Simulating the Effectiveness of Physics-informed Machine Learning in Nonlinear Model Predictive Control for Robotic Manipulators

Asa Paparo

Abstract

Existing methods of robotic motion planning rely on numerical optimization to generate control actions within constraints. One of the most successful methods of control has been Model Predictive Control (MPC), which continuously replans a trajectory by solving an online optimization problem. This means that for high dimension dynamical systems, the computational cost of MPC can rapidly become prohibitive. Physics Informed Neural Networks (PINNs) allow for the data driven creation and solving of high dimensional differential equations. Existing research has made progress in combining them, but lacks rigor and code optimization. In this paper, I develop an efficient NMPC implementation that relies on a PINN to plan movements. Then, I set up and integrate the controller with a state of the art simulation to demonstrate its effectiveness for a 7 DoF robotic arm. This development presents a significant advancement for fields that employ mobile robotics, such as manufacturing and search/rescue.

1 Introduction

A primary goal of the field of control theory is the efficient and constrained control of complex dynamical systems. A highly popular method of accomplishing this is [1]

[2]

- us government priorities: - semi automated production - make national production economically feasible - well educated laborors, robots work with them

- developed a new framework that is applicable

- antibiotics production - very important production - microchips, taiwan, etc - focus on relevant industries

- cutting edge of robotics surgery is nano robotic surgery - nanorobots swarm etc - in order to exploit specifics, it would be highly beneficial to modify architecture in X ways - claim adaptive ml algorithms are needed - adaptive algorithms for smart manufacturing and adaptive ml

analytical dynamics

2 Methods

2.1 Nonlinear Model Predictive Control (NMPC)

2.2 Physics Informed Neural Networks (PINNs)

2.3 Simulation

2.4 Derivation

- talk about what was done in methodologies before me -

$$\begin{bmatrix} l_{c1}s_1 \\ -l_{c1}c_1 \end{bmatrix}, \quad \begin{bmatrix} l_1 s_1 + l_{c2}s_{1+2} \\ -l_1 c_1 - l_{c2}c_{1+2} \end{bmatrix}, \tag{1}$$

$$T = T_1 + T_2, \quad T_1 = \frac{1}{2} I_1 \dot{q}_1^2 \tag{2}$$

$$T_2 = \frac{1}{2}(m_2 l_1^2 + I_2 + 2m_2 l_1 l_{c2} c_2)\dot{q}_1^2 + \frac{1}{2} I_2 \dot{q}_2^2 + (I_2 + m_2 l_1 l_{c2} c_2)\dot{q}_1 \dot{q}_2 \tag{3}$$

$$U = -m_1 g l_{c1} c_1 - m_2 g (l_1 c_1 + l_{c2} c_{1+2}) \tag{4}$$

$$(I_1 + I_2 + m_2 l_1^2 + 2m_2 l_1 l_{c2} c_2)\ddot{q}_1 + (I_2 + m_2 l_1 l_{c2} c_2)\ddot{q}_2 - 2m_2 l_1 l_{c2} s_2 \dot{q}_1 \dot{q}_2 \tag{5}$$

$$-m_2 l_1 l_{c2} s_2 \dot{q}_2^2 + m_1 g l_{c1} s_1 + m_2 g (l_1 s_1 + l_{c2} s_{1+2}) = 0 \tag{6}$$

$$(I_2 + m_2 l_1 l_{c2} c_2)\ddot{q}_1 + I_2 \ddot{q}_2 + m_2 l_1 l_{c2} s_2 \dot{q}_1^2 + m_2 g l_{c2} s_{1+2} = \tau \tag{7}$$

2.5 Control

To control this system, I use Model Predictive Control.

2.6 Optimization

```
    builder = DiagramBuilder()

    pendulum = builder.AddNamedSystem("pendulum", PendulumPlant())

    controller = builder.AddNamedSystem("controller",
                                        PidController(kp=[10.], ki=[1.], kd=[1.]))

    builder.Connect(pendulum.get_state_output_port(),
                    controller.get_input_port_estimated_state())
    builder.Connect(controller.get_output_port_control(), pendulum.get_input_port())

    builder.ExportInput(controller.get_input_port_desired_state())
    builder.ExportOutput(pendulum.get_state_output_port())

    logger = LogVectorOutput(pendulum.get_state_output_port(), builder)
    logger.set_name("logger")

    diagram = builder.Build()
    diagram.set_name("diagram")

    display(SVG(pydot.graph_from_dot_data(
        diagram.GetGraphvizString(max_depth=2))[0].create_svg()))

```

2.7 Physics Informed Neural Network (PINN)

3 Discussion

4 Conclusion

References

[1] M. G. Forbes, R. S. Patwardhan, H. Hamadah, and R. B. Gopaluni, "Model predictive control in industry: Challenges and opportunities," *IFAC-PapersOnLine*, vol. 48, no. 8, pp. 531–538, 2015. 9th IFAC Symposium on Advanced Control of Chemical Processes ADCHEM 2015.

[2] D. Youm, H. Jung, H. Kim, J. Hwangbo, H.-W. Park, and S. Ha, "Imitating and finetuning model predictive control for robust and symmetric quadrupedal locomotion," 2023.