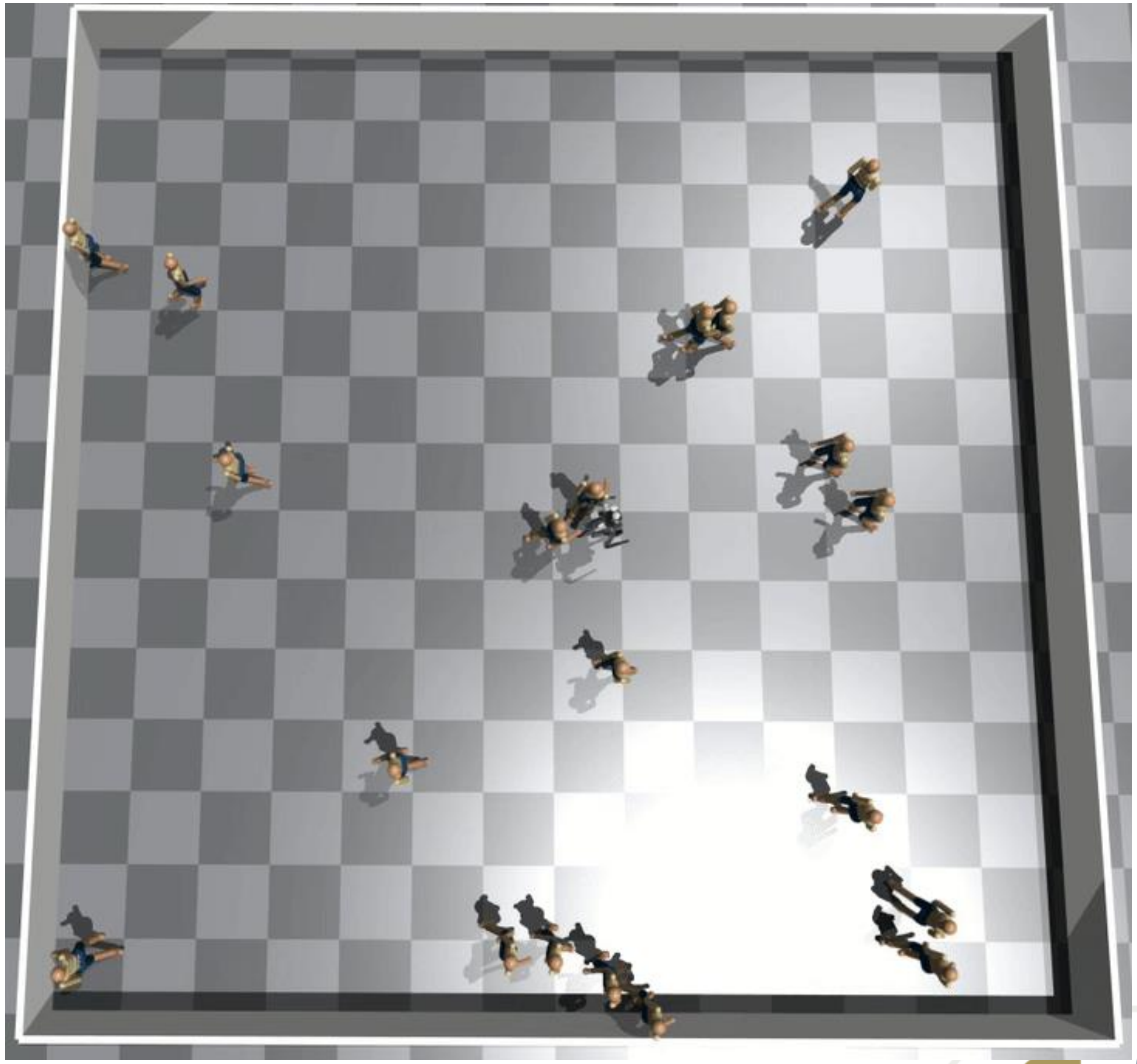
Results: SZN-MPC

Simulation Results

Results: SZN-MPC

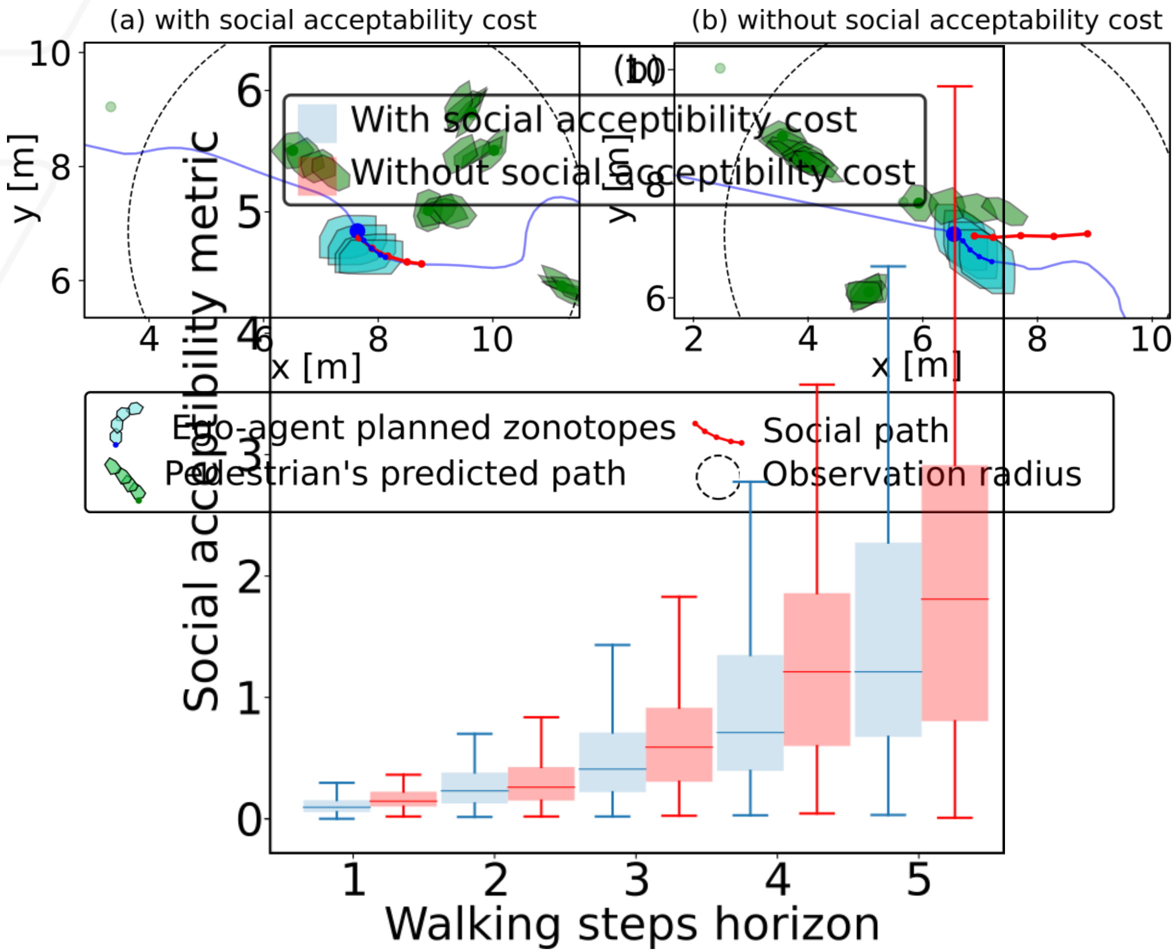




Results: Social Acceptability Metric and Locomotion Loss

Social acceptability metric

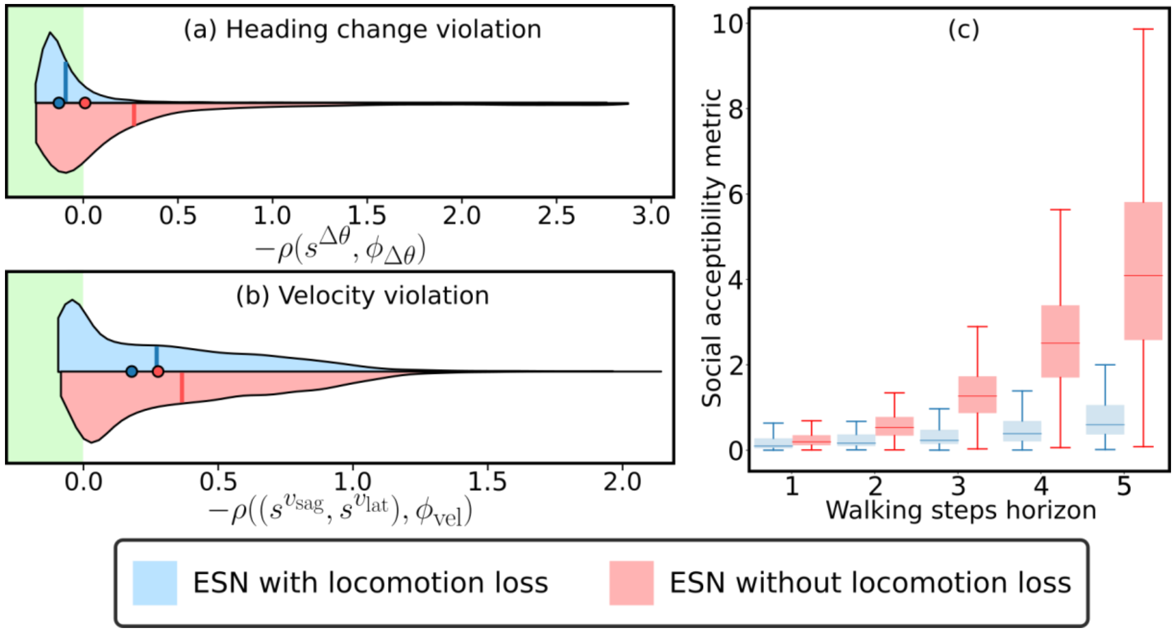
