A Constrained Iterative LQR Solver for the Trajectory Optimization Framework Horizon

Arturo Laurenzi, Francesco Ruscelli, and Nikos G. Tsagarakis



The eILQR problem

$$\min_{\substack{x_{0:N}, u_{0:N-1} \\ x_{0:N}, u_{0:N-1}}} \sum_{k=0}^{N-1} \ell_k(x_k, u_k) + \ell_N(x_N)$$
s.t. $x_{k+1} = F(x_k, u_k)$

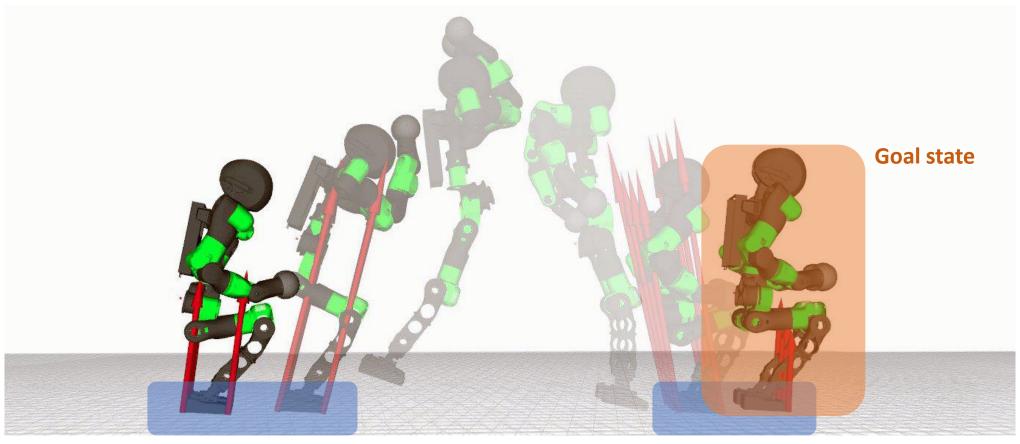
$$h_k(x_k, u_k) = 0, \quad h_N(x_N) = 0,$$

Path vs waypoint constraints

- Path constraints keep the system state-input on a manifold
 - Constraint dimension smaller than input dimension
 - Easily dealt with via **projection** (null-space) methods
 - Example: the contact manifold

- Waypoint constraints (e.g. final constraints) are useful to specify a goal
 - Constraint dimension up to the state dimension
 - Cannot be fulfilled with the choice of a single control input!
 - Example: posture at the end of a jump motion
 - Example: space travelled after taking N steps

An example



Contact Manifold

Contact Manifold

Our contribution

- A Riccati-like recursion to compute
 - The eILQR optimal policy
 - Lagrange multiplier estimates
- Lagrange multipliers are useful to autotune an L1 merit function

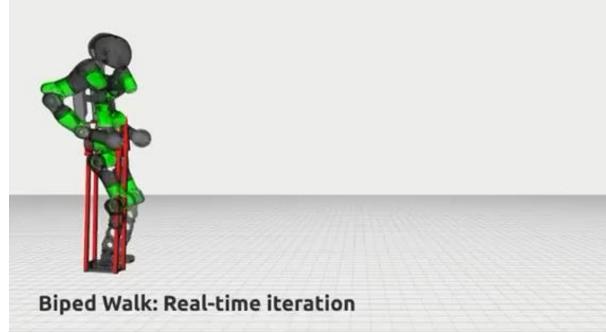
$$m(X) = L(X) + \gamma ||H(X)||_1$$

- An open-source implementation
- Extensive validation campaign









Meet me at the poster session!

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1. Contribution at a glance

- O(N) complexity w.r.t. horizon length
- Computes a linear policy for both the control input δu and Lagrange multipliers $\delta \mu$, $\delta \lambda$
- Exploit Lagrange multipliers estimate to implement an exact L1 line search strategy
- Extensive validation on complex robotic examples

2. Problem definition

A discrete-time Trajectory Optimization (TO) problem, with equality constraints

$$\min_{\substack{x_{0:N}, u_{0:N-1} \\ \text{s.t.}}} \sum_{k=0}^{N-1} \ell_k(x_k, u_k) + \ell_N(x_N)$$

$$\text{s.t.} \quad x_{k+1} = F(x_k, u_k)$$

$$h_k(x_k, u_k) = 0, \quad h_N(x_N) = 0$$

Note the final constraint cannot be deal with via projection/nullspace approaches!

3. Approach outline

Our strategy

- Apply Newton's method to the KKT conditions for the TO problem
- Solve the resulting linear system with Riccati-like recursions (backward pass + forward pass)
- 1) Hypotesize the following relation hold at node k

$$S_{k+1} \, \boldsymbol{\delta x}_{k+1} + V_{k+1}^T \, \boldsymbol{\delta \nu}_{k+1} - \delta \lambda_k = -s_{k+1}$$

 $V_{k+1} \, \boldsymbol{\delta x}_{k+1} = -v_{k+1}$

show that it holds at k-1, too.

2) Back-propagate constraint via the dynamics

$$C_k \delta x_k + D_k \delta u_k = c_k$$

- 3) Handle rank-deficiency of D_k . A generic state-only constraint cannot be solved by a single control input!
- Separate feasible-infeasible components at time k
- · Do it also for Lagrangian multipliers

Acknowledgements







4. Globalization strategy

Promote convergence to a **local minimum** by enforcing the decrease of a **merit function**

$$m(X) = L(X) + \gamma ||H(X)||_1$$

The merit function m(X) is **exact**^a if

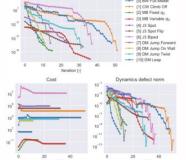
$$\gamma > \max\{\|\lambda_{0:N-1}^*\|_{\infty}, \|\mu_{0:N}^*\|_{\infty}\}$$

We can exploit the computed Lagrangian multiplier estimates to tune γ automatically

^aA merit function is said to be exact if its local minima are also local minima for he original constrained problem.

5. Validation





- Behaviors entirely obtained via constraints
- Contact model, centroidal dynamics enforced via constraints



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