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An Optimized Model for Estimation of Muscle Contribution and Human Joint Torques from sEMG Information

Diana. R. Bueno*, L. Montano*

Abstract— **This paper develops a Hill model based technique to estimate human elbow torque from sEMG measurements. Some new parameters are included in the optimization process in order to improve the resulting estimated torque. These parameters correspond to activation levels of muscles involved in motion generation. They have not previously been used in other works dealing with this kind of model. Results from experiments with several subjects in different movement conditions and using the new optimized parameters lead to some conclusions about the generality of the optimized models and the influence of the new parameters on the improvement of the estimation.**

I. INTRODUCTION

Several works have developed different models to estimate the joint torques of human limbs for different movements. These range from blackbox models (i.e. Neural Networks [3]) to more physiological-based models whose parameters have a physiological sense. Here we focus on the Hill model corresponding to the latter kind. The parameters can be modelled and tuned using physiological reasoning.

Motor rehabilitation progress can be improved by using assistive robotic exoskeletons in order to perform exercises under the *assist-as-needed* paradigm. This is one of the objectives of the HYPER project [9] in which we are involved. A Neuroestimator will process different kinds of neural and biological signals in order to control the robot under that paradigm. The robot will only provide the assistance level defined by the therapist. This will partly depend on the force/energy that the subject can exert, which has to be estimated. One of the modules of this Neuroestimator will be the human Joint Torque Estimator from sEMG sensors. A precise and adaptive model is necessary to achieve this goal. This is the focus of this paper.

During recent years various works for tuning and experimenting with exoskeleton control have been carried out using Hill models [4, 7]. In [8] an optimization method is proposed for tuning some Hill parameters such as joint angles included in the model, although other physiological parameters are not dealt with. [10] describes a two-step optimization technique to estimate force muscles from EMG, focusing on a comparison between two techniques and on some physiological-based constraints on the parameters. However, usually only a few model parameters have been tuned or optimized and experiments have been limited to one subject with limited motion conditions.

*D. R. Bueno and L. Montano are with the Aragón Institute of Engineering Research (I3A), and with the Department of Computer Science and Systems Engineering, University of Zaragoza, Spain. (e-mails: drbueno@unizar.es, montano@unizar.es)

In this work, we attempt to obtain more general conclusions about the best model parameters to be used and tuned using several subjects under different exercise conditions, including the fatigue situation.

The paper is structured as follows: Sec. II introduces the muscle model and the parameter optimization approach. The objectives, experimental protocol, equipment, and set up to be validated are described in Sec. III. Sec. IV presents the results. The paper is concluded in Sec. V.

II. JOINT TORQUE ESTIMATION FROM HILL MODEL

A crucial issue when studying generated muscle forces is to choose a suitable muscle model. Hill-based (HB) models are well-known for appropriately representing muscle behaviour. Among the various HB model formulations, one of the most consistent was that used in [4]. This also takes into account force-length (f_l) and force-velocity (f_v) muscle relationships. Moreover, its parameters have a physiological meaning, unlike those based on neural-networks. This allows new parameters to be included in accordance with physiological models, thus enabling better torque estimation.

A. Hill model and parameters

The force equations are [4, 7]:

$$F_{SE} = \left[\frac{F_{max}(F_{CEmax})}{e^{S_{SE}}}\right]\left[e^{\left(\frac{S_{SE}}{\Delta L_{max}(L_{TS})}\Delta L(L_{TS})\right)} - 1\right] \tag{1}$$

$$F_{PE} = \left[\frac{F_{max}(F_{CEmax})}{e^{S_{PE}}}\right]\left[e^{\left(\frac{S_{PE}}{\Delta L_{max}(L_{max},\, L_{Co}, L_{Ts})}\Delta L(L_{Co}, L_{Ts})\right)} - 1\right] \tag{2}$$

$$F_{CE} = F_{CEmax} \cdot u \cdot f_l(L_{Co}) \cdot f_v\big(V_{CEo}(u, L_{Co}, \alpha)\big) \tag{3}$$

