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AN OPTIMIZED EMG-DRIVEN MODEL FOR PATIENT TORQUE ESTIMATION APPLIED TO REHABILITATION ROBOTICS

Boris Sullcahuaman Jauregui
University of São Paulo, Mechanical Engineering Department, Robotic Rehabilitation Laboratory, São Carlos, SP, Brazil
boris.sullcahuamanj@usp.br

Guido Gomez Peña
University of São Paulo, Mechanical Engineering Department, Robotic Rehabilitation Laboratory, São Carlos, SP, Brazil
guidogpena@sc.usp.br

Adriano A. G. Siqueira
University of São Paulo, Mechanical Engineering Department, Robotic Rehabilitation Laboratory, São Carlos, SP, Brazil
Center for Robotics of São Carlos and Center for Advanced Studies in Rehabilitation, University of São Paulo, SP, Brazil
siqueira@sc.usp.br

Abstract. *This paper deals with EMG-driven modeling of patient torque estimation during robot-aided rehabilitation. Electromyographic (EMG) signals, taken from selected muscles acting during flexion and extension movements, are processed to get the muscles activations. A simplified and optimized model of muscles forces is used to compute the estimate of patient torque. The simplified model is justified since it will be implemented in an online adaptive control strategy of adjusting the robot assistance. The model optimization is performed by comparing the estimate torque with the torque generated by the inverse dynamics tool of the OpenSim software, considering a scaled musculoskeletal model. Experimental results obtained from a patient performing a set of movements using a variable impedance knee orthosis are presented.*

Keywords: *EMG-driven, Rehabilitation, Optimization, Musculoskeletal model*

1. INTRODUCTION

Neurological disorders are diseases of the central and peripheral nervous system, resulting in motor control disturbances which affect motor functions, such as walking or upper limb movements. Cerebral Vascular Accident (CVA or stroke) is the leading cause of permanent disability in developed and developing countries, being the cause of 10% of deaths worldwide. Each year 15 million people suffer a stroke, five million of them die and five million staying with a residual disability (Mackay *et al.*, 2004). Spinal cord injuries are approximately half a million people worldwide each year from traffic accidents mostly. For low- and middle-income countries, only 15% of people with this type of injury have the access to assistive devices they need (Lukersmith, 2013).

Reduction of walking abilities is the main result caused by neurological diseases, and loss of mobility is the activity of daily living with greater value for patients. The impact on patients is huge, with negative results on their participation in social, professional, and recreational activities (Robinson *et al.*, 2011).

Strengthening exercises in lower limbs and training tasks can be used to recovery of walking abilities in people with neurological disorders (Teixeira-Salmela *et al.*, 1999; Patton, 2004). In current clinical practice, the gait restoration with robotic devices is an integral part of rehabilitation program of patients with this type of disorder (Sale *et al.*, 2012).

The most successful robot-aided therapy is based on learning. Repeating the therapy process with high intensity provides the stimulus for the brain to re-acquire movement control and coordination (a typical session of robot-aided therapy involves over a thousand movements, whereas a typical session of human-administered therapy involves about eighty); this is confirmed by the observation that the patient's active participation is essential (passively moving a patient's limbs may help improve joint mobility but it yields no improvement of motor function). Due to physical interaction, the dynamics of an object (in this case, a patient) coupled to the robot may profoundly affect the robot controller's stability. This challenge was identified in the earliest days of research in robotic. Given a sufficiently detailed knowledge of the object's dynamics, but in this application, the *object* is a neurologically-impaired human (Hogan, 2014).

The field of robot assisted treadmill training has evolved significantly during the last ten years, and the robotic devices can be divided into exoskeletons and end effector-based system device. In particular early research in powered human exoskeleton devices began in the late 1960s with Hardiman, developed by General Electric and US Department (Bogue, 2009).

The use of exoskeletons, an external structural mechanism with joints and links corresponding to those of the human body, has very different objectives such as using in the neuro-recovery therapy, but the common problem arises: design of a human-robot interface able to understand user intent and react appropriately to provide the necessary assistance. A widely investigated methodology to achieve this objective is based on the estimate of joint torques to perform the movement, and the provision with a fraction of the estimated torque to decrease the effort of the user (Kong and Tomizuka, 2009; Ronsse *et al.*, 2011). The expected result is, thanks to the help mediated robot, the subject can perform the desired task with less muscular effort (Gordon and Ferris, 2007).

