DYNAMICS AND CONTROL OF MUSCULOSKELETAL SYSTEMS

Luciano Luporini Menegaldo  

Military Institute of Engineering, Brazil, lmeneg@ime.eb.br

Abstract: Biomechanical modeling of the human musculoskeletal system requires the gathering of several different scientific disciplines, including neurophysiology, anatomy, multi-body dynamics, control theory, among others. This invited lecture paper will address some results of the authors’ last years of research in this field in collaboration with his colleagues, showing some results in muscle modeling and its experimental validation, as well as posture biomechanics and optimal control.

Keywords: Biomechanics, musculoskeletal system, optimal control, EMG-Driven model

1. INTRODUCTION

Musculoskeletal modeling has been a mainstream topic of biomechanics research worldwide in the last three decades. Such class of models closely resembles those often found in robotic manipulators research [1], requiring the intensive use of multibody system (MBS) dynamics analysis tools. However, there are important particular aspects of the topic related to its biological nature, which must be integrated with the multi-body system: musculoskeletal geometry and actuator dynamics. Therefore, the set comprising: MBS, geometrical description and the neuro-muscular dynamics defines a musculoskeletal model.

In forward dynamics analysis of musculoskeletal systems, the inputs are normally considered as the neural activation that reaches each muscle neural junction, and the outputs the body kinematics (Figure 1). System inputs are provided by the Central Nervous System (CNS). They can result from voluntary commands generated in brain motor cortex (open-loop signal), or more or less elaborated reflex commands trigged by sensory inputs (closed-loop control). Usually, open loop signal reference signal, even a set point, is tracked by sensory-mediated commands. Inverse dynamics can also performed [2]: measured kinematics and external forces are used to find joint torques. In this case, joint torque curves with respect to time are usually sufficient for most of practical biomechanics analysis. However, some authors try to infer muscle forces or muscle inputs from the joint torques [3],[4] using or not measured muscle electrical activity (EMGs).

![Figure 1: Forward dynamics analysis of a musculoskeletal model. U(t) is the neural excitation arriving at the neuromuscular junction for one muscle, a(t) the muscle activation, F(t) the force delivered by a muscle tendon, τ the joint torques, r the moment arms matrix, that relates muscle forces and joint torques. The output of the system is joint angular kinematics.](image-url)
From the application point of view, musculoskeletal models have been historically developed mainly for normal and pathological gait analysis [5]. The most frequent analysis usually carried out, which is still nowadays, is finding joint torques from measured kinematics. Kinematics is evaluated using optoelectronic multi-camera systems, which tracks small light-reflective spheres bonded to some points of the patient or voluntary body and applies kinematical models to find joint angles, angular velocities and accelerations. In the double support phase of the gait, when both feet touches the ground, a force platform is used to measure at least one of the contact forces and ‘open’ the kinematic chain and keep the dynamic analysis more tractable. Posture analysis based of musculoskeletal modeling follows essentially the same guidelines of gait studies. However, some important differences can be highlighted. Multibody system dynamics is normally simpler, since both feet are always in contact to the ground, and whole body can be well modeled as a one or more degrees-of-freedom inverted pendulum. Force plate can be avoided to perform an inverse dynamics analysis, unless the analyst is interested in the space and time center of pressure distribution under the foot. Other usual application fields of musculoskeletal models are sports biomechanics, vehicle safety analysis, ergonomics, paleontology, to cite most frequent.

Choosing a control strategy is an essential aspect of musculoskeletal modeling, especially for forward simulations. Gait must perform essentially a stable limit-cycle, while posture should be controlled at an unstable point, unless some sensory feedback is included in the simulation model. The most common approach to such control is the Linear Quadratic Optimal Control (LQ). In these cases of voluntary tasks, forward simulations cannot be performed if no control is somehow included. The modeled body simply ‘collapses’ in the simulations. An exception is the simulation of body behavior in vehicle safety analysis, when the occupant is initially sit down and passive inertial forces largely override the voluntary ones.