where the muscles are modelled as composed of contractile (CE, active part), parallel elastic (PE, passive part), and series elastic (SE, passive part) elements. In [4] these functions are reported in detail. S_{PE} and S_{SE} denote the shape factor, L_{C0} the optimal fibre length, L_{TS} the tendon slack length, u the normalized muscle activation, α the % of fast contractile fibres, F_{max} and L_{max} the maximal force and length, and ΔL the length variation with respect to the slack length. In this work, we estimate from this model the elbow torque in flexion/extension movements from the agonist and antagonist muscles involved. In order to select the muscles that contribute most to elbow moment, we used Opensim software [1]. From this we obtained the parameters L_{max}, L_{C0}, L_{TS}, and F_{cemax}, corresponding to the data coming from [2], a complete model of the upper limb. We also used muscle tendon lengths and moment arms from this experimental research as data in our model. The parameters α, S_{PE}, and S_{SE} were taken from [4].

Previous papers on this subject [4] only consider in the model a subset of muscles to be activated. Here we add new muscles to the previously considered, Biceps Brachi long head (BIClong), Biceps Brachi short head (BICshort), Brachioradialis (BRD), Brachialis (BRA), Triceps Brachii long head (TRIlong), Triceps Brachii lateral head (TRIlat) and Triceps Brachii medium head (TRImed). The new muscles are Anconeus (ANC), Extensor Carpi Radialis Longus (ECRL), Flexor Carpi Radialis (FCR) and Pronator Teres (PT), whose activation provide new parameters to be optimized. Since some important muscles in the arm and forearm are not superficial, and therefore we are unable to measure their electrical activity, we have assumed BIClong, BRA, ANC and PT activity to be respectively the same as their neighbouring muscles, BICshort, BRD, ECRL and FCR, but taking into account a scaling factor (based on muscle synergy theory [7]).

B. *Parameter Optimization*

An optimal tuning of parameters is achieved. The method fits the estimated elbow torque with that measured with a force sensor placed on the forearm. A nonlinear 'trust-region-reflective' [5] algorithm from the Matlab Optimization toolbox is used to solve curve-fitting problems in the least-squares sense ('lsqcurvefit' matlab function). Some values of the lower and upper interval limits for the parameters are taken from [4]. In our approach, there are 60 parameters to be optimized, 5 for each muscle and 5 global factors (BIClong, BRA, ANC and PT activation factors and a scale factor). Note that the new added parameters correspond to the *u* activation levels for the new globally considered muscles in the model.

III. Objectives and Methodology

A. *Objectives*

The general objective of this work is designing optimal elbow torque estimators from sEMG signals and elbow flexion/extension movements. The three main specific objectives are achieving more general models which are: i) valid for different movement conditions (resistance levels imposed on the arm, relaxed or fatigue situations, different movement parameters); ii) tuned for different people; iii) take into account the influence of the new parameters on the accuracy of the model to estimate the torques.

B. *Subjects*

The experiments were carried out with four male volunteer subjects, between 25 and 31 years old, of average weight and height of 78 ± 15.75 Kg and 1.75 ± 0.05 m respectively.

C. *Equipment and Data Acquisition*

KENDAL Meditrace 200 EMG sensors were used, placed in accordance with to SENIAM recommendations (European project: Surface EMG for Non-Invasive Assessment of Muscles) on 8 muscles (Fig.1). The signals were amplified using a commercial gTec system. The EMG was digitized at a sampling frequency of 2.4KHz, power-line notch-filtered at 50Hz, and bandpass filtered at 5/500Hz. Signals were captured and filtered through a Simunlink Highspeed On-line Processing system from gTec with a bipolar configuration.

A LWR KUKA robot (Fig.1) was used as an experimental exoskeleton, with 7 degrees of freedom and an ATI Gamma force/torque sensor placed on the end-effector, to estimate the real elbow torque from real measurements. This torque was used to be compared with that obtained by our estimator. Moreover, the robot provided the kinematics needed for the model: joint angles, velocities and accelerations.

