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Hybrid models of the neuromusculoskeletal system improve subject-specificity

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Abstract

Muscle-actuated simulations of pathological gait have the capacity to identify muscle impairments and compensatory strategies, but the lack of subject-specific solutions prevents the prescription of personalized therapies. Conversely, electromyographic-driven models are limited to muscles for which data are available but can capture the true neural drive initiated by an individual subject. In order to improve subject-specificity and enforce physiological constraints on muscle activity, we propose a hybrid strategy for the optimization of subject-specific muscle patterns that involves forward dynamic simulation of whole body movement coupled with electromyographic-driven models of muscle subsets. In this paper we apply the hybrid approach to an example of post-stroke gait and demonstrate its unique ability to account for the unusual muscle activation patterns and muscle properties in patients with neuromuscular impairments.

Keywords

Neuromuscular; musculoskeletal; model; gait; optimization

Introduction

Coupling musculoskeletal models with forward dynamic simulation has the potential for defining muscle function and dysfunction during healthy and pathological movements. The design of therapeutic interventions for pathological movements seen in neurological or orthopedic conditions relies on accurate diagnosis of the impairment. The force-producing capacity of muscles depends on proper neural activation and muscle morphology and may be affected by such conditions. Since muscle forces cannot be measured directly during human subject experiments, we must apply computational models of the musculoskeletal system.

The utility of muscle-actuated forward dynamic simulations has been demonstrated previously.¹ Simulations of walking, pedalling, and jumping provide predictions of muscle force and have been used to identify available compensatory strategies for muscle weakness.^{2–5} Muscle-actuated simulations of pathological gait have the capacity to quantify knee joint contact forces for individuals with osteoarthritis,⁶ determine optimal kinematics to alleviate loads on a painful knee,^{7,8} compare contributions of paretic and non-paretic muscles to body weight support in post-stroke gait,⁹ and predict activation changes to overcome paretic ankle impairment.¹⁰ Although validation of predicted joint forces is

possible for cases where an instrumented knee prosthesis has been implanted,¹¹ most models have not been validated leaving only subjective criterion available to accept or reject solutions.¹² Furthermore, few tools have been developed to determine individual muscle properties that will be altered with age, disuse or pathology.¹³ The subsequent lack of subject-specific solutions prevents clinicians from prescribing personalized therapeutic regimens.

Because electromyographic (EMG)-driven models are tuned to a set of calibration conditions (often assessed by comparing estimated joint moments to those measured using inverse dynamics or a dynamometer) then applied to a novel experimental trial, they capture the true neural drive initiated by an individual subject.¹⁴ This approach has the added benefit of providing subject-specific parameters that describe muscle properties, but is limited by the need for a comprehensive set of EMG data for all muscles included in the model. As a result, predictions of muscle function about the isolated knee or ankle joint can be formed¹⁵ but have not been coupled with simulations of whole body movement.

To take advantage of the benefits of both approaches, we propose a hybrid strategy for the optimization of subject-specific muscle patterns that involves forward dynamic simulation of whole body movement coupled with EMG-driven models of muscle subsets. The objectives of this approach are to:

- a. improve subject-specificity by incorporating neural activation and morphological characteristics for muscles of particular interest;
- b. determine muscle excitations and forces that more accurately reflect physiological constraints.

In the subsequent sections, we identify experimental data required to build models of the neuromusculoskeletal system, discriminate between EMG-driven models and muscle-actuated simulations, and demonstrate the utility of the hybrid approach with an example of post-stroke gait.

Models of the neuromusculoskeletal system

Models of the neuromusculoskeletal system account for neural input used to drive muscle actuators that generate force and accelerate the individual body segments to reproduce experimentally determined movement patterns. Comprehensive datasets collected on human subjects typically include kinematic description based on three-dimensional (3D) coordinates of markers placed on anatomical landmarks, ground and other external reaction forces with associated centre of pressure data, and EMG recordings reflecting activity of key muscles during the movement of interest (i.e. walking), as well as other trials and conditions used for calibration of the model.

