

Optimal Control for Articulated Soft Robots

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Introduction (1)

- Soft robots can execute tasks with safer interactions. However, controllers that can exploit the systems' capabilities are still missing.
- Differential dynamic programming (DDP) has emerged as a promising tool for achieving highly dynamic tasks [1].
- We propose an efficient DDP-based algorithm for trajectory optimization of articulated soft robots that can optimize the state trajectory, input torques, and stiffness profile [2].

Model of Soft Articulated Arm (2)

$$\mathbf{M}(\mathbf{q}(t))\ddot{\mathbf{q}}(t) + \mathbf{C}(\mathbf{q}(t), \dot{\mathbf{q}}(t))\dot{\mathbf{q}}(t) + \mathbf{G}(\mathbf{q}(t)) + \mathbf{K}(t)(\mathbf{q}(t) - \mathbf{S}\boldsymbol{\theta}(t)) = \mathbf{0},$$

$$\mathbf{B}\ddot{\boldsymbol{\theta}}(t) + \mathbf{S}^T \mathbf{K}(t)(\mathbf{S}\boldsymbol{\theta}(t) - \mathbf{q}(t)) - \boldsymbol{\tau}(t) = \mathbf{0},$$

Links dynamic
Motors dynamic

Inertia Matrix $\mathbf{M}(\mathbf{q}) \in \mathbb{R}^{n \times n}$
Coriolis Matrix $\mathbf{C}(\mathbf{q}) \in \mathbb{R}^{n \times n}$
Gravity Vector $\mathbf{G}(\mathbf{q}) \in \mathbb{R}^n$
Stiffness Matrix $\mathbf{K} \in \mathbb{R}^{n \times n}$
Damping Matrix $\mathbf{D} \in \mathbb{R}^{n \times n}$
Control Inputs $\boldsymbol{\tau} \in \mathbb{R}^m$
Actuation Matrix $\mathbf{S} \in \mathbb{R}^{n \times m}$
Inertia Matrix $\mathbf{B} \in \mathbb{R}^{m \times m}$

$\mathbf{q} \in \mathbb{R}^n$

Optimal Control (3)

Optimal control problem:

$$\min_{(\mathbf{q}_0, \dot{\mathbf{q}}_0, \boldsymbol{\theta}_0, \boldsymbol{\tau}_0), (\boldsymbol{\tau}_e)} \ell(\mathbf{q}_N, \dot{\mathbf{q}}_N, \boldsymbol{\theta}_N, \dot{\boldsymbol{\theta}}_N) + \sum_{k=0}^{N-1} \int_{t_k}^{t_{k+1}} \ell(\mathbf{q}_k, \dot{\mathbf{q}}_k, \boldsymbol{\theta}_k, \dot{\boldsymbol{\theta}}_k, \boldsymbol{\tau}_k) dt,$$

s.t. $[\mathbf{q}_{k+1}, \dot{\mathbf{q}}_{k+1}, \boldsymbol{\theta}_{k+1}, \dot{\boldsymbol{\theta}}_{k+1}] = \psi(\mathbf{q}_k, \dot{\mathbf{q}}_k, \boldsymbol{\theta}_k, \dot{\boldsymbol{\theta}}_k, \boldsymbol{\tau}_k),$
 $[\dot{\mathbf{q}}_k, \ddot{\boldsymbol{\theta}}_k] = \text{FD}(\mathbf{q}_k, \dot{\mathbf{q}}_k, \boldsymbol{\theta}_k, \dot{\boldsymbol{\theta}}_k, \boldsymbol{\tau}_k),$
 $[\mathbf{q}_k, \boldsymbol{\theta}_k] \in \mathcal{Q}, [\dot{\mathbf{q}}_k, \dot{\boldsymbol{\theta}}_k] \in \mathcal{V}, \boldsymbol{\tau}_k \in \mathcal{U},$
 $\psi(\cdot)$ Numerical Integrator
 $\text{FD}(\cdot)$ Forward Dynamics
 \mathcal{Q}, \mathcal{V} Constraint Set

DDP (4)

Solves the Bellman optimal backward (time).

$$V(\mathbf{x}_k) = \min_{\mathbf{u}_k} \{ \ell_k(\mathbf{x}_k, \mathbf{u}_k) + V_{k+1}(\mathbf{f}(\mathbf{x}_k, \mathbf{u}_k)) \}$$

II-order approximation

$$\Delta V \approx \frac{1}{2} \begin{bmatrix} 1 \\ \delta \mathbf{x}_k \\ \delta \mathbf{u}_k \end{bmatrix}^T \begin{bmatrix} 0 & \mathbf{Q}_{\mathbf{x}_k}^T & \mathbf{Q}_{\mathbf{u}_k}^T \\ \mathbf{Q}_{\mathbf{x}_k} & \mathbf{Q}_{\mathbf{x}_k \mathbf{x}_k} & \mathbf{Q}_{\mathbf{x}_k \mathbf{u}_k} \\ \mathbf{Q}_{\mathbf{u}_k} & \mathbf{Q}_{\mathbf{u}_k \mathbf{x}_k} & \mathbf{Q}_{\mathbf{u}_k \mathbf{u}_k} \end{bmatrix} \begin{bmatrix} 1 \\ \delta \mathbf{x}_k \\ \delta \mathbf{u}_k \end{bmatrix}$$