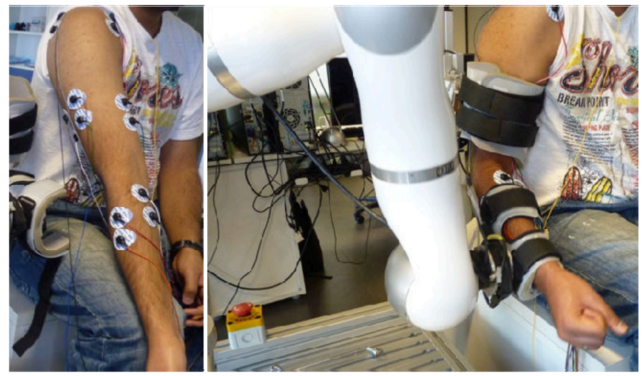

Figure 1. On the left: EMG sensors placement. On the right: Testing conducted using a LWR KUKA robot attached to the middle of the forearm

C. *Data Processing*

Converting sEMG to neural activation required: 1) a Butterworth 4th order high-pass filter (cut off frequency 30Hz); 2) full wave rectification; 3) a Butterworth 4th order low-pass filter (cut-off frequency 6Hz); 4) normalization with respect to maximal voluntary contractions.

Since the robot was attached to the middle of the forearm, we had to transfer the measured force and torque to the elbow joint based on using rigid solid techniques.

D. *Experimental Protocol*

The nominal trajectory movement was established as a flexion/extension of one degree of freedom corresponding to the elbow joint (0-110º range). The patient attaches the upper arm to a fixed structure and the forearm to the robot's end-effector to ensure an exclusive flexion/extension of the elbow (forearm movement). The processing in this experiment consists of four major stages:

- Isometric Maximal Voluntary Contraction (MVC) session: capturing MVC of different arm muscle groups according to SENIAM.
- Dynamic non fatigue session: performances of the movement guided by robot 0% assisted but with 3 different strength levels of movement opposition (50%, 75%, 98%). Three flexion/extension movements are performed for each level of resistance force.
- Isometric fatigue session: the subjects had to hold a dumbbell in a 90ª flexion position for as long as they could in order to create fatigue in the flexion muscle groups.

- Dynamic fatigue session: promptly after the isometric fatigue session the subjects perform the same exercises as in the dynamic non fatigue session.

IV. RESULTS

Fig. 2 represents the torque measured by the force sensor on the end-effector of the robot and the torque computed by the estimator for one subject and one exercise. It corresponds to one out of 3 trials for subject 2 in the 50% resistance level condition.

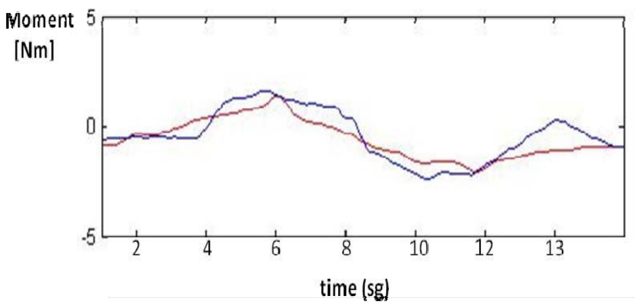

Figure 2. Blue line is the joint torque values measured by the robot force sensor. Red line is the Hill- model estimation.

For each subject, one flexion/extension movement of the 75% robot resistance level trial was used to optimize the model, and the other data collected were used to validate the modelling and tuning. The results shown in Fig.3 are the mean and standard deviation of the root mean squared error (E_{rms}) and maximum error (E_{max}) for the 3 captured trials of each movement condition as described in the experimental protocol. Both non fatigue and fatigue conditions were tested.