Several steps are taken to create a scaled model of the musculoskeletal system with movements prescribed based on the experimental marker data. A 3D musculoskeletal model of the trunk, pelvis, and lower extremities with 23 degrees of freedom and up to 92 muscle–tendon units has been developed using OpenSim.¹⁶ The dimensions of the model are scaled based on coordinate data from markers placed on anatomical landmarks of the subjects during a static calibration trial. Generic muscle properties are typically assigned but can be updated manually if desired. Inverse kinematics is performed to match the model movement with experimental data from dynamic trials (e.g. walking) and joint moments can be computed using inverse dynamics.

EMG-driven models

An EMG-driven model defines the relationship between measured EMG signals and modelled muscle activation that dictates how much force a muscle can generate. EMG and joint moments are derived from experimental data and used as input to EMG-driven models. The magnitudes of the EMG signals change as the neural command calls for increased or decreased muscular effort. Nevertheless, it is difficult to compare the absolute magnitude of an EMG signal from one muscle to that of another because the magnitudes of the signals can vary depending on many factors, such as the gain of the amplifier, the type of electrodes used, the placement of the electrodes relative to the muscles' motor points, and the amount of tissue between the electrodes and the muscles; furthermore, normalization by maximal EMG does not completely solve these problems. Thus, in order to use the EMG signals in a neuromusculoskeletal model (Figure 1), these must first be transformed into a variable referred to as muscle activation, which is unique for each muscle in the model. This step represents muscle activation dynamics and the output, $\mathbf{a}(\mathbf{t})$, varies with time and has a magnitude between 0 and 1. Muscle contraction dynamics govern the transformation of muscle activation, $\mathbf{a}(\mathbf{t})$, to muscle force, $\mathbf{F}(\mathbf{t})$, which also depends on the length and velocity of the muscle fibres.

To compute muscle activations, each EMG signal is rectified, low-pass filtered, and normalized by dividing by maximal isometric EMG.¹⁴ A two-parameter recursive filter that accounts for the time–history dependence is used to transform EMG into muscle excitation¹⁷ and ultimately to $\mathbf{a}(\mathbf{t})$ after accounting for nonlinearities in the force-EMG relationship.¹⁸ Because the input is EMG data that specifies the amount each muscle is to be activated, these models implicitly account for variation in the neural command, which can change with pathology or training.

The joint moments are determined as the product of each muscle force with the appropriate muscle-moment arm based on the musculoskeletal geometry. Joint moments estimated from the EMG-driven model are compared with those computed using inverse dynamics (see lower right part of Figure 1). Using a simulated annealing algorithm,¹⁹ the squared difference between these moments is minimized by randomly adjusting filter parameters and muscle properties in the model (e.g. **OFL**=optimal fibre length, ϕ =pennation angle, and **RTL**=resting tendon length) until a sufficiently large number of evaluations have been made without any improvement in the optimal solution. In this way, the model can be calibrated or tuned to each subject.

In order to make the models as subject-specific as possible, we could determine some parameters via imaging or burst superimposition techniques. Alternatively, model parameters can be computed by assuming generic values and then adjusting them during optimization by allowing them to vary over anatomical ranges until the difference between the inverse dynamics solution and the forward dynamics solution is minimized. Hence, parameters such as optimal fibre length and filter coefficients can be calculated by model adjustment to minimize errors between forward and inverse dynamic joint moments during a combination of tasks that include walking and dynamometer trials. The most robust models should be tuned to trials on the dynamometer or other trials that do not exactly capture the movement of interest (e.g. walking). In this way, the predictive capacity of the neuromusculoskeletal model will be most valuable for novel trials or hypothetical scenarios.

