BiorbdOptim, a New Software for Musculoskeletal Optimal Control in Biomechanics

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Abstract— **The abstract**

Keywords – TODO

I. Introduction

The introduction

II. Design and Implementation

The method

III. Illustrations

In this section, some applications are presented to illustrate the versatility of BiorbdOptim and to give a practical overview on how to use its various features. The performances and the Github links of each OCP are listed in Tab. II.

A. Muscle activation driven pointing task

The goal of this example was to achieve a muscle activation driven pointing task using a 2-DoF, 6-muscle arm model. In addition to muscle-induced torques, pure torques could compensate for the model weaknesses. The movement lasted for 2 seconds and was discretized using 51 shooting nodes.

Term #1 of the objective function (Tab. I) corresponds to the pointing tasks described by a Mayer term (heaviest weight), to superimpose two markers, the first one fixed in the ulna system of coordinates and the second one fixed in the scene. Terms #2 and #3 were added for control regularization (muscle activation and torques) and #4 for state regularization.

TABLE I: Objective terms of the activation-driven pointing task

	Type	Function	Weight
#1	Mayer	ALIGN_ MARKERS	$1e6$
#2	Lagrange	MINIMIZE_ MUSCLE_ CONTROL	$1e1$
#3	Lagrange	MINIMIZE_ TORQUE	$1e1$
#4	Lagrange	MINIMIZE_ STATE	$1e1$

The problem was solved with IPOPT and ACADOS resulting in two significantly different solutions with ACADOS proving a 16 times smaller optimized cost (Tab. II), which illustrate the pitfalls of local minima as well as the benefits of having access to different solvers with minimal effort. Indeed, the ACADOS-based solution (Fig. 1, top) makes good use of gravity to minimize the control inputs, while the IPOPT-based solution (Fig. 1, bottom) moved the arm in the opposite direction and was stuck in a local minimum (still achieving the task though). It is worth noting that no constraint was given about the shoulder range of motion to ensure physiological muscle trajectories.

IV. Discussion

The discussion

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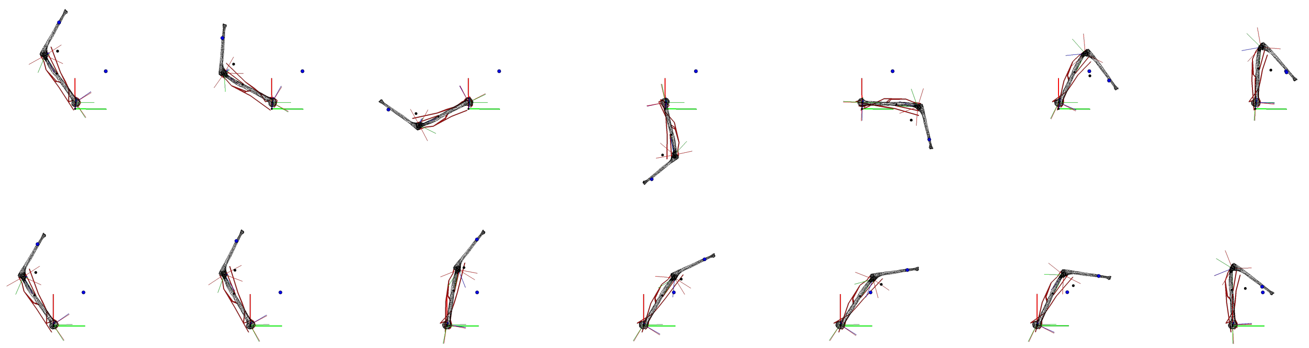

Fig. 1: Snapshots of an optimized muscle activation driven pointing task. Top: using ACADOS, optimized value = 427.5. Bottom: using IPOPT, optimized value = 6959.3.

TABLE II: Overview of computational results for the different OCPs cases and links to detailed implementations. When running with IPOpt, 6 threads were systematically used. * stands for free time OCP, otherwise it is fixed.

	Activation-driven pointing		Ex# 2		Ex# 3	
	IPOpt	ACADOS	IPOpt	ACADOS	IPOpt	ACADOS
# states $\boldsymbol{x}(t)$	4	4	–	–	–	–
# control $\boldsymbol{u}(t)$	8	8	–	–	–	–
# shooting nodes	51	51	–	–	–	–
# NLP iterations	27	21	–	–	–	–
OCP duration (s)	2	2	–	–	–	–
Optimized cost	6959.3	427.5	–	–	–	–
Time to convergence (s)	9.9	0.19	–	–	–	–

APPENDIX

The appendix