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Which data should be tracked in forward-dynamic optimisation to best predict muscle forces in a pathological co-contraction case?

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ABSTRACT

The choice of the cost-function for predicting muscle forces during a movement remains a challenge, especially in patients with neuromuscular disorders. Forward dynamics-based optimisations mainly track joint kinematics or torques, combined with a least-excitation criterion. Tracking marker trajectories and/or electromyography (EMG) has rarely been proposed. Our objective was to determine the best tracking objective-function to accurately predict the upper-limb muscle forces. A musculoskeletal model was created and EMG was simulated to obtain a reference movement – a shoulder abduction. A Gaussian noise (mean = 0; standard deviation = 15%) was added to the simulated EMG. Another noise – corresponding to the actual soft tissue artefacts (STA) of experimental shoulder abduction movements – was added to the trajectories of the markers placed on the model. Muscle forces were estimated from these noisy data, using forward dynamics assisted by six non-linear least-squared objective-functions. These functions involved the tracking of marker trajectories, joint angles or torques, with and without EMG-tracking. All six approaches used the same musculoskeletal model and were solved using a direct multiple shooting algorithm. Finally, the predicted joint angles, muscle forces and activations were compared to the reference values, using root-mean-square errors (RMSe) and biases. The force RMSe of the approach tracking both marker trajectories and EMG (18.45 ± 12.60 N) was almost five times lower than the one of the approach tracking only joint angles (82.37 ± 66.26 N) or torques (85.10 ± 116.40 N). Therefore, using EMG as a complementary tracking-data in forward dynamics seems to be promising for the estimation of muscle forces.

1. Introduction

Muscle forces quantification through musculoskeletal modeling might be beneficial to improve the design and evaluation of therapeutic programs. A better understanding of the co-contraction mechanisms into the muscle force-sharing problem would bring non-negligible clinical insights (Dao, 2016), especially in patients with neuromuscular disorders. Because of the musculoskeletal redundancy, an infinity of muscle activation patterns can produce the same movement (Buchanan and Shreeve, 1996). Optimisation approaches are therefore used to provide a unique solution; however, the nature of the objective-function remains a challenge.

In the literature, dynamic optimisation is widely acknowledged for considering the time-dependent nature of the muscles (Ackermann and Schiehlen, 2009; Engelhardt et al., 2015; Morrow et al., 2014). Based on a forward approach, dynamic optimisation accounts for activation dynamics and is mostly assisted by data tracking to find the optimal controls driving the biomechanical model (Ackermann and Schiehlen, 2009; Pandy, 2001). Dynamic optimisation is often criticized for being time-consuming; convergence times up to hundreds of hours are reported in some studies (Ackermann and Schiehlen, 2009; Menegaldo et al., 2006; Neptune, 1999; Pandy, 2001). Hence, state-of-the-art algorithms like direct collocation (Diehl et al., 2006; von Stryk and Bulirsch, 1992) and direct multiple shooting algorithms (Leineweber et al., 2003; Mombaur et al., 2010; Spagele et al., 1999) could be used to solve forward problems in a timely manner.

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In dynamic optimisation, joint kinematics is commonly tracked by minimizing the difference between experimental and predicted data through the objective-function (Neptune et al., 2001, 2004). Since musculoskeletal models are based on a kinematic chain, tracking-errors at the proximal joints will theoretically propagate to the distal segment positions. Tracking marker trajectories instead of joint kinematics could limit such error propagation.

Another type of forward dynamics-based optimisation – termed as 'hybrid' or *forward-muscular inverse-skeletal* optimisation (Lloyd and Besier, 2003; Shourijeh et al., 2016) – was recently introduced. It combines an inverse-dynamic approach with a forward workflow (Lloyd and Besier, 2003; Sartori et al., 2014; Shourijeh et al., 2016). However, due to the so-called 'soft tissue artefacts' (STA) and, above all, the successive derivations, the joint torques may be noisy (Pandy, 2001). Then, the use of an extended Kalman filter – including up to the accelerations in the state variables – may partially solve this problem (Fohanno et al., 2014).

In the literature, the tracking functions of dynamic or hybrid optimisations are commonly combined with a least-activation/excitation criterion (Chumanov et al., 2007; Sartori et al., 2014; Thelen and Anderson, 2006). However, such a criterion does not reflect the muscle co-contraction and may not provide physiological results (Cholewicki et al., 1995; Gagnon et al., 2001). This is particularly true in some pathological cases, like children with cerebral palsy, because spasticity increases muscle co-contraction (Sarcher et al., 2015, 2017). Thus, such approach should not be recommended for studying goal-directed upper-limb movements implying complex muscle coordination (Morrow et al., 2014). Instead of minimizing muscle excitations, tracking electromyography (EMG) – a direct measurement of muscular activity – may address this limitation.

