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

Inverse Estimation of Muscle Activations from Joint Torque via Local Multiple Regression

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Abstract— **The signal measured with an electromyogram (EMG) is the summation of all action potentials of motor units active at a certain time. According to previous literature, one can establish the relationship between torque and EMG/activations in a forward way, i.e., employing EMG of multiple channels to estimate the joint torque. Once the relationship is established, the torque can be predicted with EMG recordings. However, in some applications of neuroprosthetics where we need to make muscle control, it is required to inversely have an insight regarding the muscle activations under a specific motion scenario from the corresponding torque. Motivated by this point, this paper investigates inverse estimation of muscle activations in random contractions at the ankle joint. Local multiple regression is exploited for finding the relationship between muscle activations and torque. Such technique is able to rebuild the relationship between muscle activations and joint torque inversely based on experimental data obtained from five able-bodied subjects, and the resultant optimal weight matrix can indicate each muscle's contribution in the production of the torque. Further cross validation on prediction of muscle activations with joint torque with optimal weights shows that such approach may possess promising performance.**

I. INTRODUCTION

Electromyogram (EMG) signal detects the muscle electrical activity and is regarded as the direct reflection of human muscle activations, which can be widely used to control the human-interaction robot [1], [2], [3] and the prosthetic limb [4]. There is an explicit relationship between human motion and EMG signals of multiple muscle groups, making it possible to apply EMG to estimate different types of human motion in a forward way. In past decades, numerous works tried to forwardly establish the relationship between EMG/activations and motion under various biomechanics scenarios [5], [6], [7], [8], [9], [12], [13], [14], [15], [16], [17], [18]. For instance, Kent [16] applied the neurogenetic method to establish the mapping from EMG to torque. Lloyd and Besier [8] employed EMG-driven model to estimate muscle forces and knee joint moments. Bogey *et al.* [13] proposed an EMG-based approach to determine ankle muscle force. Clancy *et al.* [6] well summarized several basic forward linear/nonlinear models on multiple extension and flexion EMG signals for estimating joint torque. As an important application for human-robot interaction, surface EMG, representing the muscle activation, has to be estimated inversely from human motion to calibrate control signals for cooperation tasks [1]. However, currently there is limited work on inverse estimation of muscle activations (which are generally represented by processed EMG signals) from the muscle torque/force [10]. This mainly motivates us to develop a proper solution to inversely estimate muscle activations.

Neural activations of multiple muscles can not be determined uniquely from the joint torque or position due to the inherent redundancy of the musculoskeletal system. One typical way to handle such redundancy issue is to involve an optimization to minimize a well-defined cost function [19], for example, total muscle tension or activity. In this paper, we are focusing on establishing the preliminary work on the optimally estimating the muscle activations inversely from ankle joint torque with experimental data collected from five healthy subjects. Specifically, we investigate the inverse estimation of activation envelopes of three muscles [Medial Gastrocnemius (MG), Soleus (SOL), and Tibialis (TA)] at the human lower leg simultaneously with join torque in random (isometric) motion condition. In each circle of contractions of muscles, a local objective cost function, associated with muscle activations (represented by processed EMG signals) and ankle joint torque, is established and to be minimized. During each period for one circle of muscle contraction, through minimizing the aforementioned cost function, a weight matrix which may possess feature information of muscle activation redundancy is obtained. Different feature weight matrix corresponds to the different torque-pattern information of muscle activations. By constructing the weight ratios among the row elements of the weight matrix, each contribution to torque from the individual muscle can be e-valuated respectively. For cross-validation, the feature weight matrix is further embedded in newly-defined cost objective function to inversely predict the muscle activations for the subjects with constraint issues considered.

This paper is organized as follows. Section II presents the basic description of experiment setup for the subjects. The methodology on optimal estimation of muscle activations inversely from torque is addressed in Section III. In Section IV, verification results for five healthy subjects are presented. Final remarks are concluded in Section V.