Feedback control can be included more or less easily if the model is considered to be torque-actuated. In a more realistic model driven by muscles, which are force actuators, feedback strategies becomes more problematic due to actuation redundancy, internal non-linearities and control bounds: muscles can only push, not pull, although they offer passive resistance to stretch. Open loop optimal control allows predicting time-history curves of muscle inputs, muscle forces and kinematics, starting only from: the complete musculoskeletal dynamic model, a set of initial and terminal conditions and an assumed cost function.

Optimal control solution, however, requires a large amount of hard numerical problems to be solved or by-passed [6],[7]. Another interesting approach, which is starting to increase popularity nowadays, is the use of EMG-Driven models. In this case, EMG is pre-processed and regarded as the muscle inputs that drive the forward simulation model. It allows in some cases a more realistic and simpler analysis, since measured information of muscle activity is used, in the place of more or less plausible hypothesis of physiological optimality.

This invited lecture paper describes briefly some specific contributions of our group in part of this field, as a result of the last 15 years of work in the State University of Campinas, University of São Paulo and Military Institute of Engineering.

2. CLOSED-LOOP CONTROL OF HUMAN POSTURE

The early works developed in this field by our group aimed at modeling a human body posture as a three-links planar inverted pendulum, and control it from a semi-squatting position to upright posture [8], [9]. The main idea was to synthesize a control algorithm that should be used to deliver Functional Electrical Stimulation signals to a spinal-cord injured patient.

The model MBS model (Figure 2) was derived using Kane’s dynamics formalism. At each joint: ankle (O), knee (AB) and hip (BC), it was considered that a torque actuator was present. The MBS equations of motion of this system are:

\[
[M(x)]\ddot{x} + [C(x)]\dot{x}^2 + [g(x)] = [D]\tau
\]

where M, C are the mass and Centripetal/Coriolis terms matrices, g is the gravity terms vector, D is a matrix that relates joint actuators torques to rigid body torques and \(\tau\) the external (muscle) torque vector. The \(x\) variable corresponds to a 3x1 vector with the three links absolute angles. In the forward dynamics model, joint torques are calculated as the sum of individual muscle forces, which are related to torque by a constant moment-arms matrix, such that U are the control torques (1 to j) and F the muscle forces (1 to m):

\[
\begin{bmatrix}
U_1 \\
U_2 \\
\vdots \\
U_j \\
\end{bmatrix} =
\begin{bmatrix}
r_{11} & r_{12} & \ldots & r_{1m} \\
r_{21} & r_{22} & \ldots & r_{2m} \\
\vdots & \vdots & \ddots & \vdots \\
r_{j1} & r_{j2} & \ldots & r_{jm} \\
\end{bmatrix}
\begin{bmatrix}
F_1 \\
F_2 \\
\vdots \\
F_m \\
\end{bmatrix}
\]

(2)
Moment arms where calculated analytically using muscle insertion and origin data provided by [10]. Muscle mechanics was modeled as a 2nd order non-linear system. One differential equation is the ‘activation dynamics’, that gives the active state of the muscle as a function of neural input. The other equation corresponds to the ‘contraction dynamics’, in which tendon force is the output and activation the input. We have used a modified version of the visco-elastic Hill-type Zajac adimensional model [11], but including parallel elastic and parallel damping elements. This change improves model numerical stability properties, in special for muscle relaxing and at lower excitation levels. Contraction element is controlled by activation level, according to scaled version of force-velocity Hill hyperbole. This muscle model has been validated in vivo with electrically stimulated Canine lastissumus dorsi [12] and human triceps surae [13].

The torque control vector was calculated using a Linear Quadratic Regulator full-state feedback gain matrix. Control torques were then divide into individual required muscle forces, using an constrained optimization algorithm based on the solution of the pseudo-inverse matrix proposed by Yamaguchi [14].FES signal delivered to the muscle is found using inverse models of muscle activation and contraction dynamics. The block diagram of the overall system is shown in Figure 4 and, the limb angles in Figure 5 and three of the nine muscles forces in Figure 6. Others studies carried out based on this model included varying FES stimulating frequency, Q and R linear optimal control weighting matrices and introducing a sinusoidal vibrating movement in the support platform [15].
3. OPEN-LOOP OPTIMAL CONTROL OF HUMAN POSTURE

