35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Multijoint upper limb torque estimation from sEMG measurements

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Abstract—**Estimation of joint torques through musculoskeletal models and measurements of muscle activations can be used for real-time control of robotic devices for rehabilitation. Many works developed models for analytic one joint motion, but less are found that develop models for functional multijoint movements. In this work we develop a methodology for tuning and optimizing Hill-based EMG-driven models oriented to the force control of robotic exoskeletons for the upper limb, selecting the more suitable parameters to be optimized. The model is tuned from experimental data obtained from healthy people. The torques estimated by that model will serve as reference for force-based control of an exoskeleton for rehabilitation.**

I. Introduction

Many works have been developed related to single-joint movements of the human limbs. They are useful when the objective is the study of analytic motions for rehabilitation of disabled people. But in the daily life activities the motions are multi-joint, and then both the perception systems of biosignals and the control of prosthetic devices have to deal with that interaction. [8] addresses a EMG-driven neuromusculoskeletal model, based on the Hill one, for coordinate movements of legs. This model improves the models used for single-joint movements but that lead to unrealistic estimations of forces when applied to multi-joint motions. In [5] an analysis of the influence of interaction torques between the elbow and shoulder joints driving a multi-joint movement of the arm is developed. This effect is reflected in the muscle activation obtained from sEMG measurements. [3] highlights the importance of torque interaction between the joints. The results suggest that errors in the use of interaction torques will result in kinematic deficits. The mismatch in interaction appeared in patients with different neurological diseases is related to abnormal muscle torques.

As a consequence of all those studies, it seems very important to develop muscle activity models that explicit or implicitly consider the joint torque interactions in coordinate movements. In [1] a Hill-based optimized model for a single-joint elbow flexion-extension movement was presented. In this work we extend the model to multi-joint arm movements in a drinking task. The objective is to optimize the parameters of Hill-based models for the joints, shoulder, elbow, and wrist, taking into account the activation of the muscles involved, computed from sEMG signals. An analysis and assessment of the proposed models are achieved from experimental measurements from four healthy persons. The models have been implemented in the Neuroestimator (NE) briefly described in [1], which takes a part of the control system of a Neurorobot (NR) – Neuroprosthetic (NP) device developed for rehabilitation tasks. The Neurorobot (NR) will control the rehabilitation movements under the paradigm assist-as-needed for patients. The developed models will be used as patterns for the control of the upper limbs.

This study has been partially funded by the Spanish project HYPER CSD2009-00067 and the project DGA-FSE- 2013-T04

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II. Experimental Protocol

The experimental data have been obtained from healthy and disabled people in the *Hospital de parapléjicos de Toledo* (Spain). The experimental protocol [7] was approved by the local ethics committee and all subjects signed an informed consent form before joining the study. For the work presented here four healthy people have been selected to compute optimal models for coordinate movements of the upper limbs, which will be used as a pattern for the control system in the rehabilitation of patients.

A. Subjects

Four healthy subjects with the following characteristics:

TABLE I. SUBJECTS CHARACTERISTICS

Subject	Age	Gender	Weight	Height
1	22	Female	65	1.6
2	22	Male	79	1.8
3	27	Female	57	1.68
4	28	Male	81.5	1.88

B. Data collection

Kinematic data are obtained with the three-dimensional computer CODA motion analysis-motion (CODA System.6, Charnwood Dynamics, Ltd, UK). It is recorded at a frequency of 200 Hz.

The forces and moments are not measured but calculated or estimated from the records made by CODA and through a biomechanical model (which has dimensions and inertial properties of the body segments of trunk, arm, forearm and hand) based on rigid body techniques. In the upper limb, the forces and moments in joints heavily depend on the weight of an external load in hand. During the phase in which the subject takes the glass in hand, we have simulated an additional load of 0.3Kg in hand.

Conductive adhesive surface electrodes (Noraxon) were placed to measure 8 muscle groups: Posterior Deltoid (PD), Middle Deltoid (MD), Anterior Deltoid (AD), Pectoralis Major (PECM) (clavicular head), Biceps Brachii, Triceps Brachii, forearm flexors, and forearm extensors.

