National Aeronautics and Space Administration

Task-Relevant Machine Learning for Fast Rover Model Predictive Control

Principal Investigator: Changrak Choi (347); Co-Investigators: Abhishek Cauligi (347), Kyongsik Yun (349)

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Objective:

Our R&TD research work aimed to develop a framework to combine machine learning and numerical optimization to efficiently generate trajectories for planetary rovers on resource-constrained embedded systems. In particular, we focused on addressing the critical issue of finding dynamically-feasible solutions for such systems that enable an order of magnitude faster traverse rate than currently possible. Seeding from this R&TD work, our long term goal is mature feasibility and effectiveness of the learning-based to enable real-time on-board autonomous trajectory generation for surface exploration rovers as well as host of other space vehicles (e.g., Mars-Helicopter, CubeSats).

Background:

Surface rovers have a rich history of use at JPL, but current rover missions are limited to low operational speeds and are capable of traversing only hundreds of meters in a day. Consequently, current trajectory generation methods for planetary rover missions forgo using complex dynamics and physical models of the rovers to propose simple geometric paths that avoid collisions with obstacles. However, for future missions such as the proposed Endurance lunar rover, significantly faster operating speeds are required to accomplish the mission tasks and objectives, thereby requiring the use of trajectory generation methods that account for the full system constraints to generate dynamically-feasible trajectories. Generating such trajectories inevitably involves solving nonlinear and non-convex optimization, that is computationally heavy even with the state-of-the-art solvers and not compatible with the specifications of existing radiation hardened computing units. To this end, our goal is to provide a key-enabling technology that can quickly generate dynamically-feasible trajectories in real-time on low-power embedded systems, leveraging recent advances in machine learning and numerical optimization.

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\begin{array}{lll}
\underset{x_{0:N},\, u_{0:N}}{\text{minimize}} & \sum_{t=0}^{N} g_t(x_t, u_t; \theta) & \\
\text{subject to} & x_0 = x_{\text{init}}(\theta) & \\
& x_{t+1} = \psi_t(x_t, u_t; \theta), & t = 0, \ldots, N-1 \\
& f_{t,i}(x_t, u_t; \theta) \leq 0, & t = 0, \ldots, N, \quad i = 1, \ldots, n_{\mathrm{f}},
\end{array}
$$

Figure 1: Given a vector of problem parameters $\theta \in \mathbf{R}^{n_p}$, a parametric OCP can be written as above, where the state $x_t \in \mathbf{R}^{n_x}$ and control $u_t \in \mathbf{R}^{n_u}$ are the continuous decision variables. Here, the stage cost $g_t(\cdot)$ and terminal cost $g_N(\cdot)$ are assumed to be convex functions, but the dynamical constraints $\phi_t(\cdot)$ and inequality constraints $f_{t,i}(\cdot)$ are assumed smooth but possibly non-convex. The objective function and constraints are functions of the parameter vector $\theta \in \Theta$, where $\Theta \subseteq \mathbf{R}^{n_p}$ is the admissible set of parameters.