The above posture model has been lately refined in some of its biomechanical aspects [16][17]. The main one was introducing a joint-angle variable version of the moment arm matrix. SIMM (Software for Interactive Musculoskeletal Analysis, Musculographics Inc.) was used to calculate 44 lower-limb muscles moment arms and musculotendon length, as a function of 1 up to 4 joint angle variables, for all 7 joints range of motion defined in the open-source model delivered with the software [18]. The large amount of data was condensed in a set of derivable and continuous polynomial regression equations, using a lest-squares fitting [19]. Figure 7 shows an comparative example of the fitted and original tibialis anterior moment arm curves as a function of ankle and subtalar angles.

To reduce model size and complexity, some less-important muscles were excluded from the model, and others grouped together, given a simplified model with only 10 actuators (Figure 8). The overall non-linear state-space model including MBS equations, geometry and muscle dynamics is given by:

\[
\begin{bmatrix}
    \dot{x}_1 \\
    \dot{x}_2 \\
    \vdots \\
    \dot{x}_n
\end{bmatrix} = 
\begin{bmatrix}
    f_1(x_1, x_2, \ldots, x_n) \\
    f_2(x_1, x_2, \ldots, x_n) \\
    \vdots \\
    f_n(x_1, x_2, \ldots, x_n)
\end{bmatrix}
\]

\[
\begin{bmatrix}
    x_1 \\
    x_2 \\
    \vdots \\
    x_n
\end{bmatrix} = 
\begin{bmatrix}
    g_1(x_1, x_2, \ldots, x_n) \\
    g_2(x_1, x_2, \ldots, x_n) \\
    \vdots \\
    g_n(x_1, x_2, \ldots, x_n)
\end{bmatrix}
\]

(3)
In this work, the objective was finding the open-loop muscle excitations, activations, forces and kinematics of human posture by formulating and solving a non-linear optimal control problem (OCP). The above equation corresponds to the set of differential constraints of the OCP. It can be formulated as minimizing an integral cost function:

$$\min_u \left\{ f(u) = \int_0^{10} \sum_{i=1}^{6} \dot{F}^2_i (u, x) \, dt \right\}$$

where $\dot{F}_i$ is the time-derivative of adimensional muscle force and $u$ is the vector of muscle excitations. This problem is subject to control bounds $0 \leq u_i(t) \leq 1$, to the dynamic constraints and endpoint equality constraints $g_e(x_i, i=1,...,6, t_f) = 0$, where the states $x$ (1 to 3) are the final joint angles and $x$ (4 to 6) the joint velocities. This problem was solved using the Matlab toolbox RIOTS [20][21], which is based on Polak Consistent Approximations theory for optimal control [22]. The algorithm is based on iterative integration/discretization using Runge-Kutta, interpolation in a spline functional space and numerical solution of the resulting static optimization problem with a SQP algorithm. This solution presents numerous numerical problems, especially due to fact that dynamic and numerical instability occurs simultaneously, requiring several ad hoc strategies to be solved [4]. Figure 9 shows a solution of the kinematics for two simulation times and Figure 10 the muscle activations (results are also available for muscle excitations and forces). This result took 31 days of CPU in a Pentium III 600 MHz to be obtained.

**Figure 9:** Body kinematics for the open-loop control of the posture, as a result of the optimal control problem solution

**Figure 10:** Activation history for the open-loop control of posture, as a result of the optimal control problem solution

### 4. INVERSE DYNAMICS OPTIMAL CONTROL

Optimal control solution of the complete posture model has shown to spend a very large amount of CPU time, presenting also several convergence problems. Thus, we proposed an alternative approach, called Inverse Dynamics Optimal Control (IDOC), to estimate muscle forces on musculoskeletal systems, testing it into the already formulated posture problem [4]. The IDOC consists of using experimental or numerical inverse dynamics solution, or a forward dynamics with torque controls as well, of a musculoskeletal system to formulate an augmented optimal control problem. Optimal Control problem is written without Multi-Body equations, and the cost function is augmented with a moment-tracking error function. Muscle dynamics is still taken into account (unlike classical static optimization that is usually applied in this class of problem) as the differential constraints of the OCP, and most of the dynamic instability due to MBS is eliminated from it. It can be formulated as minimizing the cost function:

$$f_{IDOC}(u, x) = \int_0^{10} \left[ \sum_{i=1}^{6} \dot{F}^2_i (u, x) + w_1 \| [rFom] [F] - [\tau] \| \right] \, dt$$

