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Computational details for : “Differential Dynamic Programming for Maximum a Posteriori Centroidal State Estimation of Legged Robots”

François Bailly^{a,b,*}, Justin Carpentier^c and Philippe Souères^a

This document complements the paper entitled “Differential Dynamic Programming for Maximum a Posteriori Centroidal State Estimation of Legged Robots” [1]. The purpose of this work was to estimate the centroidal dynamics of legged robots by formulating a maximum a posteriori problem and solving it thanks to differential dynamic programming (DDP). In the following, the computations of the partial derivatives of the unoptimized value function (Q_k) are provided for the DDP algorithm. Then, the hypothesis about the 0–mean property of the stochastic part of the dynamics is validated by Fig. 1 (result of the simulation) which demonstrates that the DDP minimization of Eq.(11) does keep ω_k 0–mean.

APPENDIX I PARTIAL DERIVATIVES OF Q_k

- $Q_{xk} = \nabla_{\mathbf{x}_k} l_k + \nabla_{\mathbf{x}_k} \mathcal{V}_{k+1}(f(\mathbf{x}_k, \omega_k)),$

$$\nabla_{\mathbf{x}_k} l_k = 2 \frac{\partial(g(\mathbf{x}_k) - \mathbf{y}_k)^T}{\partial \mathbf{x}_k} \Sigma_{\eta_k}^{-1} (g(\mathbf{x}_k) - \mathbf{y}_k),$$

$$\frac{\partial g(\mathbf{x}_k)}{\partial \mathbf{x}_k} = \frac{C(\mathbf{x}_k)}{\partial \mathbf{x}_k} \mathbf{x}_k + C(\mathbf{x}_k) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2c_k \times 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \doteq \tilde{C}(\mathbf{x}_k),$$

$$Q_{xk} = 2\tilde{C}(\mathbf{x}_k)^T \Sigma_{\eta_k}^{-1} (g(\mathbf{x}_k) - \mathbf{y}_k) + A^T \mathcal{V}'_x.$$

- $Q_{\omega k} = \nabla_{\omega_k} l_k + \nabla_{\omega_k} \mathcal{V}_{i+1}(f(\mathbf{x}_k, \omega_k)),$

$$\nabla_{\omega_k} l_k = \frac{\partial \|\omega_k\|_{\Sigma_{\omega_k}^{-1}}^2}{\partial \omega_k} = 2\Sigma_{\omega_k}^{-1} \omega_k,$$

$$Q_{\omega k} = 2\Sigma_{\omega_k}^{-1} \omega_k + B^T \mathcal{V}'_{\omega}.$$

- $Q_{xxk} = \nabla_{\mathbf{x}_k}^2 l_k + \nabla_{\mathbf{x}_k}^2 \mathcal{V}_{i+1}(f(\mathbf{x}_k, \omega_k)),$

where, the element of $\nabla_{\mathbf{x}_k}^2 l_k$ at the i^{th} row and j^{th}

column is denoted by:

$$[\nabla_{\mathbf{x}_k}^2 l_k]_{ij} = \sum_{m=1}^Y \sum_{n=1}^Y [\Sigma_{\eta_k}^{-1}]_{mn} \left(\frac{\partial \tilde{C}_{im}^T}{\partial \mathbf{x}_j} [g(\mathbf{x}_k) - \mathbf{y}_k]_n + \tilde{C}_{im}^T \frac{\partial [g(\mathbf{x}_k)]_n}{\partial \mathbf{x}_j} \right),$$

$$[\nabla_{\mathbf{x}_k}^2 l_k]_{ij} = [\tilde{C}^T \Sigma_{\eta_k}^{-1} \tilde{C}]_{ij} + \sum_{n=1}^Y \sum_{m=1}^Y \frac{\partial \tilde{C}_{km}^T}{\partial \mathbf{x}_l} [\Sigma_{\eta_k}^{-1}]_{mn} [g(\mathbf{x}_k) - \mathbf{y}_k]_n,$$

$$[\nabla_{\mathbf{x}_k}^2 l_k]_{ij} = [\tilde{C}^T \Sigma_{\eta_k}^{-1} \tilde{C}]_{ij} + \tilde{\mathbf{c}}_{ij}^T \Sigma_{\eta_k}^{-1} (g(\mathbf{x}_k) - \mathbf{y}_k),$$

where, $\tilde{\mathbf{c}}_{ij} \in \mathbb{R}^Y$ is the stacked vector of $\frac{\partial \tilde{C}_{im}^T}{\partial \mathbf{x}_j}$ for $m \in [1..Y]$.

- $Q_{\omega \omega k} = \nabla_{\omega_k}^2 l_k + \nabla_{\omega_k}^2 \mathcal{V}_{i+1}(f(\mathbf{x}_k, \omega_k)),$

$$\nabla_{\omega_k}^2 l_k = 2\Sigma_{\omega_k}^{-1} \frac{\partial \omega_k}{\partial \omega_k} = 2\Sigma_{\omega_k}^{-1}$$

$$Q_{\omega \omega k} = 2\Sigma_{\omega_k}^{-1} + B^T \mathcal{V}_{\omega \omega} B$$

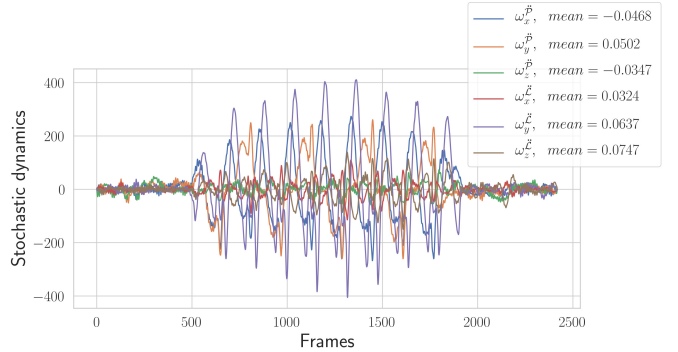


Fig. 1: Time evolution of the stochastic control inputs of the dynamics for the simulated walk of the HRP-2 robot.

REFERENCES

- [1] F. Bailly, J. Carpentier, and P. Souères, “Differential dynamic programming for maximum a posteriori centroidal state estimation of legged robots,” in *Internat. Conf. on Robotics and Automation*. IEEE, 2021.

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