C. Drinking from a glass

Drinking from a glass was selected as a functional movement involving multiple joints and muscle activation.

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The subject performed the test seated in front of a table with adjustable height dimensions 120x60cm. The angle between the backrest and the seat ranged 90-100°. The distance from the subject to the table was 20cm. The table was adjusted in height so that all subjects started from the same position, the arm attached to the trunk, the elbow flexed 90° position, the pronation-supination neutral, and the hand resting on the surface of the table with medially open palm. Once located the subject, he proceeded to take the glass. The glass was located at 75% of the maximum range of the subject.

III. EMG-Driven model to estimate joint torques

An EMG-driven Hill type model was used for joint torque estimation. This model processed sEMG signal as input. A scheme of the estimation technique is shown in Fig. 1.

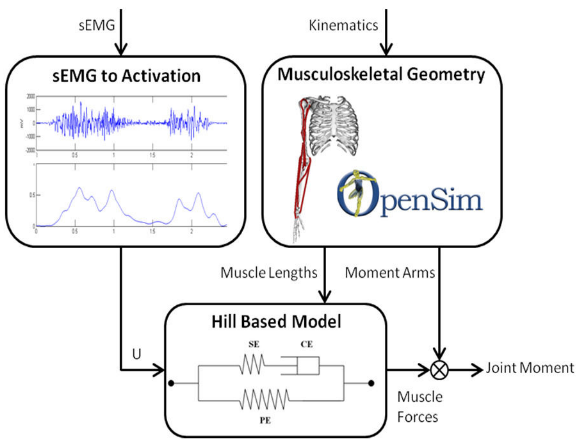


Figure 1. Joint torque estimation scheme.

Although only the myosignal activity of the above mentioned 8 muscles is measured, 11 muscles involved in the movements were modeled to evaluate the model performance. As concluded in [4], the inclusion of the activity of all these muscles that have a physiological sense based on the synergy theory showed its influence in the improvement of joint torque estimation. The muscles are: Biceps Brachi long head (BIClong), Biceps Brachi short head (BICshort), Posterior Deltoid (PD), Middle Deltoid (MD), Anterior Deltoid (AD), Pectoralis Major (PECM), Triceps Brachii long head (TRIlong), Triceps Brachii lateral head (TRIlat) and Triceps Brachii medium head (TRImed), Extensor Carpi Radialis Longus (ECRL), Flexor Carpi Radialis (FCR). From their normalized neural activation the kinetics of four degrees of freedom (DoF) is computed: **S1**, internal rotation of the humerus (shoulder); **E1**, forearm pronation-supination (elbow); **E2**, elbow flexion-extension (elbow); and **W1**, ulnar-radial deviation of the wrist (wrist).

Joint kinematics is used to obtain the musculoskeletal geometry demanding by the process, both lengths and moment arms of each muscle. This information comes from [2] and [4]. Using these inputs we adopt a mechanistic model [1], to estimate muscle forces, instead of a phenomelogical model since we consider that allows a better understanding of human movement.

A. *Parameter optimization and torque estimation*

Some of the parameters to optimize in the EMG-driven model are directly related to the measured activity of the 8 muscles. For the other three no measured muscles, three Global Parameters (GPs) were set as factors for BIClong activity with respect to the BICshort activity, and for TRIlong and TRImed, both with respect to the TRIlat. The fourth GPs is a scale geometrical factor. Table II includes all these parameters and their initial nominal values [1].

TABLE II. OPTIMIZATION NOMINAL VALUES AND INTERVALS

Muscles	Parameters				
	L_{C0} [cm]	F_{max} [N]	α [%]	S_{PE}	S_{SE}
PD	13.67	259.88	58	9	2.8
MD	10.78	1142.6	58	9	2.8
AD	9.76	1142.6	58	9	2.8
PECM	14.42	364.41	58	9	2.8
BIClong	11.57	624.3	56	9	2.8
BICshort	13.21	435.56	56	9	2.8
TRIlat	11.38	624.3	66	10	2.3
TRIlong	13.4	798.52	66	10	2.3
TRImed	11.38	624.3	66	10	2.3
ECRL	8.1	304.89	50	8	3
FCR	6.28	73.96	58	6	3
Interval	[0.5, 1.5]	[0.5, 1.5]	[0.8, 1.2]	[0.8, 1.2]	[0.8, 1.2]