$\dot{F}_i$ muscle force

$[\tau]_{6\times1}$ moments vector

$w_{1,2}$ relative weights

$[rFom]$ matrix of polynomials

$$\text{(4)}$$

$rFom$ is a matrix of moment arms polynomials (as found in [19]) multiplied by each muscle maximum force. $\tau$ is a vector of smooth torque curves fitted also as polynomial expressions. Both expressions are explicit functions of time. The relative weights allow balancing between the
physiological and torque fitting parts of the cost function. The OCP can thus be formulated as:

\[
\begin{align*}
\min_u & \{ f_{\text{IDOC}}(u, x) \} \\
\text{s.t.} & \quad 0 \leq u_i(t) \leq 1, \quad i = 1, \ldots, 10 \\
\dot{x}_i &= a(u_i, a_i) \\
\end{align*}
\]

(5)

The previously implemented human posture control problem, solved using a Forward Dynamics Optimal Control approach [17], was solved with IDOC. It provides, for most of the studied muscles, reasonably similar force patterns, when compared to the forward dynamics solution. In addition, the computational cost is much smaller (around 400x) and the numerical robustness is significantly increased.

5. EMG-DRIVEN MODELS

In previous works based on the solution of OCP, no input data was provided other than system model, objective function and constraints. The result was the entire state and control vectors with respect to time. In some cases, the focus of the analysis may be essentially the muscle force that have produced a measured movement or torque pattern in real subjects. In an EMG-Driven model, muscle dynamics, normally Hill-type, is fed by an excitation signal considered equivalent to the rectified and low-pass filtered EMG and tendon force is the output (Figure 11). However, in practice, no human joint is spanned by a single muscle. Therefore, direct validation of such system is not usually possible in humans, as muscle force measurement in situ is still a highly invasive procedure. Such validation can be inferred by measuring associated physical phenomena such as joint torques. For a mono-articular 1 DOF problem, muscle force can be assessed indirectly as the output of a system where the inputs are the EMGs and the output the joint torque. An adapted version of the already used Hill-type muscle [17], [12] model was used to find isometric ankle torques from EMGs [13], [23], [24]. We have evaluated experimentally (Figure 12) the error level that can be expected if a set of parameters from literature is applied to solve a forward dynamics EMG-Driven model of isometric plantar flexion contractions, with the ankle in neutral position. Additionally, we investigated the role of applying in such simulations some simple muscle model parameters scale factors. The associated errors were evaluated with and without applying the proposed scale factors to some of the muscle model parameters.

Three different "correction factors" were applied on some of the parameters, based on anthropometric and dynamometric measurements: leg length (LL), bimalleolar diameter (BD) and the maximum measured torque TMAX. Such factors were determined by dividing the individual measurement by the respective mean value of the entire group of volunteers. The maximal muscle force was scaled by TMAX, the tendon slack length by LL and the moment arm by BD. Model torque agreement (Root Mean Square Error between dynamometer measured and EMG estimated torques) was recalculated with the parameter scales. It was observed that the relative torque estimation error decreased when all factors were applied simultaneously 12.92± 4.94% without scaling to 10.12±1.73, resulted mainly from the correction of the maximal muscle force parameter.

6. CONCLUSIONS AND FUTURE DIRECTIONS

This paper had briefly described some results that have been obtained by our group in the field of musculoskeletal modeling in the last years. In our opinion, the main contributions to field that has been achieved are: solution of the optimal control problem of posture, the description of some important characteristics of human leg geometry in terms of derivable polynomial functions and showing
that individual parameter scaling can reduce estimation errors in EMG-driven models. Further work is being directed nowadays towards to: use of ultrasound to measure individual specific muscle parameters, study of muscle force patterns in the ankle complex for several tasks and limb positions and use of Bayesian estimation for muscle force estimation from EMGs.

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