II. EXPERIMENT SETUP AND DATA PROCESSING

The data sets were collected through the following experiment for five able-bodied subjects (three are males and the other two are females). The subjects were seated on a chair with their right foot attached to a Biodex dynamometer (Biodex Medical Systems Inc., New York, USA). The setting was 90 degrees for ankle joint and 110 degrees for the

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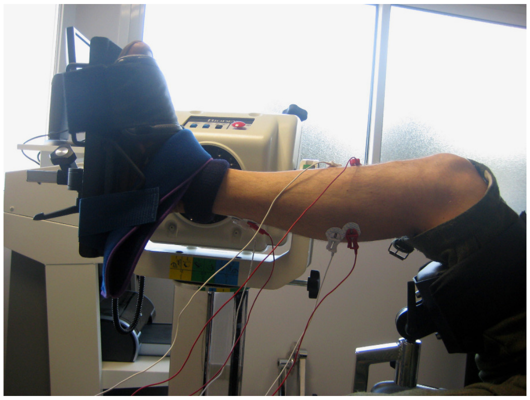


Fig. 1. Experiment setup for one of the subjects

TABLE I

TORQUE CONTRIBUTION BY MUSCLES FOR SUBJECT V1

Contraction period (s)	Torque contributions (r_{2i})		
	MG (r_{21})	SOL (r_{22})	TA (r_{23})
[3.75 5.22]	2.21%	16.59%	81.20%
[8.75 9.76]	38.22%	54.56%	7.22%
[11.33 13.94]	56.82%	37.02%	6.16%
[17.50 18.58]	4.04%	16.63%	79.53%

knee joint, straps were used on the pelvis and shoulders to secure subjects position on the chair. The electrodes were placed on muscles MG, SOL, and TA at each subject's lower leg respectively because contraction of these muscles can be relatively relevant to the ankle joint movement. Synchronous acquisition of the force and differential EMG signal was performed with a sample frequency of 2048Hz by the EMG100 amplifier and Biopac MP100 system (Biopac Systems, Inc., Santa Barbara, USA). The experiment setup for one subject is shown in Fig. 1. After raw EMG signals were recorded, the EMG signals were rectified and low-pass filtered with a 2Hz cut-off frequency. The processed EMGs [whose unit is milli-Volt (mV)] can be regarded as the activation envelopes of muscles to be used in the ensuing sections.

III. ESTIMATION OF MUSCLE ACTIVATIONS FROM JOINT TORQUE

In this work, after identification finished, only ankle joint torque information is considered for reconstructing the activations of three muscles in the lower leg, so the redundancy may exist in such solution for producing activations. Owing to this, optimization technique can be exploited for the solution. Our aim is to obtain the muscle activations from the ankle joint torque. To achieve this, the following objective function for local multiple regression during each contraction process (cp), which maps the relationship between muscle activations and ankle joint torque, is constructed to be minimized as follows,

$$\|\Phi_{cp}W_{cp} - U_{cp}\|_F^2, \tag{1}$$

where weight matrix W_{cp} is to be obtained, matrix Φ_{cp} incorporates information of ankle joint torque τ_{cp}, matrix U_{cp}

TABLE II

DIRECT-VALIDATION ERRORS FOR FIVE SUBJECTS ON LONG-TERM (25S) CONTRACTION PERIODS

Subject	Direct-validation RMS error (mV)		
	MG	SOL	TA
V1	0.0036	0.0049	0.0109
V2	0.0044	0.0043	0.0206
V3	0.0011	0.0040	0.0090
V4	0.0015	0.0058	0.0075
V5	0.0007	0.0023	0.0105

is composed of the three muscle activations. All of the three matrices are evaluated during each muscles' co-contractions period. $\|\cdot\|_F$ denotes the Frobenius norm of matrix. In this paper, based on the experimental data we collected, three types of muscle for their activations are considered, SOL, MG, and TA. During each contraction period, matrix Φ_{cp} is constructed as

