Journal of Biomechanics 47 (2014) 3613–3621

Contents lists available at ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech
www.JBiomech.com

Hybrid neuromusculoskeletal modeling to best track joint moments using a balance between muscle excitations derived from electromyograms and optimization

Massimo Sartori [a,*], Dario Farina [a], David G. Lloyd [b,c]

[a] Department of Neurorehabilitation Engineering, University Medical Center Goettingen, Georg-August University, Goettingen, Germany
[b] Centre for Musculoskeletal Research, Griffith Health Institute, Griffith University, Southport, QLD, Australia
[c] Faculty of Science and Faculty of Engineering, University of Western Australia, Crawley, WA, Australia

ARTICLE INFO

Article history:
Accepted 5 October 2014

Keywords:
Neuromusculoskeletal modeling
EMG
Static optimization
Locomotion
Muscle excitation

ABSTRACT

Current electromyography (EMG)-driven musculoskeletal models are used to estimate joint moments measured from an individual's extremities during dynamic movement with varying levels of accuracy. The main benefit is the underlying musculoskeletal dynamics is simulated as a function of realistic, subject-specific, neural-excitation patterns provided by the EMG data. The main disadvantage is surface EMG cannot provide information on deeply located muscles. Furthermore, EMG data may be affected by cross-talk, recording and post-processing artifacts that could adversely influence the EMG's information content. This limits the EMG-driven model's ability to calculate the multi-muscle dynamics and the resulting joint moments about multiple degrees of freedom. We present a hybrid neuromusculoskeletal model that combines calibration, subject-specificity, EMG-driven and static optimization methods together. In this, the joint moment tracking errors are minimized by balancing the information content extracted from the experimental EMG data and from that generated by a static optimization method. Using movement data from five healthy male subjects during walking and running we explored the hybrid model's best configuration to minimally adjust recorded EMGs and predict missing EMGs while attaining the best tracking of joint moments. Minimally adjusted and predicted excitations substantially improved the experimental joint moment tracking accuracy than current EMG-driven models. The ability of the hybrid model to predict missing muscle EMGs was also examined. The proposed hybrid model enables muscle-driven simulations of human movement while enforcing physiological constraints on muscle excitation patterns. This might have important implications for studying pathological movement for which EMG recordings are limited.

1. Introduction

Human movement emerges from synaptic commands generated by central and peripheral neural circuitries, ultimately converging to pools of alpha motor neurons (Farina and Negro, 2012). Muscles innervated by firing motor neurons are recruited and their coordinated activity generates reaction forces throughout the skeletal system and interaction with the environment. The transformations involved are non-linear and neuromusculoskeletal modeling is a promising approach to understand how neural commands are translated into mechanical output by multiple musculotendon units (MTUs) spanning multiple degrees of freedom (DOFs) (Buchanan et al., 2004; Geyer and Herr, 2010; Lloyd and Besier, 2003; Sartori et al., 2012a).

Surface electromyography (EMG) indirectly reflects the neural drive to muscles and is easily recorded during movement. Subsequently, EMG-linear envelopes have been used to drive neuromusculoskeletal models (i.e. EMG-driven modeling) during a variety of dynamic motor tasks and predict resulting joint moments (Besier et al., 2009; Krishnaswamy et al., 2011; Manal et al., 2002; Sartori et al., 2012a). In these, the underlying musculoskeletal model is scaled and calibrated to an individual's anthropometry and EMG-force generating properties. However, calibrated EMG-driven models do not always well predict the experimental moments around multiple DOFs (Sartori et al., 2012a). This is partly due to intrinsic limitations in surface EMG including (1) the inability to access deep muscles, (2) noise contamination from cross-talk and movement artifacts, and (3) the EMG-linear envelope extraction procedure that may not properly demodulate neural excitations from the motor neurons action potentials (Farina and Negro, 2012). Furthermore, EMG-linear

* Correspondence to: Universitaetsmedizin Goettingen, Georg-August-Universitaet, Department of Neurorehabilitation Engineering, Bernstein Focus Neurotechnology Goettingen, Bernstein Center for Computational Neuroscience, Von-Siebold-Str. 3, D – 37075 Goettingen, Germany. Tel.: +49 551 39 20 406; fax: +49 551 39 20 110.
E-mail address: massimo.srt@gmail.com (M. Sartori).

http://dx.doi.org/10.1016/j.jbiomech.2014.10.009
0021-9290/

envelopes are normalized to peak values to reflect percentage excitation levels. This adds uncertainties, as true EMG-maxima are difficult to attain. Therefore, amplitude-normalized EMG-linear envelopes roughly approximate muscle excitations and may limit EMG-driven models' abilities in predicting musculoskeletal dynamics. Therefore, there is a need for modeling methods that can generate EMG-informed simulations of human movement, while accounting for surface EMG limitations.

An alternative to EMG-driven modeling is to use optimization to solve for muscle excitations (Anderson and Pandy, 2001; Erdemir et al., 2007; Seth and Pandy, 2007). However, even though optimization methods can represent EMG-linear envelopes in some instances (Hamner and Delp, 2013; Thelen and Anderson, 2006), it has been shown that, for the same joint moments and angles, different individuals use different excitation patterns depending on the control tasks (Buchanan and Lloyd, 1995; De Serres and Milner, 1991; Tax et al., 1990), pathology (Besier et al., 2009; Fregly et al., 2012; Shao et al., 2009), and training (Menegaldo and Oliveira, 2011; Norton and Gorassini, 2006). Nevertheless, optimization does ensure close tracking of experimental joint dynamics: so can combined EMG-driven and optimization methods be used to overcome limitations of both approaches?.

