MYOBOLICA TOOLBOX TO EXCEED THE INDIVIDUAL MUSCLE CONTROL SOLUTION

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Summary

Myobolica is a toolbox based on the stochastic approach, to identify several physiologically plausible solutions, thus allowing to model suboptimal muscle control. In this study, we report on two case examples where the tool was employed to simulate upper limb and lower limb tasks.

Introduction

Due to the inherent redundancy of the musculoskeletal system, different motor control strategies may be selected to reach the same motion. This redundancy may be solved by optimizing a cost function (representative of a physiological criterion), possibly exploiting experimental EMG data, to identify one specific solution. Alternative approaches, e.g. the stochastic approach, based on the Uncontrolled Manifold theory, aim to explore the solution space to estimate several "good enough" solutions. One such method is Myobolica, recently introduced [1].

Methods

Myobolica – through Bayesian Statistics and a Markow Chain Monte Carlo algorithm – samples a wide spectrum of physiologically plausible solutions, i.e. sets of non-negative muscle forces never exceeding the tetanic limits and able to equilibrate the external joint torques. Furthermore, the force generation capacity of all muscles is constrained so that muscles cannot change the level of force too abruptly, from one instant to the next [1].

We hereby show two case studies, where Myobolica was used to simulate (1) a walking trial and (2) a shoulder abduction, exploiting publicly available data from the fourth Grand Challenge Competition [2] and the Orthoload project [3], respectively. The generic Full Body Model [4] and an adapted version of the Delft Shoulder and Elbow Model [5] were linearly scaled to match the anthropometry of the two subjects under studies.

Within Myobolica, in both cases, we looked for 100k solutions, once joint kinematics, joint kinetics and the muscle moment arms had been determined through OpenSim (via an inverse approach). Of note, for the shoulder abduction, we also performed the simulations introducing a second constraint: EMG data from the deltoid muscles were used to inform the simulation (EMG-informed Myobolica), thus limiting the overall variability. In addition, to reduce the computational time, we subsampled the data provided to Myobolica (every one in 30 timeframes). The shoulder abduction trial was almost twice as long as the walking trial.

Figure 1 shows the resulting knee and shoulder joint contact forces as a function of time (for the walking trial) and of the shoulder elevation angle (for the shoulder abduction), normalized to the subjects' bodyweight. We assessed the results in terms of R^2 and root mean square error (RMSE) between the median value of the solution band and the experimentally measured joint contact force.

Results and Discussion

The predicted solution spaces are on average 0.84 BW wide (ranging from a minimum of 0.50 to a maximum of 1.90) for the walk simulation with a good correlation to the experimental value (R^2=0.64, RMSE=1.13) and 1.4 BW wide (range: 0.06-2.1) for the shoulder abduction. In this second case, the correlation significantly increased when the EMG new constraint has been introduced (R^2=0.16, RMSE=1.75 without EMG; R^2=0.41, RMSE=1.1 with EMG).

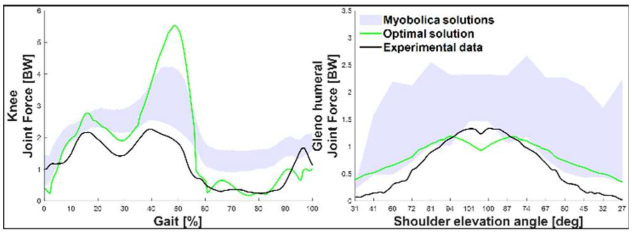

Figure 1: Joint contact force predicted with Myobolica (blue), OpenSim (green) and the experimental measure (black).

Conclusions

In both case studies, the stochastic approach allowed to predict a large number of plausible solutions which, together with optimization solutions, may improve the understanding of several suboptimal control strategies typical of subjects with neuromuscular disorders. Shoulder results correlation, even if low as an absolute value, represent a promising result when all timeframes will be simulated.

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