$$\Phi_{cp} = \begin{bmatrix}\mathbf{1} & \tau_{cp} & 2\tau_{cp}^2 - \mathbf{1}\end{bmatrix},$$

with vectors $\mathbf{1} = [1, \cdots, 1]^T$, $\tau_{cp} = [\tau_{cp}(t_{cb}), \cdots, \tau_{cp}(t_{ce})]^T$, and $\tau_{cp}^2 = [\tau_{cp}^2(t_{cb}), \cdots, \tau_{cp}^2(t_{ce})]^T$ (t_{cb} and t_{ce} denote the muscle-contraction beginning and ending time instants respectively). The matrix U_{cp} is constructed as

$$U_{cp} = \begin{bmatrix}\mathbf{u}_{cp}^{MG} & \mathbf{u}_{cp}^{SOL} & \mathbf{u}_{cp}^{TA}\end{bmatrix},$$

where

$$\mathbf{u}_{cp}^{MG} = [u_{cp}^{MG}(t_{cb}), \cdots, u_{cp}^{MG}(t_{ce})]^T,$$
$$\mathbf{u}_{cp}^{SOL} = [u_{cp}^{MG}(t_{cb}), \cdots, u_{cp}^{SOL}(t_{ce})]^T,$$
$$\mathbf{u}_{cp}^{TA} = [u_{cp}^{TA}(t_{cb}), \cdots, u_{cp}^{TA}(t_{ce})]^T,$$

respectively denote the activations of MG, SOL, and TA muscles respectively during one contraction period $[t_{cb} \quad t_{ce}]$. The optimal weight matrix W_{cp}^* is obtained as

$$W_{cp}^* = \Phi_{cp}^{\dagger} U_{cp}, \tag{2}$$

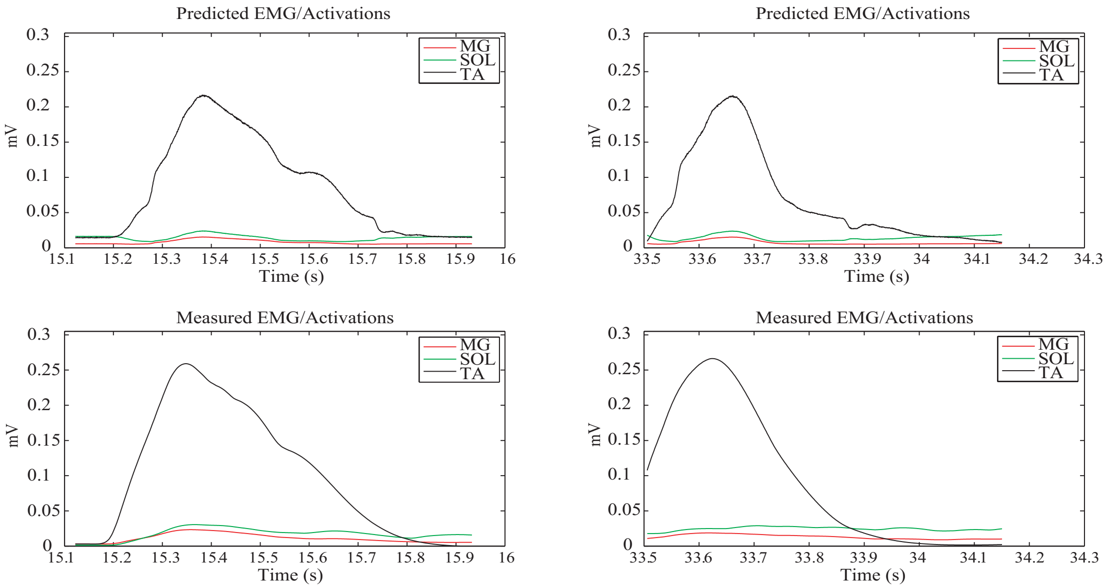
where $\Phi_{cp}^{\dagger}$ is the pseudo inverse of matrix Φ_{cp} [11]. The estimated activation is $\tilde{U}_{cp} = \Phi_{cp} W_{cp}^*$.