Forward dynamic simulations

Muscle-actuated forward dynamic simulations can be generated with open source software such as OpenSim,¹⁶ which employs optimization procedures to find a set of excitation patterns that will drive the neuromusculoskeletal model to reproduce observed movement

patterns (Figure 2). This method depends on accurate equations of motion representing the rigid body dynamics such that the correspondence between applied muscle forces and subsequent body accelerations can be found. A residual reduction algorithm (RRA) is employed to minimize the resultant forces at the pelvis needed to stabilize the model and results in recommended segment mass adjustments.²⁰ Computed muscle control (CMC)²¹ is used to solve for the muscle excitation patterns, $\mathbf{e}(\mathbf{t})$, that will reproduce the experimental accelerations with minimal effort (subject to a default objective function). This algorithm also takes into account the muscle activation dynamics described previously. Finally, a forward simulation is produced that relies on the excitation of the muscle actuators and the application of external forces in order to accurately reproduce movement patterns measured experimentally.

The OpenSim model is actuated by a large set of Hill-type muscle–tendon units that control movement of the degrees of freedom at the spine and lower extremities.¹⁶ As opposed to the neural command being determined from EMG (as described above), these models estimate the neural command through optimization. Thus, these models implicitly account for muscles for which EMG data are not readily available and typically use generic muscle properties. The resultant forward simulation is representative of the subject-specific movement pattern measured during experimentation.

Hybrid optimization algorithm

The development of a hybrid optimization algorithm that combines EMG-driven models with muscle-actuated forward dynamic simulations will take advantage of the features offered by both modelling frameworks described above (Figure 3). In this approach, experimental data acquired on human subjects is imported to OpenSim or similar platform. The model is scaled to subject-specific dimensions before performing inverse kinematics. The residual reduction algorithm is employed to avoid any inconsistencies between ground reaction GRF and centre of mass movement. At this stage, inverse dynamics is computed and all joint moments are known.

A two-stage optimization process is performed to determine muscle activation patterns for all modelled muscles. EMG data from the muscles of interest are imported to the EMG-driven model to determine subject-specific muscle properties using simulated annealing. The optimized parameters used to fit the EMG-driven models to the inverse dynamics data are used to update the generic muscle properties in the OpenSim model. The resultant activation patterns $\mathbf{a}(\mathbf{t})$ for this subset of muscles are reported and used to constrain the CMC solution within a user-specified threshold, in order to solve for the remaining muscle excitation patterns that track the experimental accelerations while minimizing the squared sum of muscle activations.²⁰

Once the activation patterns $\mathbf{a}(\mathbf{t})$ for all muscles have been determined with the hybrid optimization approach, we apply muscle contraction dynamics to estimate forces generated by each muscle. Since the musculoskeletal geometry and equations of motion are already known, we can find the resultant effect of each muscle force on segmental and joint accelerations, velocities and positions (Figure 3).

Hybrid optimization: preliminary results and discussion

The primary benefits of the hybrid approach include improved subject-specific model parameters (i.e. OFL, RTL) and accurate neural commands. To demonstrate the utility of this approach, we generated a set of neuromusculoskeletal simulations of walking in a subject with post-stroke hemiparesis (48 years, right paretic). 3D kinematic and kinetic data were collected using a split-belt instrumented treadmill (Motion Analysis Corp., Santa Rosa,

CA, USA; Bertec Corp., Columbus, OH, USA) and processed in Visual 3D (C-Motion Inc., Germantown, MD, USA). EMG was also recorded from the medial gastrocnemius (MG), lateral gastrocnemius (LG), soleus (SOL), and tibialis anterior (TA) on the paretic side.

A musculoskeletal model with generic muscle parameters, 23 degrees of freedom, and 70 muscles was created in OpenSim.¹⁶ Subject-specific anthropometric scaling parameters and motion data for one gait cycle were determined and RRA was performed (OpenSim v. 1.5.5). All joint moments were calculated using inverse dynamics and the ankle joint moment was used as input to the EMG-driven model. Individual muscle EMG were processed, normalized to the subject's maximum EMG during data collection, and used as input to the EMG-driven model.¹⁴ Optimal subject-specific muscle properties were determined as described above.

