Physics informed Neural Networks based MPC and Dynamic Obstacle avoidance

Pranav Gunreddy, Vaidehi Som

ABSTRACT

- MPC is a flexible and intuitive control scheme but for the model for nonlinear systems with nonconvex constraints, to be real time capable is a bottleneck
- Physics Informed neural networks differ from regular neural networks in exploiting the underlying known physical law during the training process and hence can replace the nonlinear dynamics
- While Trajectory following could then be quickened by PINN controller, Dynamic agent trajectories could be accurately predicted by using state of the art RNNs (LSTM)

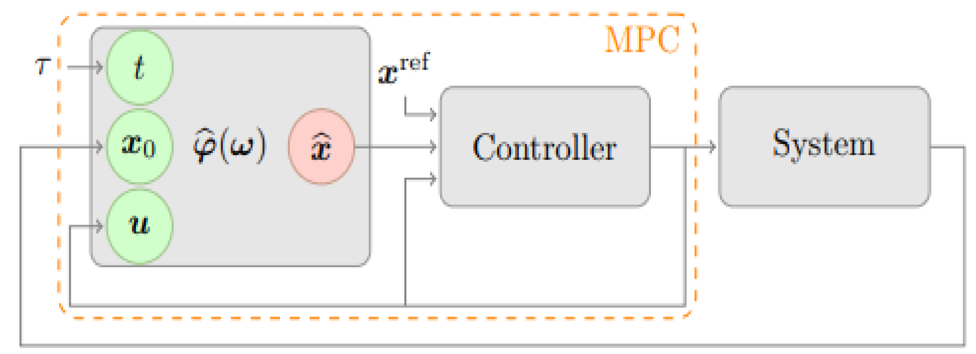
BACKGROUND

- Data driven approaches such as ML techniques have been touted not fit for control tasks. But with PINN, Due to the efficient computation of the partial derivative of the PINN with respect to the controller, the optimal control problem can be solved efficiently with a gradient-based method, without any adjoint computations or linearization
- Long short term memory (LSTM) networks are special recurrent neural networks (RNN) that can capture nonlinear and long-term trends. We use them to predict trajectories of pedestrians who are dynamic obstacles for our robot

CONCLUSIONS

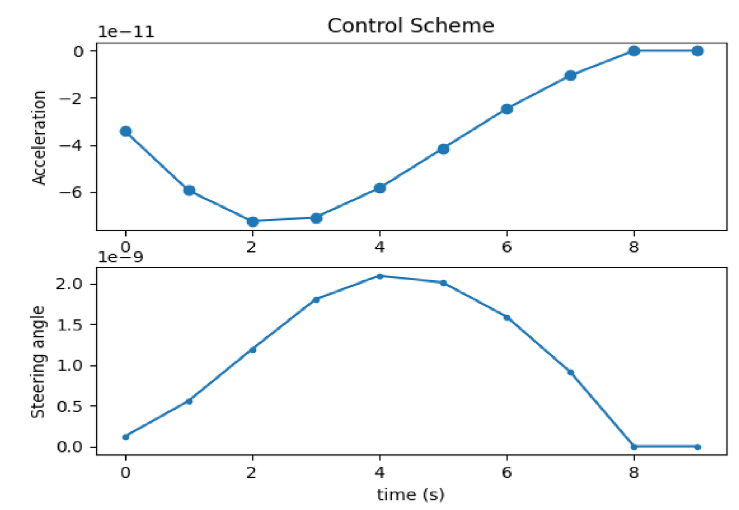
- We demonstrated our method by taking the case of a self driving car. Lifelong A* planning algorithm gives us the desired reference trajectory when we consider the temporal data of our pedestrians.
- A* also proved to be effective in generating paths that downright avoided trajectories. Since its updated at every time step, even if our control actions predicted by PINN MPC do not consider obstacles, the reference trajectory they take make sure they do not collide. To train the PINN, IPOPT solver in CASADI framework has been used to generate reference trajectories
- Our GRU models works well with very low error to predict 6 steps in future. Being computationally effective it can be run in real time for trajectory prediction