Now we define the ratio $r_i = |w_{ij}^*| / \sum_{j=1}^{3} |w_{ij}^*| (i = 2,3, \ j = 1,2,3)$ with the entries w_{ij}^* of W_{cp}^*. The ratio can reflect the each muscle's contribution to devote the corresponding joint torque, which is similar as the concept of muscle synergy.

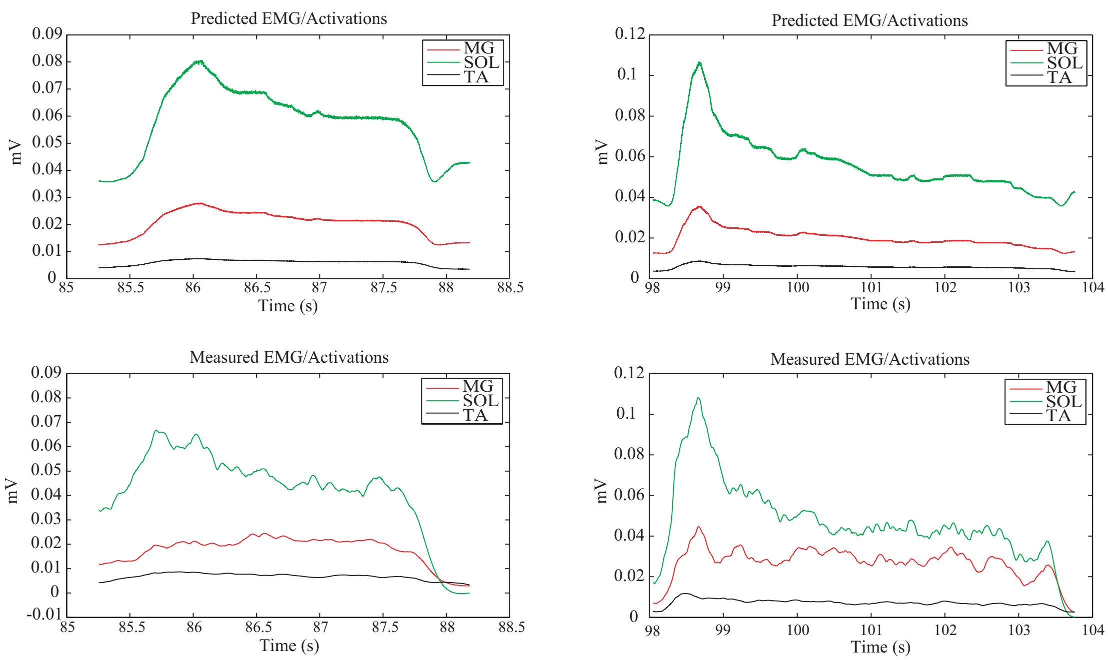
After the identification is done, in the new prediction (pr) phase within time period $[t_{pb}, t_{pe}]$, we can construct a new cost function to be minimized with several constraints

$$\begin{aligned} min. \quad & \|\Phi_{pr}W_{pr} - U_{pr}\|_F^2, \\ s.t. \quad & \|\tau_{pr}^{max} - \tau_{cp}^{max}\| + \|\tau_{pr}^{min} - \tau_{cp}^{min}\|, \\ & \|\int_{t_{ce}}^{t_{cb}} \tau_{cp}(t)dt - \int_{t_{pe}}^{t_{pb}} \tau_{pr}(t)dt\|, \\ & \|W_{pr} - W_{cp}^*\|_F. \end{aligned} \tag{3}$$

Such constraints may guarantee the robustness of predictions with optimal weight matrices determined during similar contraction in estimation phase. To improve the prediction performance we should make calibration of weight matrices



(a)



(b)

Fig. 2. Prediction of muscle activations for Subject V1 for different time periods for cross validation

according to the differences of torque information (peak, integration, or etc.) between one contraction process and the other, which seems complicated for practical use if the optimal weight matrix appears sensitive.