	Global Parameters			
	fBIClong	**fTRIlong**	**fTRImed**	**fscale**
Nominal values	1	1	1	1
Interval	[0.5, 4]	[0.5, 4]	[0.5, 4]	[0.5, 1.5]

We use the trust-region-reflective algorithm [6] to optimize the 59 parameters: 5 parameters for each muscle and 4 global parameters. The parameters in each muscle are: S_{PE} and S_{SE} which are the shape factor of the parallel and serial element of each muscle (Fig. 1), L_{C0} the optimal fiber length, α the % of fast contractile fibers, F_{max} maximal force for each muscle. More details about these parameters can be found in [1].

Many methodologies can be applied in order to optimize the parameters for estimating the joint torques from the experimental data. Due to the complexity of the drinking movement, we have grouped them in five phases associated to the following events (see Fig. 2): 1) *Reaching*: time from start cycle until it reaches the object (glass). 2) *Take-glass*: time from reaching the object until the glass is caught. 3) *Glass-mouth*: time since the glass has been taken until it leads to the mouth. 4) *Finish-drinking*: time since the glass was carried to the mouth until they finish drinking. 5) *Release-glass*: distal transport time, including when the glass is contacted with the surface of the table until was released.

The model involves many parameters to be optimized. In order to study if the process can be simplified by reducing the number of parameters, two kind of optimization have been applied:

Selective optimization: the 11 muscles were clustered in their most influential joint: 1) Shoulder: AD, MD, PD, PECM; 2) Elbow: BIClong, BICshort, TRIlat, TRImed, TRIlong, ECRL; 3) Wrist: FCR. The algorithm is run three times separately, first to adjust 4 muscles and GPs with S1, secondly to fit the 6 muscles and GPs with E1 and E2 together, and finally W1 with its only muscle involved and GPs. Final GPs are computed as the average of the ones obtained in each of the three optimizations. In consequence, this implies that muscles activated with the movement of other joint are not considered in the procedure.

Multijoint optimization: the 11 muscles and GPs are used to optimize each DoF. In combined upper limb movements, shoulder-elbow-wrist muscles are not correlated with alternative movements and all muscles are activated. Here, this biarticular muscles phenomenon is taken into consideration contemplating all muscles for each DoF at the same time.

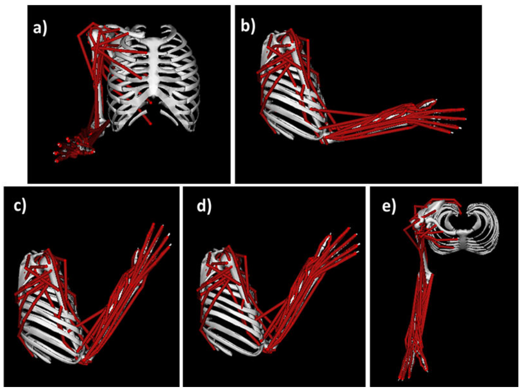


Figure 2. OpenSim screenshots of drinking from glass motion, the stages: a) Reaching, b) take glass, c) glass-mouth, d) finish-drinking, e) release-glass. In order to extract the geometrical data used in the model, OpenSim uses the kinematics given by the CODA equipment. Meanwhile, the software allows us to perform a rough visual inspection of how good subjects execute the movement.

In the model training stage we launched the process separately with data from the phases 1 to 2, 2 to 3, 3 to 4 and 4 to 5, using the data from the other phases for model cross-validation. The objective was to find if there is any stage (with its involved movements) more representative than the others. Tuning the model with the data from the 2 to 3 phases, achieves the best results. It leads to believe that, in functional movement, the stage used to compute the model should be representative enough to obtain the optimal parameters and suit the rest of the motion.

IV. Results

Fig. 3 depicts the angles and torques for all the degrees of freedom of one of the subjects. In green (-) the non-optimized Hill model (using generic nominal parameters), in red (--) the estimated torques with the optimized model, and in blue (-) the torque computed by means a solid rigid skeletal dynamic model [7]. Fig. 4 represents the maximal error (E_{max}) and root mean square error (E_{rms}) of the whole task for each subject.