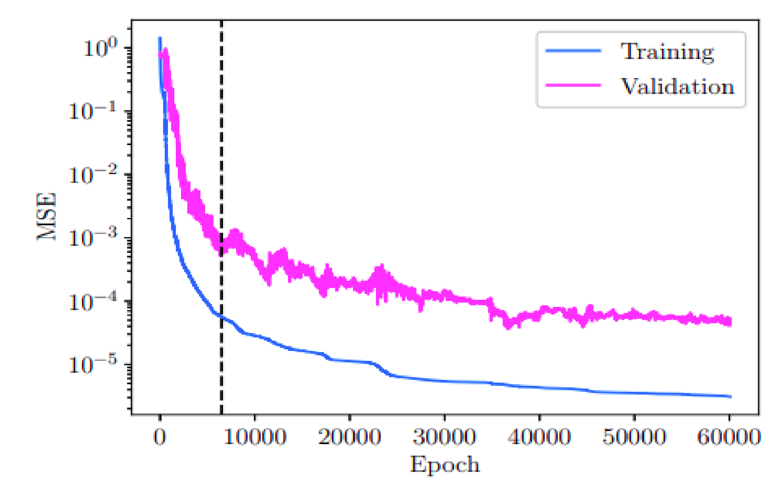
RESULTS



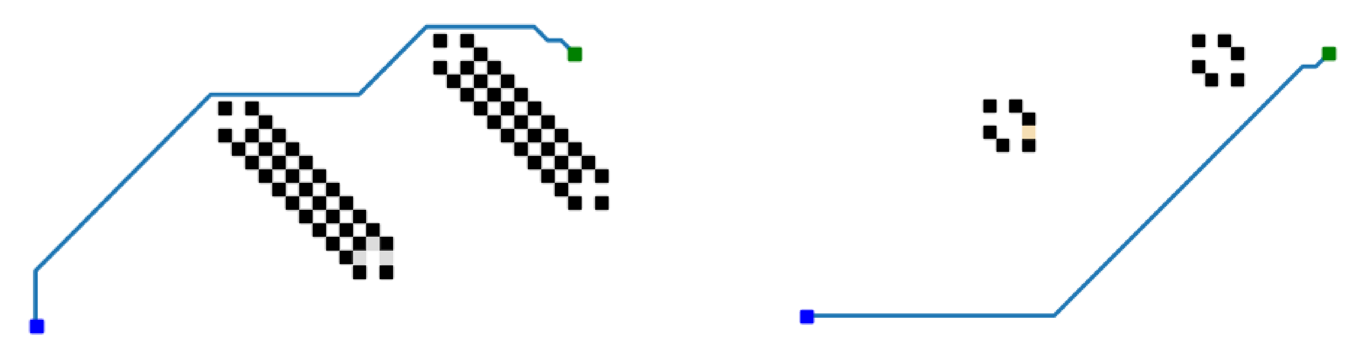
GRU: 8 obs. frames, 8 pred. frames			
Learning rate	0.0005	0.0007	0.0017
Avg train loss	0.1639	0.1491	0.1759
Avg test loss	1.7303	2.1536	2.8133
Avg train disp err.	0.5853	0.5529	0.5307
Final train disp err.	0.9363	0.8921	0.8583
Avg test disp err.	1.2648	1.3957	1.5666
Final test disp err.	2.1357	2.3529	2.5491