IV. Results and Discussions

In this section, we present and discuss the results of inverse estimation of muscle activations for the three muscles: MG, SOL, and TA under isometric condition, with ankle joint torque information. The reconstruction of the three-muscle activations during different contraction periods is validated by the data collected from the five healthy subjects. Further cross validation tests are performed as well. From Tab. I, we could see how the weight ratios reflect such contributions of muscles for producing the torque, for instance, in contraction period [8.75 9.76], the MG (with $r_{21} = 38.22\%$) and SOL

TABLE III

PREDICTION ERRORS OF ACTIVATIONS FOR SUBJECT V1

Weight matrix used for prediction	Contraction period for prediction (s)	RMS error of muscle activations (mV)			$\|\tau_{pr}^{max}-\tau_{cp}^{max}\|+\|\tau_{pr}^{min}-\tau_{cp}^{min}\|$ (Nm)	$\|\int_{t_{ce}}^{t_{cb}}\tau_{cp}(t)dt-\int_{t_{pe}}^{t_{pb}}\tau_{pr}(t)dt\|$ (Nms)
		MG	SOL	TA		
W_{cp}^* in [3.51 5.20]	[15.12 15.93]	0.0050	0.0086	0.0362	2.8055	14.9166
W_{cp}^* in [3.51 5.20]	[33.51 34.15]	0.0064	0.0116	0.0534	1.5926	17.3475
W_{cp}^* in [17.40 19.57]	[20.32 21.83]	**0.0007**	**0.0017**	**0.0061**	**3.6070**	**2.5943**
W_{cp}^* in [17.40 19.57]	[27.29 29.63]	**0.0006**	**0.0024**	**0.0096**	**2.4996**	**2.1020**
W_{cp}^* in [8.82 9.79]	[22.50 23.01]	0.0147	0.0415	0.0062	7.5727	15.6670

(with $r_{22} = 54.56\%$) muscles provided the main contributions for conducting the corresponding torque in a plantar flexion. To evaluate the overall performance, the root mean square (RMS) error is defined as $\|\tilde{U} - U_{measured}\|/\sqrt{L}$ where L is the number of time sampling during the contraction process. Tab. II shows the RMS errors of inverse estimation during the time period $[0 \quad 25]$ for the five subjects in direct validation, which are around 0.01 mV. Direct validation means that the performance of the idetified model was evaluated with the data which was used for the identification.

For cross validation the identified model was verified with the other group of the data which was not used for the identification, after the optimal weight matrix is obtained, depending on the aforementioned constraints on torque, we could make prediction with given torque for the newly incoming torque variations with the identified model. Those predictive activations were compared with the measured values. From Fig. 2, we could see that the prediction results well track the variation tendency and amplitudes of muscle activations during the four new periods $[15.1 \quad 16]$, $[0 \quad 16]$, $[85 \quad 88.5]$, and $[98 \quad 104]$. Tab. III shows the prediction errors. It is important to be noted that, the prediction errors will increase if either of $\|\tau_{pr}^{max}-\tau_{cp}^{max}\|+\|\tau_{pr}^{min}-\tau_{cp}^{min}\|$ or $\|\int_{t_{ce}}^{t_{cb}}\tau_{cp}(t)dt-\int_{t_{pe}}^{t_{pb}}\tau_{pr}(t)dt\|$ becomes larger.

V. CONCLUSIONS

This work has presented estimation of activations/processed EMG of the three muscles (MG, SOL, and TA) inversely from ankle joint torque. To establish relationship between activations and torque, local multiple regression technique of weights is exploited for the estimation. The addressed estimator/predictor shows promising performance in estimation/prediction. The optimal weight matrix ratios through estimation is able to imply the muscle synergy which reflects distinct muscles' contributions to conducting the joint torque. However, the mapping between muscle activations and torque are considered independently in this local multiple regression. We will further investigate the computational method which can take into account the multiple muscles' synergetic combinations in a systematic way.

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