A possible strategy for estimating the torque needed to perform a movement consists in measuring the activation of the involved muscles through electromyography (EMG). EMG signals, resulting from the motor neuron impulses that activate the muscle fibers, can be correlated with the force produced by muscles and the resulting torque at the joint level. The main drawback of EMG-based torque estimation methods is intrinsic in the complex subject- and session-dependent calibrations that are required to produce an accurate and reliable model (Lenzi *et al.*, 2012).

This paper shows the development of an optimized EMG-driven model of patient torque for rehabilitation robotics. For this, the torque estimation approach starts with the neural command and then uses muscle activation dynamics, muscle contraction dynamics, and musculoskeletal geometry to calculate the joint torque. These joint torques are also computed using inverse dynamics tools and position data from the robotic device. An optimization procedure, where the EMG-driven model's parameters are adjusted, is performed aiming to minimize the difference between the estimate joint torques.

The paper is organized as follows: Section 2 describes the EMG-driven and inverse dynamics approaches to estimate joint torques; Section 3 presents the torque estimation, describing the elements involved in the process; Section 4 shows the selection of parameters to be calibrated; experiments and results are presented in Section 5; and a short conclusion is given in Section 6.

2. TORQUE ESTIMATION

In the process of torque estimation proposed by (Buchanan *et al.*, 2005), Fig. 1, two approaches are considered. First an EMG-driven model is used (from left to right). Second, inverse dynamics is considered (from right to left). The torque estimation based on EMG starts with a measure of neural command using surface electrodes. This signal is preprocessed and transformed to muscle activation with a function of neural activation; then, we compute the resulting force using a muscle contraction model and, considering the moment arms, compute the torque τ_{EMG}. The inverse dynamics approach uses position and external forces acting on the body to calculate the torque, τ_{ID}, based on the dynamic model of the system. The error between these torques is used to adjust the EMG-driven model's parameters during the optimization phase.

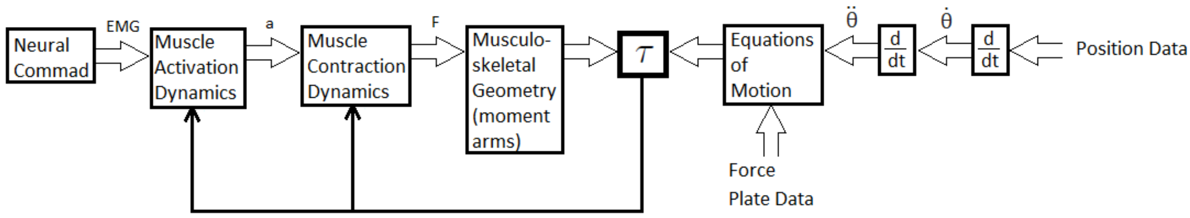

Figure 1. EMG-driven and inverse dynamics torque estimation approaches, (Buchanan *et al.*, 2005).

In Delp *et al.* (2007), it is developed the open-source software system OpenSim that allows users to develop models of musculoskeletal structures and create dynamic simulations of a wide variety of movements (Fig. 2). In this work, we are using the OpenSim inverse dynamics tool which, considering position and torque data from the robotic device and the musculoskeletal proprieties, provides us a reliable estimate of the joint torque.

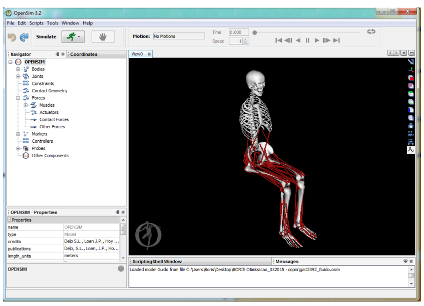

Figure 2. OpenSim.