In this paper, we hypothesized that tracking both EMG and marker trajectories would improve the muscle forces realism. Our objective was to determine which kind of data should be tracked when using forward-dynamic optimisation to accurately predict muscle forces in case of pathological co-contraction.

2. Methods

2.1. Upper-limb musculoskeletal model

A 3D upper-limb model was created from a custom-made modeling package (S2M Dynamic Library) adapted from the Rigid Body Dynamic Library (Felis, 2011). Three rigid segments were articulated by two joints, namely: the glenohumeral (3 DOFs: elevation, plane of elevation, axial rotation) and elbow (1 DOF: flexion/extension) (Fig. 1). A total of eight markers – four on the arm (M1–M4) and lower-arm (M5–M8) – were placed on the right upper-limb.

The geometry and properties of the bones and 18 Hill-type lines of action included in the model were implemented into the S2M Dynamic Library, according to the generic musculoskeletal model of Holzbaur et al. (2005) available in OpenSim. They were actuated by generic force-length, force-velocity and parallel passive elastic force-length relationships (Zajac, 1989). Activation dynamics was implemented as described in Appendix.

2.2. STA-noise extraction and joint kinematics

Joint kinematics and skin marker STA were obtained from the experimental protocol described in Begon et al. (2015). Briefly, markers were placed on skin and on intracortical-pin clusters screwed in the left humerus of four healthy participants (Begon et al., 2015). A skeletal model was then created and joint kinematics was reconstructed from both skin and intracortical-pin markers (Begon et al., 2015; Laitenberger et al., 2015). The 3D displacement

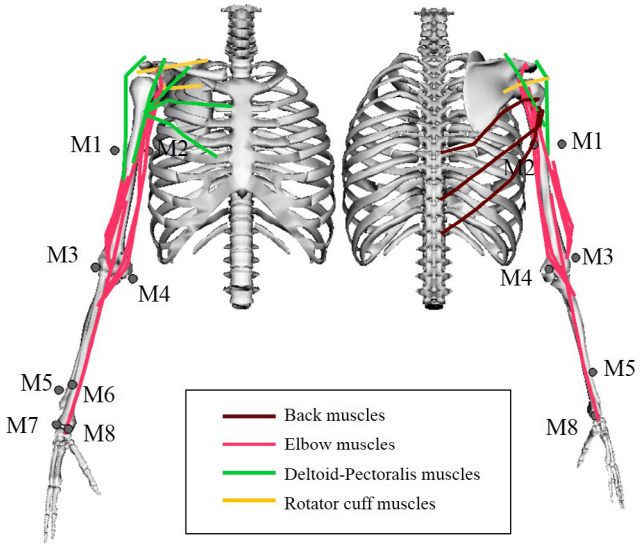

Fig. 1. Anterior (A) and posterior (B) views of the right upper-limb musculoskeletal model from the S2M Dynamic Library. Colored lines and dark-circled dots represent the 18 Hill-type muscle lines of action and the 8 markers, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of the skin markers expressed in the bone system-of-coordinates corresponded to the STA.

In the present study, shoulder abductions from the anatomical position performed by one subject (27 years; 1.65 m; 57 kg) were analysed. For each of the three repetitions of the movement, the STA-noise was extracted. As no pin was screwed into the subject's lower-arm, the calculated noise was smaller for the four markers placed on this segment. The corresponding joint kinematics was then smoothed using a Fourier interpolation on MATLAB (Mathworks, Nantucket, MA). The experimental joint angles matching the DOFs of our right upper-limb model were kept, while the others were ignored.

2.3. Simulated muscle excitations

Since no EMG data were recorded in combination with the pin and skin markers trajectories in the previous work of Begon et al. (2015), EMG (also termed as *muscle excitations*) was simulated for each repetition of the movement, using a forward approach. The optimal control problem was solved with a direct multiple shooting algorithm implemented into the MUSCOD-II software (Leineweber et al., 2003) (Appendix). The movement duration was 2 s. Controls were muscle excitations; states were joint angles, velocities and muscle activations. Controls were discretized into a piecewise-constant representation on a 51-node grid (Mombaur et al., 2010); they were optimised, so that the experimental joint angles were strictly reproduced. Estimated joint angles, velocities and muscle activations were obtained as output.

First, the redundancy of the musculoskeletal model was assessed by calculating a viable control space, using 200 random controls initial guesses without objective-function (Fig. A1 in Fig. A1 in Appendix). Second, the reference excitations were obtained, with enforced levels of co-contraction to reproduce the magnitude of those observed in cerebral palsy patients (Sarcher et al., 2015, 2017). Similar to previous studies modeling the EMG signal (Farina and Merletti, 2000; Zardoshti-Kermani et al., 1995), a zero-mean Gaussian noise (standard deviation = 15%) was finally added to the optimised excitations to mimic the measurement errors observed with real data (Chowdhury et al., 2013). This noise