PINN LOSS & CONTROL SCHEME

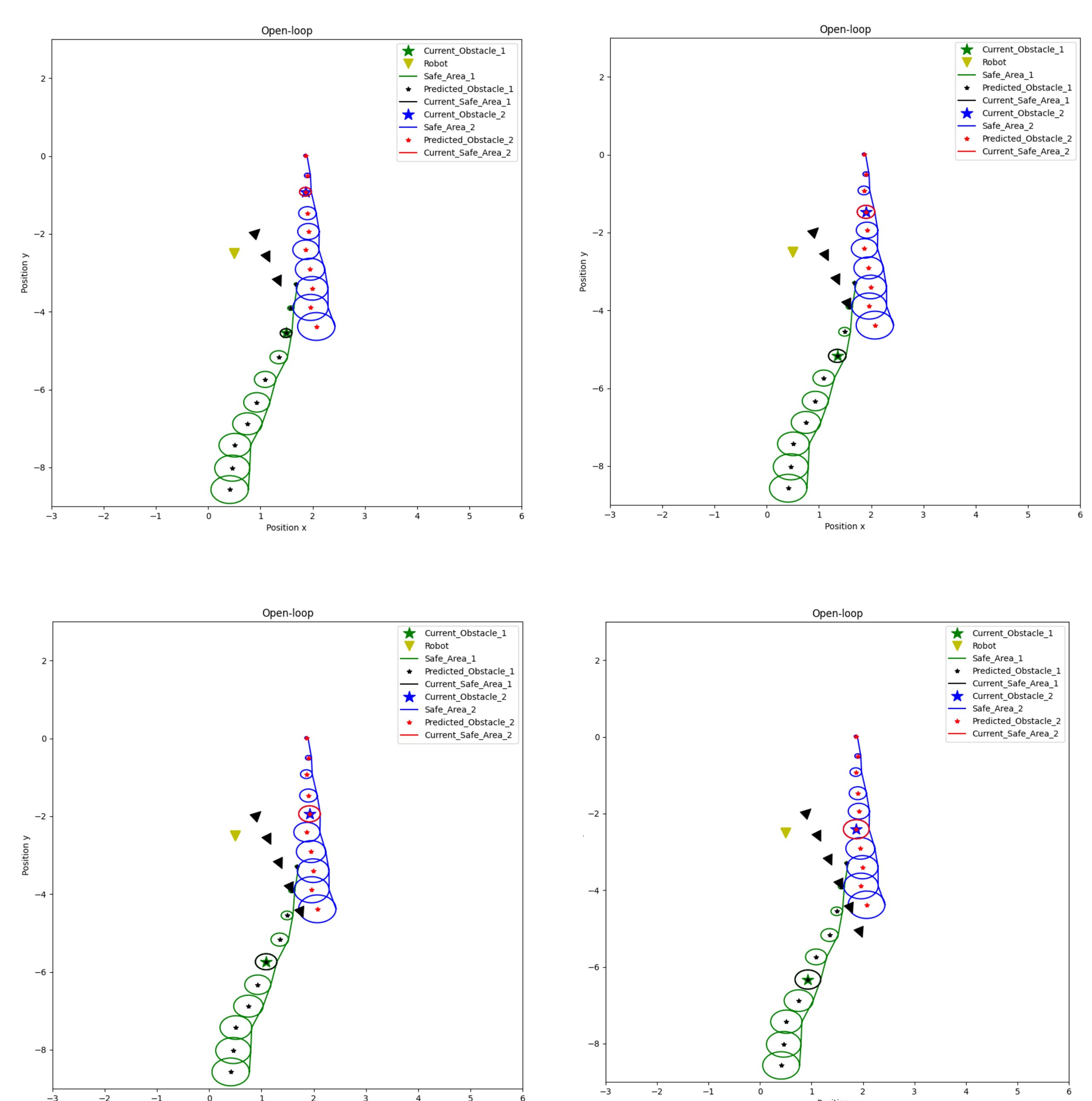


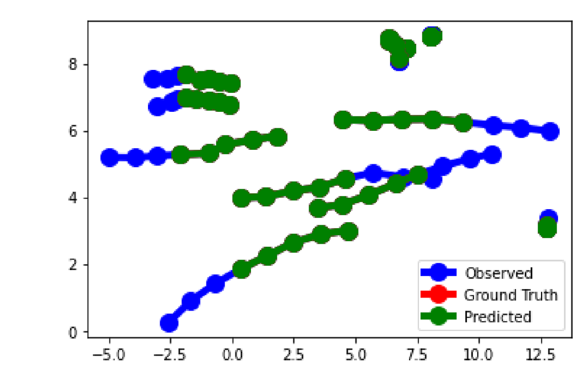


REFERENCE TRAJECTORY GENERATION

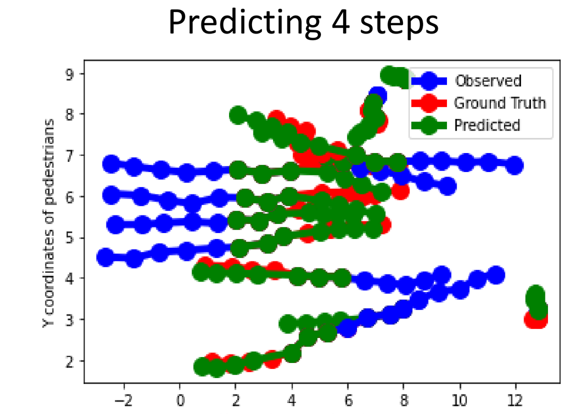


OBSTACLE AVOIDANCE

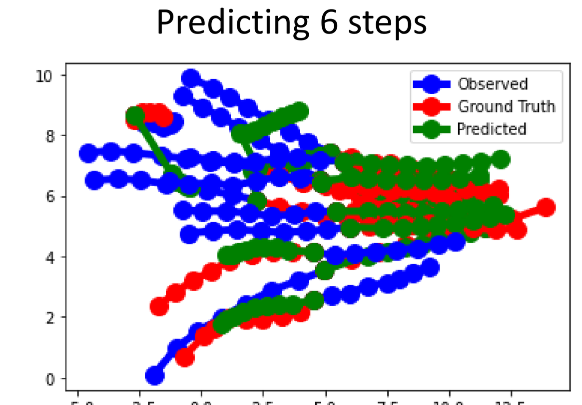




Predicting 4 steps



Predicting 6 steps



Predicting 8 steps

METHODS

- We demonstrated our method by taking the case of a self driving car. Lifelong A* planning algorithm to get reference trajectories during ergo vehicle motion. The algorithm plans in real time and gets updated whenever a pedestrian is in its path.
- The PINN based MPC controller is initially trained(offline) on Nonlinear MPC with Bicycle model dynamics for different initial conditions and control actions. This trained controller follows the reference trajectory generated while incorporating dynamic obstacle trajectories that are predicted by GRU
- To predict pedestrian's trajectory, we use GRU with 4 step future time prediction. Dataset for GRU training is ETH open dataset. We train using their temporal data and fixed observation length.

FUTURE EXTENSIONS

- The primary problem to encounter would be to make the PINN model robust by training it on relevant data. Statistical tools need to be used to quantify uncertainty
- PINNs are capable of predicting trajectories by considering dynamic obstacles. Hence LSTMs could be integrated so that our robot traverses safely.
- More pedestrians and other types of dynamic agents (cars, etc) and how to efficiently predict trajectories in a crowded place without blowing computationally
- Design PINN for closed loop MPC and explicitly compare time of computation between methods to prove PINN's utility
- Use Transformers to predict pedestrian's trajectory. (Social) Transformers can be used to predict more steps into the future with more certainty while considering pedestrian's surroundings into account

ACKNOWLEDGEMENTS

- Antonelo, E.A., Camponogara, E., Seman, L.O., de Souza, E.R., Jordanou, J.P., and Hubner, J.F. (2021). Physics informed neural nets-based control
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- Michael Posa, Brian Acosta, Will Yang, Alp Aydinoglu