3. EMG-DRIVEN MODEL

In this section the EMG-driven model for torque estimation is presented. We are considering a simplified model to compute the muscles forces, with active and passive components depending only on the muscle length. No velocity-dependent components are taking into account. The simplified model is justified since it will be implemented in an online adaptive control strategy of adjusting the robot assistance.

3.1 Muscle activation

The postprocessed EMG signal (with DC offset elimination, rectification and subtraction of the measured offset when the muscle is relaxed, and low-pass filtering) is transformed to muscle activation through the function:

$$a(u) = \frac{e^{AuR^{-1}} - 1}{e^{A} - 1}, \tag{1}$$

where u is the postprocessed EMG value, R a mean value of maximum voluntary isometric contraction, and A a nonlinear shape factor defining the curvature of the function with $A < 0$. For $A \to 0$, the function approximates a linear relationship.

3.2 Musculoskeletal model

Once the muscle activation is obtained, we can estimate the force using a simplified Hill-type model (Fleischer and Hommel, 2007) of muscle contraction (Fig. 3).

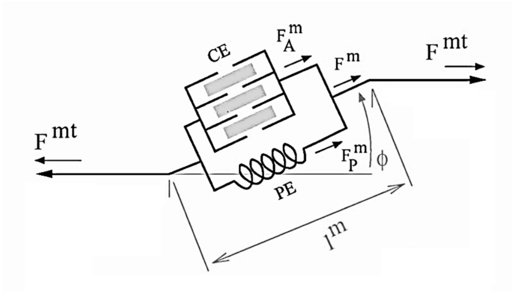

Figure 3. Muscle model (Fleischer and Hommel, 2007).

It consists of two elements: a contractile element (CE) producing the active muscle force, F_A^m, and a parallel elastic element (PE) that produces the passive force, F_P^m, when the muscle is stretched. The muscle force is given by:

$$F^m = F_A^m + F_P^m. \tag{2}$$

The force of the contractile element is calculated by:

$$F_A^m = f_A(\tilde{l}^m).F_0^m.a(u), \tag{3}$$

where $f_A(\tilde{l}^m)$ is the normalized active force-length function, F_o^m is the maximum isometric force at optimal muscle fiber length l_o^m, $a(u)$ is the muscle activation, and $\tilde{l}^m$ is the normalized muscle fiber length given by:

$$\tilde{l}^m = \frac{l^m}{l_0^m}, \tag{4}$$

where l^m is the muscle fiber length. The passive force is calculated as a product of F_o^m and the normalized passive force-length function $f_P(\tilde{l}^m)$:

$$F_P^m = f_P(\tilde{l}^m).F_0^m. \tag{5}$$

According to Fig. 3, the force of the musculotendinous unit F^{mt} is calculated by:

$$F^{mt} = (F_A^m + F_P^m).cos\phi. \tag{6}$$

The angle between the orientation of muscle and tendon fibers, named pennation angle, ϕ, can be compute by:

$$\phi = arcsen\left(\frac{l_0^m.sen\phi_0}{l^m}\right), \tag{7}$$

where ϕ_0 is the pennation angle at optimal fiber length.

3.3 Joint torque

Once the muscle forces are estimated (Eq. 6) and the moment arms (data taken from software Opensim) of all chosen muscles acting on the joint are available, we are able to convert the muscle forces to joint torque τ by means of the following equation:

$$\tau = |\sum_{i=1}^{n} F_i^{mt} r_i|_{Agonist} - |\sum_{j=1}^{m} F_j^{mt} r_j|_{Antagonist}, \tag{8}$$

where n and m are the number of agonist and antagonist muscles acting on the joint, respectively.

3.4 Selection of parameters

Since the exoskeleton is in close interaction with the human operator, there are parameters in the system that have to be adapted to the individual operator and to his/her current body state (Fleischer, 2007). Table1 shows the parameters of the EMG-driven model selected for optimization.