$$J_{\text{social}}(\boldsymbol{x}_q) = \|\hat{\boldsymbol{c}}_q - \boldsymbol{p}_q^{\text{ego}}\|_{W_3}^2 + \|\theta_{\text{social}} - \theta_q\|_{W_4}^2$$



Locomotion loss

$$\mathcal{L}_{\phi_{\text{vel}}} = \underbrace{\text{ReLU}(-\rho((s^{v_{\text{sag}}}, s^{v_{\text{lat}}}), \phi_{\text{vel}}))}_{\textit{velocity violation}}$$

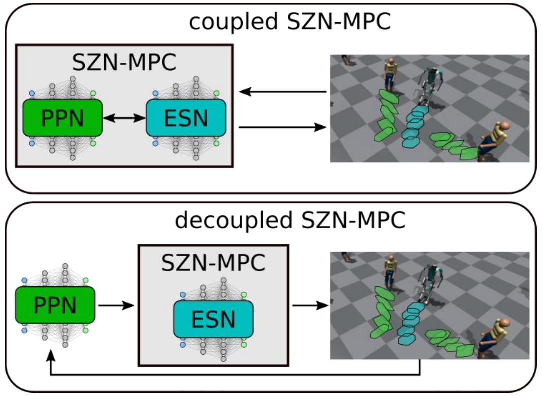
$$\mathcal{L}_{\phi_{\Delta\theta}} = \underbrace{\text{ReLU}(-\rho(s^{\Delta\theta}, \phi_{\Delta\theta}))}_{\textit{heading change violation}}$$