We present the development of combined EMG-driven modeling (Lloyd and Besier, 2003; Sartori et al., 2012a) with static optimization methods (Anderson and Pandy, 2001; Erdemir et al., 2007). We call this a hybrid EMG-informed neuromusculoskeletal model, or hybrid model. The hybrid model minimizes joint moment tracking errors by balancing the information content extracted from experimental EMG data with that generated by a static optimization method.

We describe and explore the theoretical aspects of this methodology to minimally adjust EMG-linear envelopes, which we now call excitations, and predict muscle excitations for which EMGs are not available, while attaining best tracking of joint moments. We then investigate if the hybrid model can generate excitations reflecting muscle patterns across individuals and motor tasks. We finally assess the hybrid model's ability of estimating missing EMG-excitations.

2. Methods

2.1. Human movement data collection

The Human Research Ethics Committee at the University of Western Australia approved all procedures and all participants provided their informed, written consent. Motion capture data were recorded from five healthy male subjects (age: 26.6 ± 1.3 years, weight: 73.9 ± 11.8 kg, height: 1.77 ± 0.1 m) who performed one static anatomical pose, and eight repeated trials of ground level walking (2.0 ± 0.19 m/s) and running (4.7 ± 0.4 m/s). Dynamic trial recordings included the full stance phase of the subjects' right lower extremity. Each subject had 27 retro-reflective markers placed on the right and left lower extremities as well as on the pelvis and trunk (Dempsey et al., 2009). Three-dimensional marker locations were recorded (250 Hz) using a 12-camera system (Vicon, Oxford Metrics, Oxford, UK). Ground reaction forces (GRFs) and EMG data were recorded (2000 Hz) using an in-ground force plate (AMTI, Watertown, MA) and a 16-channel acquisition system (Noraxon, Scottsdale, USA) respectively. Both GRFs and marker trajectories were low-pass filtered with the same zero-phase fourth-order Butterworth filter. Cut-off frequencies (between 8 and 14 Hz) were determined by trial-specific residual analysis (Winter, 2009). EMGs were collected from 16 muscle groups of the right lower extremity (Table 1) and underwent band-pass filtering (30–450 Hz), full-wave rectification, and low-pass filtering (6 Hz) using a zero-phase second-order Butterworth filter. For each subject and muscle, the resulting linear envelopes were normalized with respect to peak-processed values obtained from the entire set of recorded trials. One dataset was created for the hybrid model calibration and tuning, i.e. two walking and two running trials per subject. Another was created for the hybrid model validation, i.e. six walking and six running trials per subject.

2.2. Movement modeling

We used OpenSim (Delp et al., 2007) to scale a generic whole-body model of the musculoskeletal geometry (Hamner et al., 2010) to match each subject's anthropometry. The musculoskeletal geometry model had 12 segments and 19 DOFs across trunk, pelvis and right/left lower extremities and had 34 MTUs in the right lower extremity (Table 1) as previously described (Sartori et al., 2012a). During the scaling process virtual markers were placed on the generic musculoskeletal geometry model based on the position of the experimental markers from the static poses. The model anthropomorphic properties were then linearly scaled on the basis of the relative distances between experimental and corresponding virtual markers (Delp et al., 2007). The OpenSim inverse kinematics (IK) algorithm solved for joint angles that minimized the least-squared error between experimental and virtual marker locations. The IK-generated kinematics and the experimental GRFs were used to obtain joint moments via inverse dynamics (ID) and

Table 1
Muscle groups from which experimental electromyography (EMG) signals were recorded and the associated musculotendon units (MTUs) that were driven by these EMGs. In this, the gluteus medius EMGs also drove the gluteus minimus MTUs. The vastus intermedius EMG activity was derived as the mean between the vastus lateralis and vastus medialis EMGs (Lloyd and Besier, 2003). The biceps femoris long head and short head were driven by the same EMG signal. The same applied to the semimembranosus and semitendinosus as well as to the peroneus longus, brevis and tertius. The iliacus and psoas MTUs did not receive experimental EMG input.

Experimental muscle EMG	Musculotendon units
Adductor group	adductor magnus (addmag1, addmag2,addmag3)
	adductor longus (addlong)
	adductor brevis (addbrev)
Gracilis	gra
Gluteus maximus	gmax1, gmax2, gmax3
Gluteus medius	gmed1, gmed2, gmed3
	gluteus minimus (gmin1, gmin2, gmin3)
Tensor fasciae latae	tfl
Lateral hamstring	biceps femoris long head (bicfemlh)
	biceps femoris short head (bicfemsh)
Medial hamstring	semimembranosus (semimem)
	semitendinosus (semiten)
Rectus femoris	recfem
Sartorius	sar
Vastus lateralis	vaslat
Vastus medialis	vasmed
(Vastus lateralis + Vastus medialis)/2	vastus intermedius (vasint)
Gastrocnemius lateralis	gaslat
Gastrocnemius medialis	gaslat
Soleus	sol
Peroneus group	peroneus longus (perlong)
	peroneus brevis (perbrev)
	peroneus tertius (pertert)
Tibialis anterior	tibant