Table 1. Parameters selected for optimization

Description	Parameters
Shape factor of the activation function	A
Expected maximum EMG signal	R
Maximum isometric force	F_0^m
Optimal muscle fiber length	l_0^m
Optimal pennation angle	ϕ_0
Moment arm	r
Shape factor of active force-length function	S_1
Shape factor of passive force-length function	S_2
Factor that defines the estimated torque $\tau_{EMG} = \alpha\tau$, where τ is given by Eq. 8	α

4. OPTIMIZATION PROCESS

In this section it is proposed an optimization procedure to adjust the EMG-driven model's parameters aiming to minimize the difference between the EMG-based estimate joint torque, τ_{EMG}, and the ID-based one. Results obtained from an active knee orthosis is also presented. The optimization process is represented in Fig. 4.

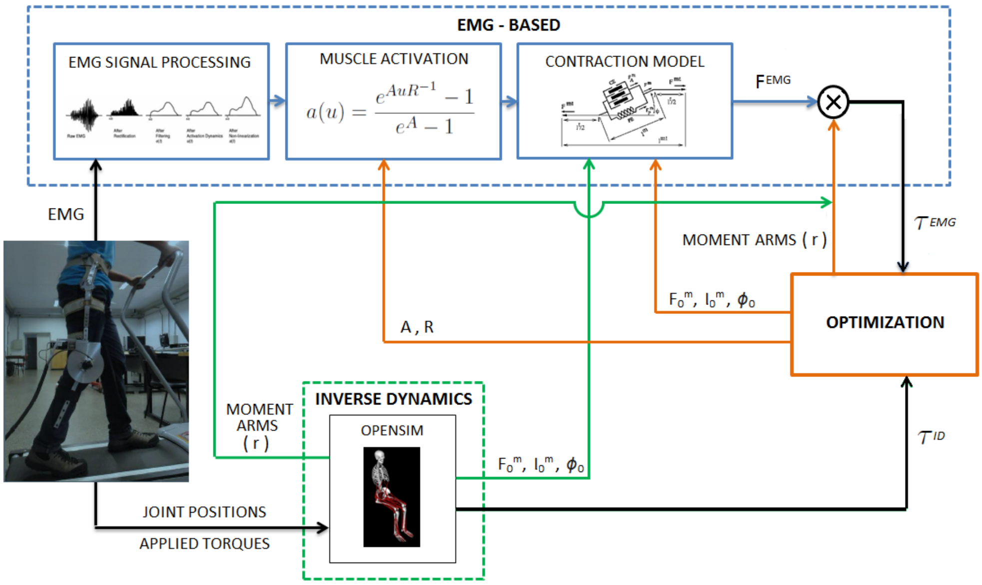

Figure 4. Detailed diagram of optimization procedure.

The EMG signals pass through signal processing (with DC offset elimination, rectification, low-pass filtering, and subtraction of the measured offset when the muscle is relaxed); the processed signal is introduced into the muscle activation function. The result is used in the contraction model to generate muscle forces. Finally, the estimate torque is computed considering the the moments arms, obtained from the OpenSim model.

On the other hand, joint positions and applied torques obtained from an active knee orthosis is loaded to the OpenSim model, and the Inverse Dynamics tool is used to compute τ_{ID}. The active knee orthosis is shown in Fig. 5. The orhtosis' actuator is an rotary series elastic actuator, which allows to set the mechanical impedance of active knee orthosis, (dos Santos and Siqueira, 2014).

The experiment considers a healthy subject wearing the orthosis and performing movements of flexion and extension of knee, with the mechanical impedance of the actuator set to: 0 Nm/rad, 30 Nm/rad, and 60 Nm/rad. The user is sited with, initially, the knee in flexion at 90^o.

Figure 5. Active knee orthosis.

After obtained the estimate torques, the optimization process adjust the parameters: A and R (muscular activation function); F_0^m, l_0^m, and ϕ_0 (muscle contraction model); and r, the moment arms. In Fig. 4, the green arrows are used to indicate that the parameters are taken from the Opensim software only at the beginning of the optimization process, which uses the *lqscurvefit* algorithm of Optimization MATLAB®toolbox.

EMG signals from five muscles involved in the movement of flexion/extension of knee are acquired: Rectus femoris, Vastus lateralis and Vastus medialis of the extensors group; and Biceps femoris e Semitendinosus, of flexors group.