It can be seen from both figures how the optimized model using all the parameters adapts better to the motion pattern and torque computed by the dynamic model. Optimizing the model only with clustered muscles in each joint exhibits higher errors with respect to the theoretical torque computed from the dynamic model, as can be appreciated in Fig 4, although are always lower than the obtained with the nominal parameters. This result matches well and confirms that all the muscles associated to joints (shoulder, elbow, wrist) are activated, influencing by means of interaction torques in the other joints, as also deduced in [3] and [5]. So, they cannot be avoided in the optimization process.

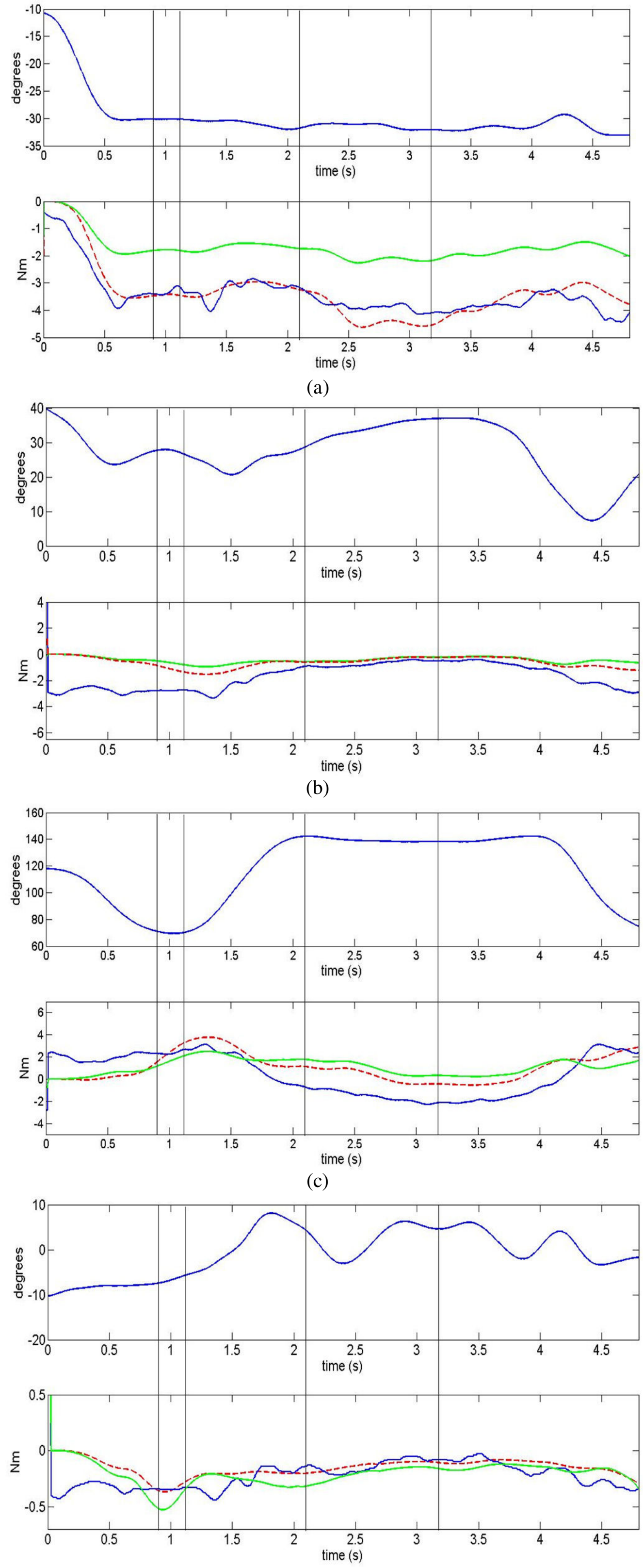
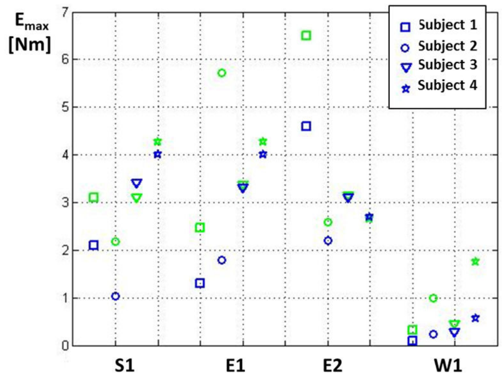
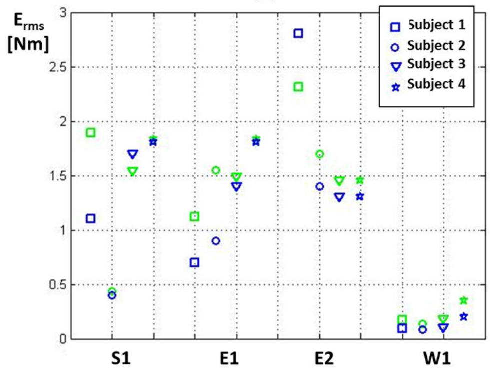