Regarding the resistance level in non fatigue conditions, the model fits in all cases, but there seems to be a growing increase in the error with the increase in the level of robot resistance. However, it should be noted that there is also an increasing excursion (peak to peak value) of 7.8 ± 0.23 Nm, 7.94 ± 0.89 Nm, 8.37 ± 0.41 Nm for the 25%, 50% and 98% resistance conditions respectively. Therefore, the relative error values (for instance, 0.62, 0.68, 0.65 in E_{max} for subject 1 at 50%, 75% and 98%) are maintained for the different conditions. The movement was performed at 0.3 ± 0.1 rad/sg. Even though previous works have shown that this model provides worse estimations for slow velocities, the errors here are lower than those presented in [7] for equivalent velocities.

In relation to the fatigue condition, although the model seems to be adjusted, if we consider the torque excursion in this conditions, 3.98 ± 0.28 Nm, 5.65 ± 1.54 Nm, 6.47 ± 0.42 Nm for 25%, 50% and 98% resistance, respectively, a decrease in torque generation with muscle fatigue can be appreciated. Thus, in terms of normalized values, the results lead to an increase in error.

Although the errors are acceptable compared to related works, further analysis will be necessary to determine how these errors in the limb moment estimation should be managed in assistive exoskeleton control.

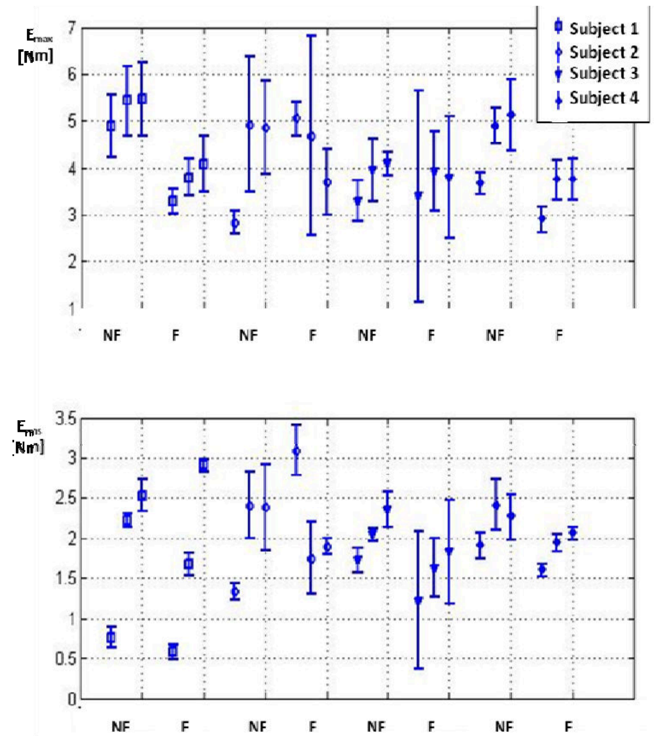

Figure 3. Mean and standard desviation of E_{max} and E_{rms} for different conditions (25%, 75%, 98% robot resistance). NF denotes non fatigue and F fatigue conditions.

In order to analyze whether the model is general or has to be tuned for each individual, we have presented the statistical data relating to 3 subjects at 75% resistance level (non fatigue conditions) with 3 different parameters. The results are shown in Fig. 4.

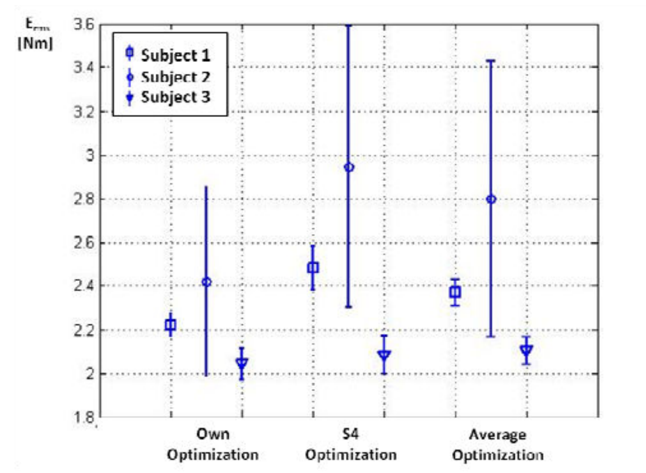

Figure 4. E_{rms} for the different subjects (S1, S2, S3) comparing different sets of optimized parameters: their own optimized set, those with respect to those of S4, and using an average value of the optimized parameters.