Table1 presents the parameters to be optimized and the limits values used during the optimization process. The factors S_1 and S_2 modify the shapes of the active and passive force-length functions as shown in the Fig. 6, respectively.

Table 2. Upper and lower limits imposed in the optimization process

Parameters	Limits	Observations
A	[-3,-0.1]	value, by muscle
R	[0.935,1.066]	factor, by muscle
F_0^m	[0.709,1.205]	factor, by muscle
l_0^m	[0.8,1.2]	factor, by muscle
ϕ_0	[1,2]	factor, by muscle
r	[0.9,1.2]	factor, by muscle
S_1	[0.74,1]	factor, global, of active force-length function
S_2	[0.6,1]	factor, global, of passive force-length function
α	[0.8,1.2]	factor, global, of estimated torque

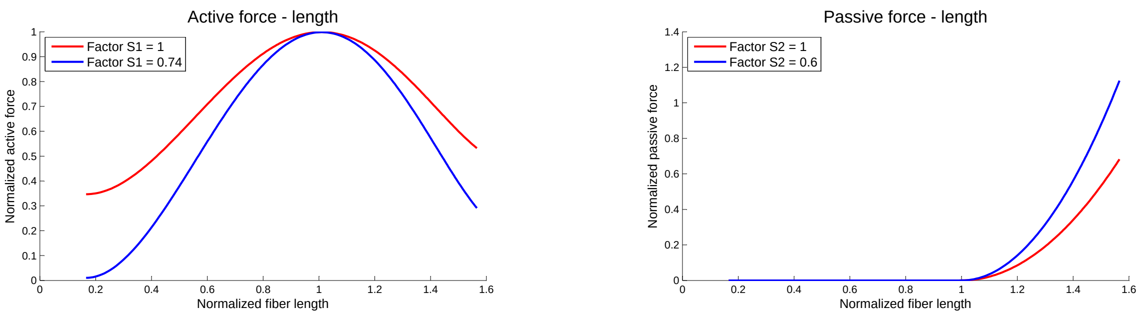

Figure 6. Active and passive force-length functions, factors S_1 and S_2.

5. RESULTS

To evaluate the optimized process and the appropriate number of parameters to be optimized, we considered four conditions: only A, F_0^m, and l_0^m are optimized; the previous parameters along with ϕ_0, R, and r are optimized; all 33 parameters are optimized; and all parameters are optimized, with larger limit values for α and A ($\alpha \in$ [0.2,1.2] and $A \in$ [-5,0.1]).

To compare the conditions, the Mean Square Error (MSE) is computed as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\tau_{EMG} - \tau_{ID})^2. \tag{9}$$

Table 3 shows the MSE values for all conditions.

Table 3. MSE for different number of optimized parameters.

Optimized parameters	MSE (N^{2}m^2)	Observations
A, F_0^m, l_0^m	44.14	15 parameters
A, F_0^m, l_0^m, ϕ_0, R, r	30.83	30 parameters
A, F_0^m, l_0^m, ϕ_0, R, r, S_1,S_2, α	15.0	33 parameters
A, F_0^m, l_0^m, ϕ_0, R, r, S_1,S_2, α	5.995	33 parameters, α and A with larger limits

Figure 7 shows the EMG-based estimate torque (blue) in comparison with the ID-based torque (red) of the three experiments with variable impedance. In this figure it is observed that the EMG-based estimate torque has better approximation to the ID-based torque when the number of parameters increases; in the lower graph of this figure, it is also shown the estimated torque with parameters α and A with larger limits.