Backward Pass $\delta \mathbf{u} = \arg \min_{\delta \mathbf{u}} \mathbf{Q}(\delta \mathbf{x}, \delta \mathbf{u}) = -\hat{\mathbf{K}} - \hat{\mathbf{K}} \delta \mathbf{x}$

$$\hat{\mathbf{K}} = \mathbf{Q}_{\mathbf{u}_k}^{-1} \mathbf{Q}_{\mathbf{u}_k \mathbf{x}_k} \quad \hat{\mathbf{K}} = \mathbf{Q}_{\mathbf{u}_k}^{-1} \mathbf{Q}_{\mathbf{u}_k \mathbf{x}_k}$$

Forward Pass $\hat{\mathbf{u}}_k = \mathbf{u}_k + \alpha \hat{\mathbf{K}} + \hat{\mathbf{K}}(\hat{\mathbf{x}}_k - \mathbf{x}_k)$
 $\hat{\mathbf{x}}_{k+1} = \mathbf{f}_k(\hat{\mathbf{x}}_k, \hat{\mathbf{u}}_k)$

Analytical Derivatives (5)

Forward Dynamics

$$\begin{bmatrix} \ddot{\mathbf{q}} \\ \ddot{\boldsymbol{\theta}} \end{bmatrix} = \begin{bmatrix} \mathbf{M}(\mathbf{q}) & \mathbf{0} \\ \mathbf{0} & \mathbf{B}_m \end{bmatrix}^{-1} \begin{bmatrix} \boldsymbol{\tau}_1 \\ \boldsymbol{\tau}_m \end{bmatrix}$$

$$\boldsymbol{\tau}_1 = -\mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} - \mathbf{D}\dot{\mathbf{q}} - \frac{\partial U(\mathbf{q}, \boldsymbol{\theta})}{\partial \mathbf{q}} + \mathbf{G}(\mathbf{q})$$

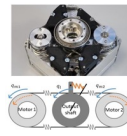
$$\boldsymbol{\tau}_m = -\mathbf{D}_m \dot{\boldsymbol{\theta}} - \frac{\partial U(\mathbf{q}, \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} + \mathbf{S}^T \boldsymbol{\tau}$$

Analytical Derivatives

$$\begin{bmatrix} \delta \ddot{\mathbf{q}} \\ \delta \ddot{\boldsymbol{\theta}} \end{bmatrix} = - \begin{bmatrix} \mathbf{M}(\mathbf{q}) & \mathbf{0} \\ \mathbf{0} & \mathbf{B}_m \end{bmatrix}^{-1} \left(\begin{bmatrix} \frac{\partial \boldsymbol{\tau}_1}{\partial \mathbf{x}} \\ \frac{\partial \boldsymbol{\tau}_m}{\partial \mathbf{x}} \end{bmatrix} \delta \mathbf{x} + \begin{bmatrix} \frac{\partial \boldsymbol{\tau}_1}{\partial \mathbf{u}} \\ \frac{\partial \boldsymbol{\tau}_m}{\partial \mathbf{u}} \end{bmatrix} \delta \mathbf{u} \right)$$

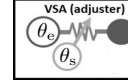
Experimental Setup (6)

Qb Move [3]

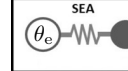


Agonist-Antagonist

$\mathbf{K}(\mathbf{q}, \boldsymbol{\theta})$



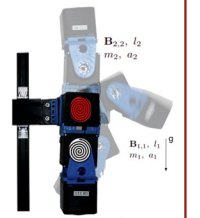
$\mathbf{K}(\mathbf{q} - \boldsymbol{\theta})$



Experiments:

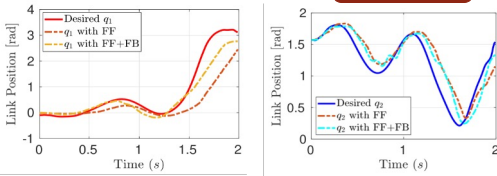
- 4 DoFs SEAS/VSAs
- 2 DoFs VSAs/SEAs

- Active SEA
- Passive SEA

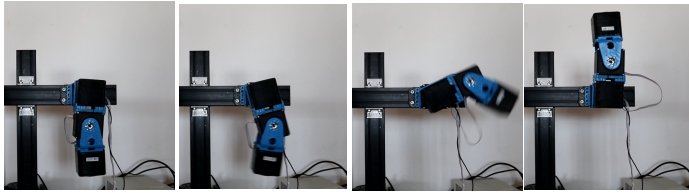
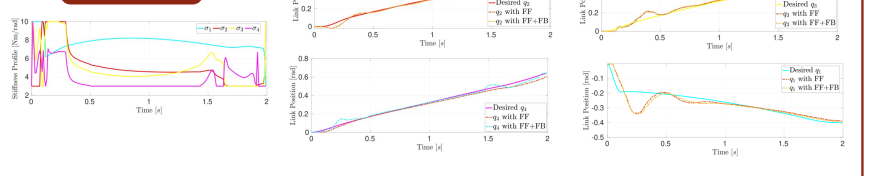


Results (6)

Exp #1



Exp #2



We proposed an efficient way to compute the dynamics and analytical derivatives of soft articulated. The state-feedback controller based on local and optimal policies from Box-FDDP/FDDP helped to improve all tasks

Conclusion

Future Works

Future work will include MPC solutions.

References

- [1] Mastalli, C., et al. (2020, May). Crocodyly: An efficient and versatile framework for multi-contact optimal control. In 2020 IEEE International Conference on Robotics and Automation (ICRA) (pp. 2536-2542). IEEE.
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