As can be expected, we achieved the best results optimizing the model for each person. However, if we use mean optimal parameters of the population, we obtain sufficiently good results to consider that the same average parameters can be used for different subjects. Moreover, it is worth noting that the error is worse when we test the model with the parameters optimized for another subject (subject 4 in this case).

The authors believe that the reason why subject 2 has worse statistical results is due to the limits of the tuning parameters. The best optimal parameters for this subject are out of the bounds. Increasing the bounds in the optimization phase would lead to better optimal parameters for this subject and the statistical results would be improved: 1.92 ± 0.52 Nm with extended bounds instead of 2.42 ±0.43 Nm in the case of 75% resistance level in non fatigue conditions. Whereas the mean decreases considerably and reaches magnitudes similar to subjects 1 and 3, the standard deviation maintains its value.

Fig. 5 shows a comparison of the results when the activation levels of the proposed group of 11 muscles are used as parameters with respect to the 7 suggested in [4]. Naturally, if we take into account more muscles that contribute to the torque in a joint, we clearly improve the accuracy of the torque estimation.

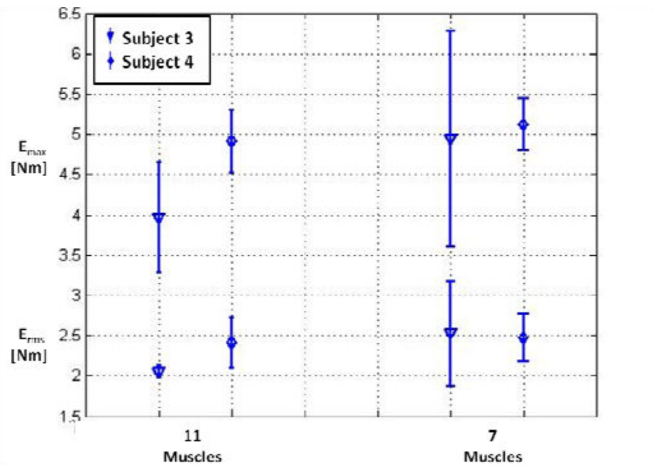

Figure 5. Mean and standard deviation of the maximum error and the root mean squared error of 11 muscles compared with 7 muscles.

V. Conclusion and Future Work

This research has shown the influence on the improvement of the joint torque estimation of new parameters with a physiological sense, included in the Hill model from sEMG for different movement conditions. Experiments were carried out on four subjects.

The results indicate that a general muscle model is possible for a population group with similar physiological characteristics (as in this study). To deal with the heterogeneity of the population, in a physical sense, the authors believe that the population can be clustered into groups and that a 'bank' of sub-optimal parameters can be provided for each group instead of each person. This could represent a breakthrough in rehabilitation engineering as it would reduce the tedious task of calibrating the model for different people. The study also shows that the inclusion of new parameters corresponding to the activation level of muscles involved in the motion, not considered in previous works, improve the Joint Torque Estimator.

The proposed model is capable of estimating torque for different resistance conditions with a low margin of error even at low velocities. However, in fatigue conditions the approach can be improved. There are already studies in this line of research [11]. Muscular fatigue will appear during rehabilitation sessions and the model could be required to cope with this change in sEMG signals.

Since testing data from four subjects is insufficient for drawing universal conclusions, future work will include larger populations, and will include discussions about trends and patterns of each muscle in detail. Moreover, we will extend the study design models for other rehabilitation movements for upper and lower limbs (such as reaching and walking). Similarly, we will include more muscles in the torque estimation study. We will also extend the methodology to disabled people with different kinds of motor disorders and different degrees of motor capabilities. These models will be used in the Neuroestimator for assist-as-needed exoskeleton control.

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