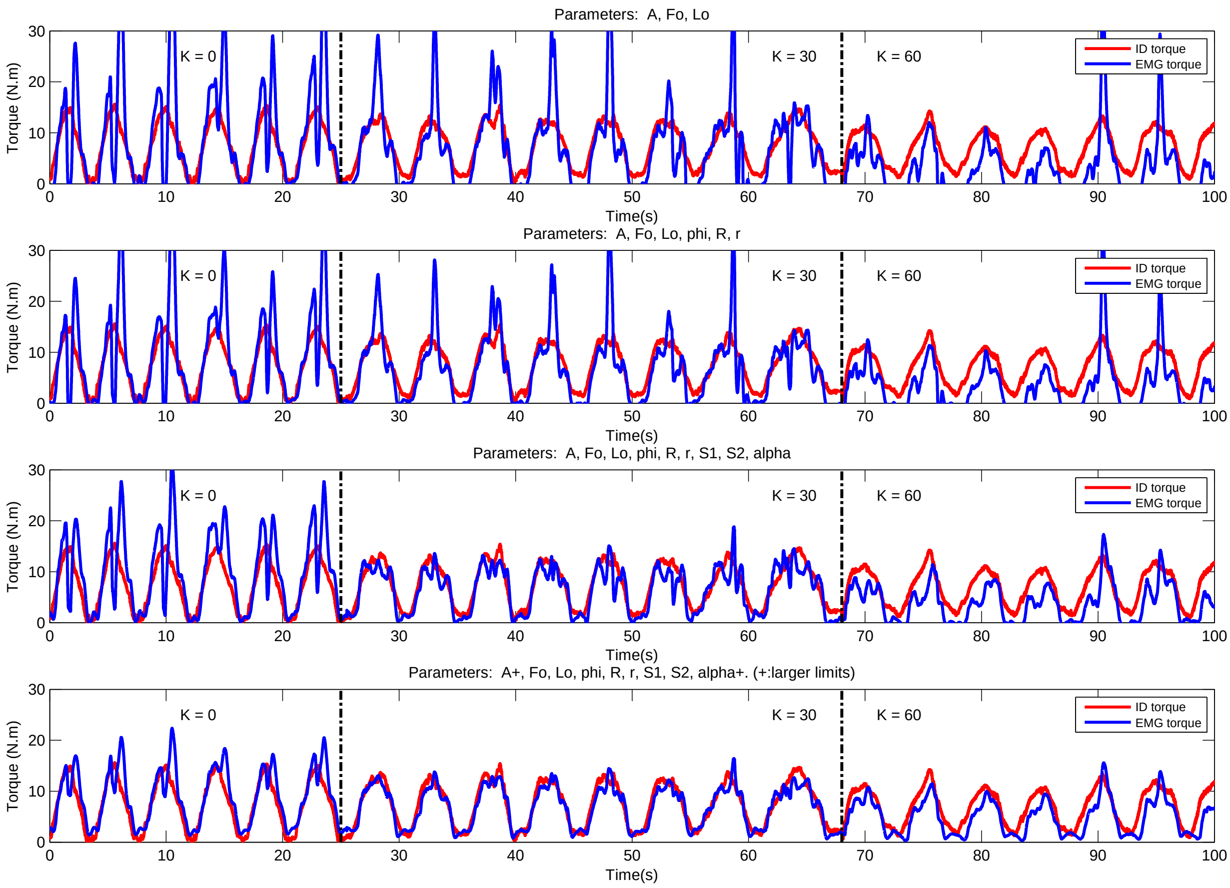

Figure 7. Comparison of torques estimated and calculated of the three tests with variable impedance.

6. CONCLUSIONS

This paper presented an optimized model to estimate joint torques from EMG signals. In the EMG-based estimation process, a activation function, a Hill-type model, and the joint geometry is used to estimate the torque; this torque is verified by comparing it with the torque computed using inverse dynamics and a musculoskeleton model of the OpenSim software. The error between the estimate joint torques is used to adjust the model parameters. Increasing the number of parameters decreases the mean square error. This is a topic of conversation among authors. There are many works where the number of parameters is huge (hundreds). In Buchanan *et al.* (2004), the authors present a very accurate torque estimation with many parameters, named over-adjusted model, but the model needs adjustment every second of movement. An over-adjusted model can only be used to estimate torque in a particular movement, but can not be used to estimate torque in other movements.

Also, the time the optimization process requires to converge varies with relation to the number of parameters. In the results presented in the previous section, the optimization process for the last condition (all parameters, with larger limits) requires about 15 minutes to be finished. To improve this time, we are considering the adoption of muscle contraction models with fewer parameters, mathematical models of EMG-torque relationship, or the use other optimization methods such as artificial neural networks.

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