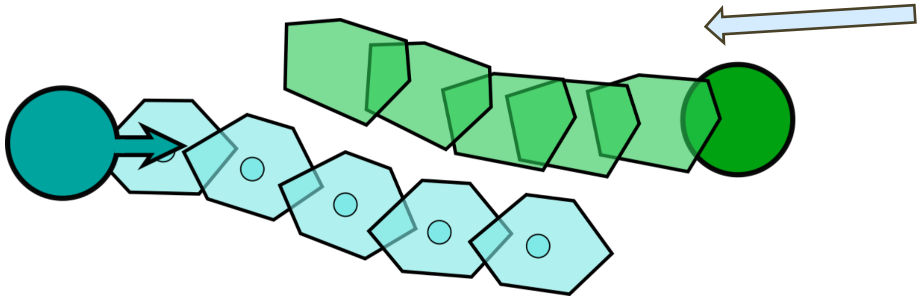
Results: Benchmarking

- Compare **two versions** of our proposed SZN-MPC with baseline DCBF-MPC [8]

$$h(\boldsymbol{p}_{q+1}^{\text{ego}}, \boldsymbol{p}_{k_{q+1}}) \geq (1-\gamma) h(\boldsymbol{p}_q^{\text{ego}}, \boldsymbol{p}_{k_q}) \ \forall \ k_q$$



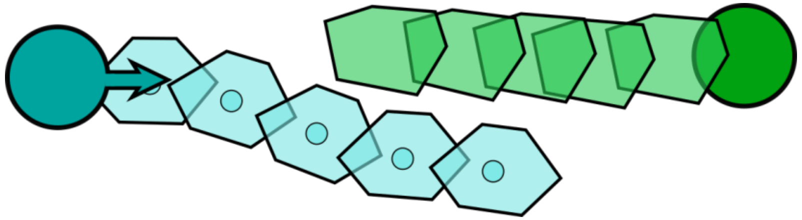
- **Coupled SZN-MPC**
  - SZN-MPC optimizes through **both PPN and ESN** networks



PPN prediction is affected by the ego-agent's future path

$$\begin{aligned} \min_{X,U} \quad & \sum_{q=0}^{N-1} J(\boldsymbol{x}, \boldsymbol{u}) + J_{\text{social}}(\boldsymbol{x}_q, \boldsymbol{u}_q) \\ \text{s.t.} \quad & \boldsymbol{x}_{q+1} = \Phi(\boldsymbol{x}_q, \boldsymbol{u}_q) \\ & \boldsymbol{x}_0 = \boldsymbol{x}_{\text{init}}, \ (\boldsymbol{x}_q, \boldsymbol{u}_q) \in \mathcal{XU}_q \\ & \boldsymbol{x}_{q+1} \in \mathcal{Z}_{q+1}^{\text{ego}}(\Delta \boldsymbol{p}_q^{\text{ego}}, E_q) \\ & \mathcal{Z}_{q+1}^{\text{ego}}(\Delta \boldsymbol{p}_q^{\text{ego}}, E_q) \bigcap \boxed{\mathcal{Z}_{q+1}^{p_{k_q}}(\Delta \boldsymbol{p}_q^{\text{ego}})} = \emptyset, \ \forall \ k_q \end{aligned}$$

- **Decoupled SZN-MPC**
  - SZN-MPC optimizes through **ESN,** while PPN output **is fixed**

