GNN-MPC for Path Following of Deformable Bodies

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Objective & Research Question:

The goal of this project is to design a framework that uses a Graph Neural Network (GNN) embedded in Model Predictive Control (MPC) to achieve real-time tracking and control for deformable robots.

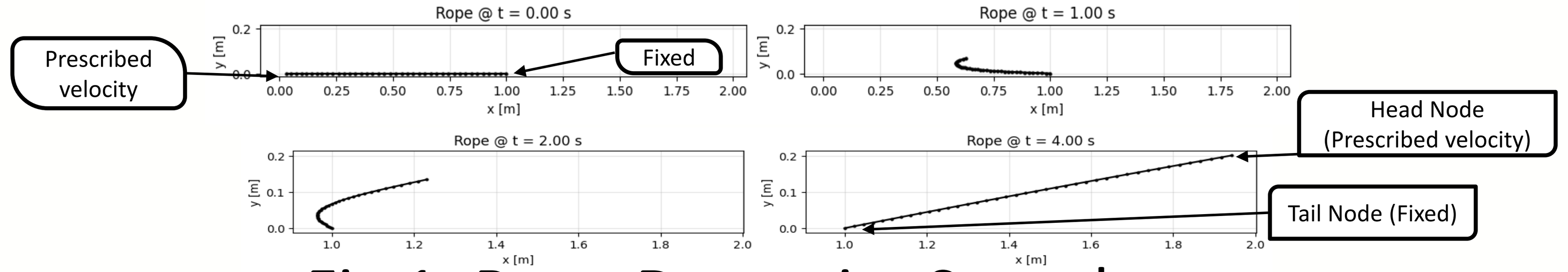

Fig 1: Rope Dynamics Snapshots

Methodology:

Represent rope as a chain of points (nodes)

- Assume quasi-static equilibrium for node constraints
- Apply external velocity (control input) to head node; tail fixed; rest of nodes free (DER constraint)
- Objective: apply control inputs to match shape to a prescribed reference shape

MPC for control input optimization integrated with DER as plant model

- MPC: performed over prediction & control horizon; predict states over prediction horizon and optimize future control inputs over control horizon
    - Cost function to determine how much to punish deviations from the reference, large control inputs, and large changes in control inputs
- DER: Lightweight elastic rod model that uses stretching, bending, and twisting energy to predict how shape changes due to control inputs; plant model for MPC

Background:

Deformable bodies are notoriously difficult to model

- High-fidelity models are too slow for real-time applications
- Hand-tuned models break when conditions change

This project will investigate whether these methods decrease computational effort or improve robustness/reproducibility

Results/Outcomes:

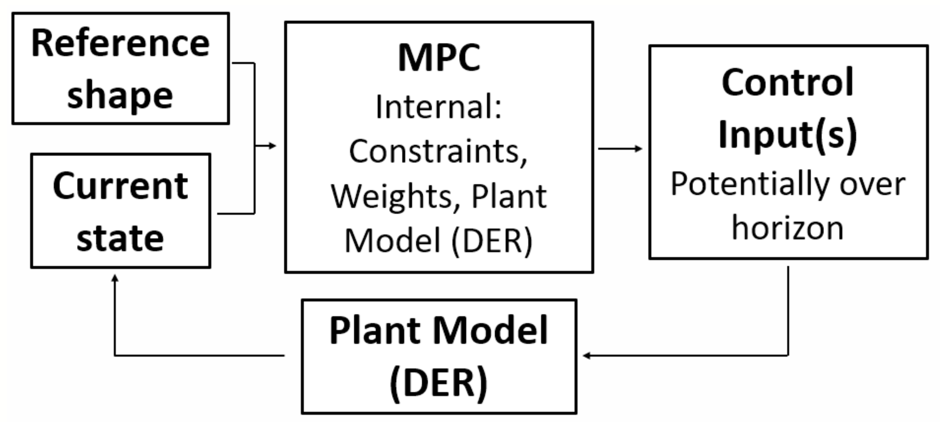

Fig 2: Closed-Loop MPC Diagram

Reference Values:

Weights

- $w_{track} = 200$
- $w_{smooth} = 0.05$
- $w_{ctrl} = 0.001$
- $u_{max} = 0.6$ m/s

MPC:

- $N_p = 20$
- $N_c = 20$
- dt = 0.05 s
- $t_{total} = 5$ s

Graph size:

- $n_v = 40$
- L = 1 m

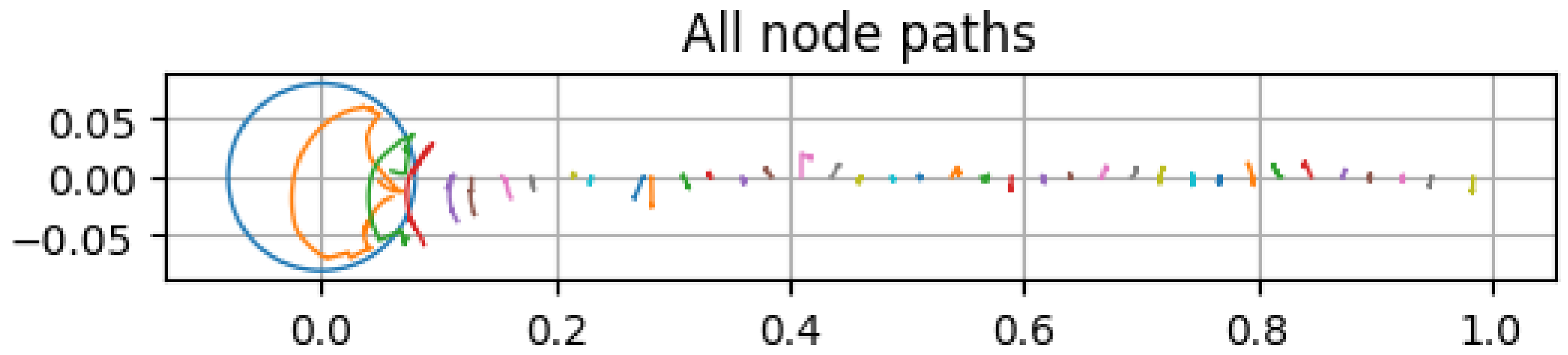

Fig 3: DER Simulation (Circular Top Node Path)

* Different colors ≡ different nodes *

References:

Fiedler, Felix, *et al.* “do-mpc: Towards FAIR Nonlinear and Robust Model Predictive Control.” *Control Engineering Practice*, vol. 140, 2023, article 105676. DOI: 10.1016/j.conengprac.2023.105676.

A. J. Abougarair and I. B. Attawil, "Enhancing Lateral Control of Autonomous Vehicles through Adaptive Model Predictive Control,“ 2024 IEEE 4th International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA), Tripoli, Libya, 2024, pp. 148-155, doi: 10.1109/MI-STA61267.2024.10599733

Challenges & Future Work:

Stability with DER caused early blow-ups in the model

- Solution: Fix tail & quasi-static equilibrium at each step as well as guarded bending/twisting

MPC trade-off between smoothness & accuracy

- Control input magnitude penalties often led the controller to prefer smaller movements for more complicated geometries

Though sufficient, rolling DER repeatedly in a predictive controller becomes expensive as the number of nodes or horizon increases

- Future direction: GNN plant model with same ideology; train GNN on DER data to maintain physics accuracy while decreasing computation time & processing power