The optimized subject-specific muscle properties were used to update the musculoskeletal model in OpenSim, and three simulations were generated and compared with the EMG-driven model results. First, CMC was used to estimate all muscle excitations and activations during the gait cycle using the default cost function.²¹ In the second simulation, muscle activations from the EMG-driven model were used to constrain the muscle patterns calculated by CMC for four ankle muscles. Finally, two arbitrarily chosen muscles (MG, TA) were constrained to the EMG-driven activations while CMC estimated the remaining activations to generate a third gait simulation. Output muscle activations and forces for plantar and dorsiflexors were compared.

The EMG-driven model calculated muscle activations between 0 and 0.7 for the paretic ankle plantar and dorsiflexors that may reflect neural impairment in this stroke subject (Figure 4). Without constraining any muscle excitations in OpenSim, muscle activation predictions were higher, nearly reaching 1.0 for TA. As a result, muscle forces were more than double that of the EMG-driven model forces for MG and TA but lower for SOL (Figure 5, compare (a) and (b)). In neurologically impaired populations such as stroke, this activation range is likely to be unrealistic and the muscle forces may not be accurate.

When all muscle excitations were constrained in CMC to the activations from the EMG-driven model, muscle forces began to resemble those from the EMG-driven model (except for MG, see Figure 5(c)). Constraining the MG and TA resulted in both the activations and muscle forces for the remaining muscles, LG and SOL, to revert back to patterns similar to the original CMC estimation (Figure 4(d) and 5(d)).

For this particular stroke subject, CMC produced inaccurate muscle activations and unnecessarily high muscle forces when unconstrained during gait. Using EMG to tune a simulation can be advantageous when simulating gait in subjects with impaired muscle control such as stroke, even when data for only a limited set of muscles are available. We may achieve more realistic solutions by providing additional constraints on muscle activation, updating additional subject-specific muscle parameters, or selecting a novel cost function. This case study suggests that combining EMG-driven modelling with forward dynamic simulation gives models of the neuromusculoskeletal system the unique ability to account for the unusual muscle activation patterns and morphological characteristics observed in patients with neuromuscular impairments and produces more reasonable muscle force predictions.

Conclusion

The hybrid optimization approach can be used to predict muscle coordination patterns that reproduce observed movement patterns and improve subject-specificity by accounting for muscle properties and known neural commands. By enabling additional constraints on

muscle activation patterns or defining a novel cost function, this approach can be used to test theories about organization of the central nervous system. For example, novel solutions can be predicted given altered muscle properties or activation patterns. Perhaps the most exciting application of the hybrid simulations is that the activation signals required to achieve a desired movement pattern can be found and used to establish a goal for therapeutic intervention for a specific individual.

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Figure 1. EMG-driven models. Optimization is performed to minimize the difference between experimental and computed joint moments as the model parameters are adjusted. See text for details.

Figure 2.

Muscle-actuated forward dynamic simulation. Optimization is performed to minimize the difference between experimental and computed joint and segment accelerations as the input excitation patterns $\mathbf{e}(\mathbf{t})$ are adjusted.

Figure 3.

Hybrid optimization. Experimental data are used to scale the model, adjust masses, and perform inverse dynamics. Optimization can utilize EMG-driven models or computed muscle control to estimate muscle activations. Muscle forces can accelerate all joints and segments.

Figure 4. Individual muscle activations using (a) EMG-driven model (b) CMC, unconstrained (c) CMC, all four muscles constrained (d) CMC, MG, and TA constrained. MG: medial gastrocnemius; LG: lateral gastrocnemius; SOL: soleus; TA: tibialis anterior.

Figure 5.

Individual muscle forces using (a) EMG-driven model (b) CMC, unconstrained (c) CMC, all four muscles constrained (d) CMC, MG, and TA constrained.

EMG: electromyographic; CMC: computed muscle control; MG: medial gastrocnemius; LG: lateral gastrocnemius; SOL: soleus; TA: tibialis anterior.