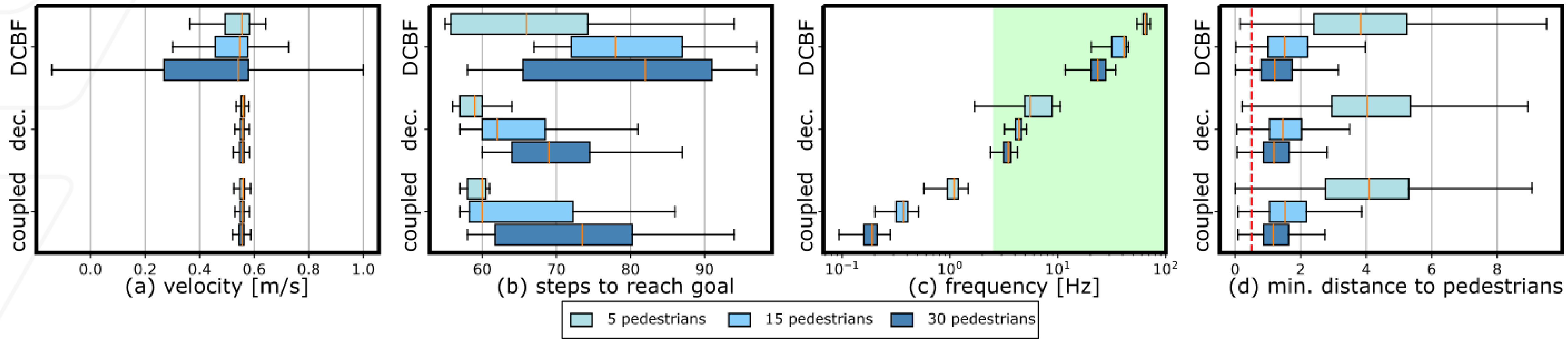


PPN prediction is fixed based on SZN-MPC last optimal solution

$$\begin{aligned} \min_{X,U} \quad & \sum_{q=0}^{N-1} J(\boldsymbol{x}, \boldsymbol{u}) + J_{\text{social}}(\boldsymbol{x}_q, \boldsymbol{u}_q) \\ \text{s.t.} \quad & \boldsymbol{x}_{q+1} = \Phi(\boldsymbol{x}_q, \boldsymbol{u}_q) \\ & \boldsymbol{x}_0 = \boldsymbol{x}_{\text{init}}, \ (\boldsymbol{x}_q, \boldsymbol{u}_q) \in \mathcal{XU}_q \\ & \boldsymbol{x}_{q+1} \in \mathcal{Z}_{q+1}^{\text{ego}}(\Delta \boldsymbol{p}_q^{\text{ego}}, E_q) \\ & \mathcal{Z}_{q+1}^{\text{ego}}(\Delta \boldsymbol{p}_q^{\text{ego}}, E_q) \bigcap \boxed{\mathcal{Z}_{q+1}^{p_{k_q}}} = \emptyset, \ \forall \ k_q \end{aligned}$$

[8] Narkhede, Kunal S., et al. RA-L (2022)

Results: Benchmarking



- **Conservativeness and success rate:** SZN-MPC produce more **consistent velocity, more efficient.**
- **Social Acceptability: Predictable behavior** of the ego-agent.
- **Safety and optimality:** SZN-MPC produce **comparable safety** performance, in **fewer steps.**
- **Computational cost:** DCBF is computationally efficient, SZN-MPC can be solved in **real-time** for hardware implementation.

Standing Group

Moving randomly	Moving randomly
Moving in a row	Moving in groups

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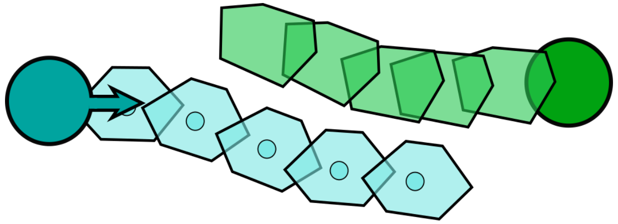
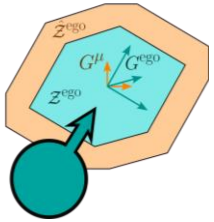
Social Navigation Summary



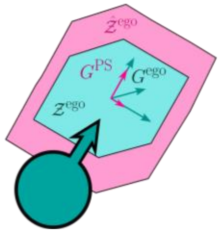
Uncertain environment and obstacles

- Human crowds
- Partially observable environment



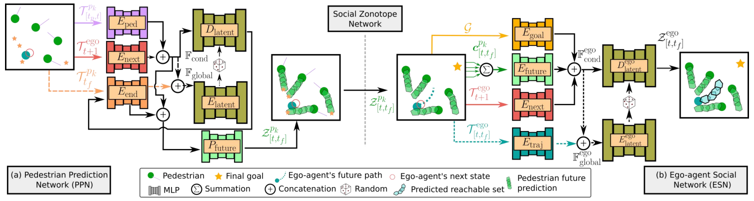
Uncertain model

- Compensating for learned model errors online
- Reachability-based path planning



Social interaction

- Social path learned from human crowd data sets
- Personal space compensation



Thank You

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