Figure 3. Kinematic and torque profiles for: (a) **S1**: internal rotation of the humerus (positive); (b) **E1**: forearm pronation-supination (supination positive); (c) **E2**: Elbow flexion-extension (extension positive); (d) **W1**: ulnar-radial deviation of the wrist (ulnar deviation positive). The beginning of motion stages are also drawn as vertical lines.



(a)



(b)

Figure 4. (a) Maximal error for each subject and degree of freedom. (b) Root mean square error for each subject and degree of freedom. The errors are higher for the selective optimization (green) that for the multi-joint optimization (blue).

The calculated parameters are optimum for each subject and this particular movement. We suppose these parameters could work in different types of tasks. However, we cannot guarantee they are the optimal for other tasks, may simply belong to the sub-optimal parameters group [1].

Several limitations explain the errors and must be considered when using this model. OpenSim model has constrained the motion of clavicle and scapula [4], therefore the geometrical information could have some inaccuracies. Moreover, it is well reported in the literature, and indeed happens, that it is difficult to estimate the rotational movement from sensors placed on the skin surface due to the displacement of the skin markers and sometimes we lost visibility of markers. This cannot be avoided due to the movement in question. So it is highly possible that at some brief moment the CODA computed an interpolation. Even though errors improve in magnitude the ones reported until now in similar works, it is required a deeper analysis to determine real constraints in terms of torque control when implementing the model in a Neurorobot.

V. Conclusion

The rehabilitation sessions to restore motor disorders, due to Cerebrovascular Accidents, Cerebral Palsy or Spinal Cord Injury, include wide range of task, not only analytical but also functional movements. Therefore, it is essential that the Neuroestimator manages multijoint movements to keep the system accuracy and the smoothness of motions.

As referenced in the literature, in coordinate motions for upper limbs shoulder-elbow-wrist muscles are not correlated with alternative movements and all the muscles are activated. This explains the better performance obtained in the presented experiments when all the involved muscles for each degree of freedom are considered in the measurement and the optimization. It takes implicitly into account the interaction torques between joints, needed for reaching smooth and healthy human-like motions. The torque estimated in real time by the Neuroestimator using this model will yield good setpoints for the force-based control of the Neurorobot, because it will be the force patterns for the rehabilitation movements guided by the robot.

This preliminary study is being extended in an on-going work in several lines: use of data from more healthy people to strongly validate the model as torque pattern for rehabilitation of disabled people; assessment of the available data from disabled people to analyze their kinematic and torque profiles. As EMG activity of patients is altered, the model will estimate abnormal joint torques, which might be resolved with the development of Neurorobot control strategies based on the patterns and on the measured data for compensation and adaptation activities for individuals with disorders. We hope that this study will contribute to better understand the generalization of muscle models for a wide range of rehabilitation tasks to estimate control parameters of hybrid rehabilitation devices and use them to adapt the motion strategy variables.

Acknowledgment

We would like to thank to researchers of the *Hospital de Parapléjicos de Toledo* (Spain) for the patients data provided for this research.

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