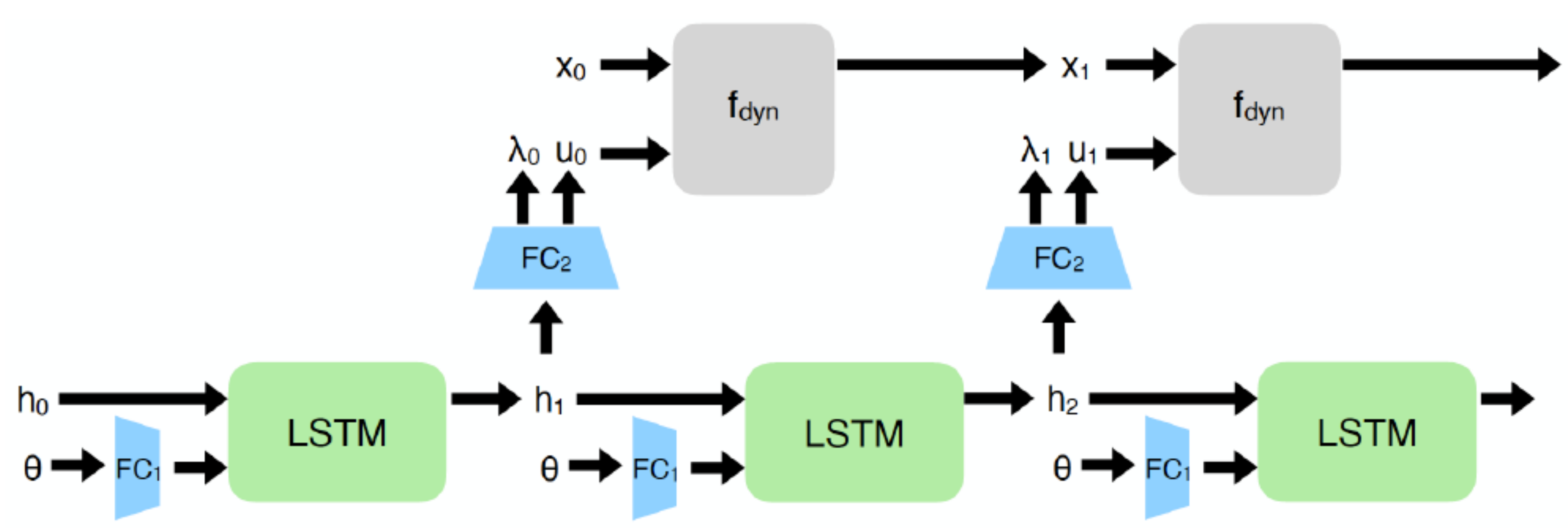

Figure 2: We seek to learn a solution mapping $f(\theta)$ that maps problem parameters θ to the optimizer (x^*, u^*) through use of a recurrent neural network (RNN) as shown above. Instead of learning the full mapping from a problem parameter θ to the full primal solution $(\hat{x}, \hat{u})$, we learn the time-varying policy using long short-term memory (LSTM) inference that has better scalability and naturally incorporates temporal structure of the problem.

Approach and Results:

We seek to leverage recent advances in infusing machine learning and nonlinear optimization to generate dynamically-feasible trajectories for planetary rovers. In particular, we focus on model predictive control (MPC), a framework that models the rover trajectory planning as an optimization problem and uses numerical optimization to solve for a new control action while satisfying a rich set of user-specified constraints. Although MPC has been used with great success in the aerospace and robotics communities, solving the optimization problem on resource-constrained hardware can be prohibitively expensive, motivating our use of data-driven methods to accelerate solution times.

Our framework consists of three major components – 1) formulation of MPC as a parametric optimal control problem (OCP) that can captures high-fidelity dynamics of the rover, 2) neural network-based approach to learn an initialization for the OCP to accelerate convergence of the numerical optimization online, and 3) utilization of task-relevant machine learning, to develop loss functions for the learning that are cognizant of the downstream use of the neural network. We emphasize that, unlike purely model-free approaches, our approach retains the underlying theoretical guarantees provided by the numerical optimization-based solver.

Significance/Benefits to JPL and NASA:

Our proposed task-relevant machine learning framework shows promise of reducing the computational time required to generate rover trajectory by at least an order of magnitude compared to the current state-of-the-art. Further, the generated solution trajectories are dynamically-feasible and safe such that it can directly be followed without ground or human operator in the loop. Such technical capability will be a crucial component of autonomy for upcoming rover surface missions that strive to increase the rate of the exploration through faster operating speeds. Our work through this R&TD effort is the first step in closing the apparent technology gap that exists for this much needed capability. The team will pursue follow-on proposals to mature this technology towards infusion to NASA/JPL future missions, where learning-based solutions combined with numerical optimization can enable real-time on-board trajectory planning for systems such as surface rovers as well as a host of other space vehicles.

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National Aeronautics and Space Administration

Jet Propulsion Laboratory
California Institute of Technology
Pasadena, California

PI/Task Mgr. Contact Information:
Email: changrak.choi@jpl.nasa.gov