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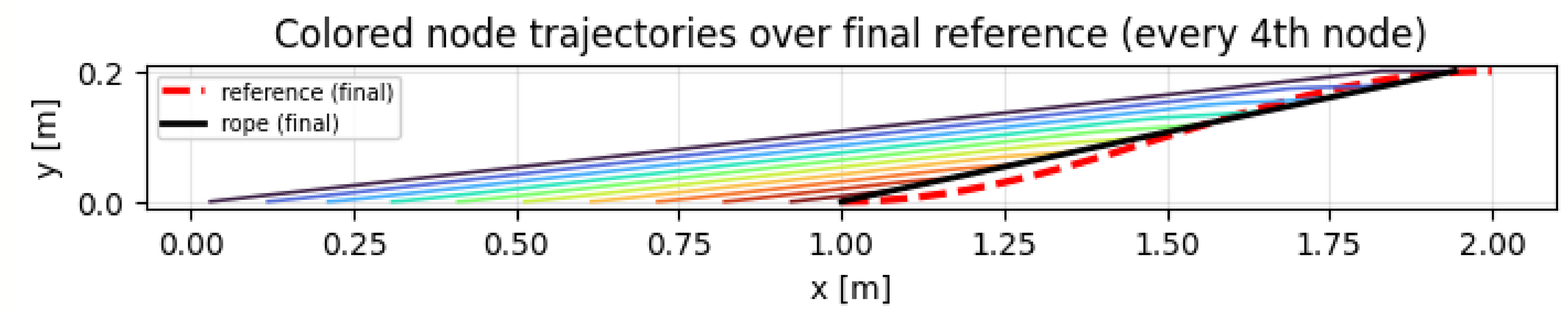

Fig 4: MPC Simulation (All Node Trajectories vs. Reference)

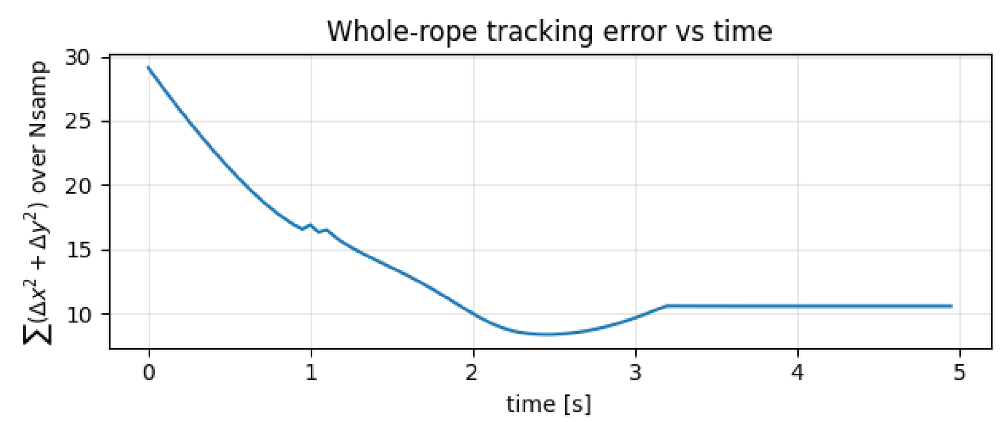

Fig 5: MPC Simulation (Whole Rod Error)

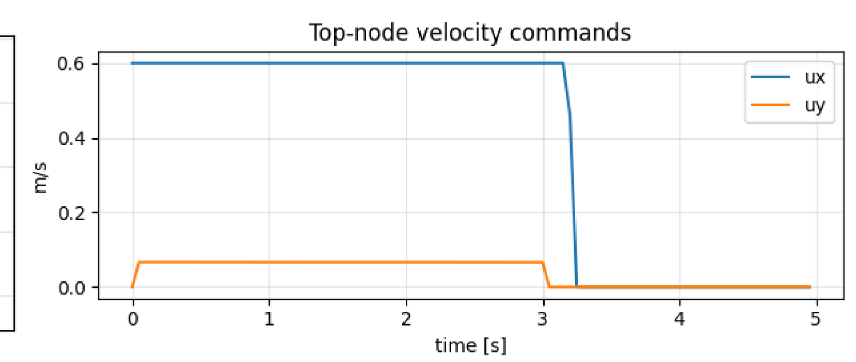

Fig 6: MPC Simulation (Control Input Values)

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