Multiple-Input/Single-Output Identification of the Dynamic Relation Between EMG and Torque at the Human Ankle During Isometric Contractions*

Diego L. Guarin[1], *Student Member, IEEE, EMBS*, and Robert E. Kearney[1], *Fellow, IEEE*.

***Abstract*— Generation of torque around a joint usually involves the activation of several agonist muscles and may also involve the co-activation of antagonist muscles. Therefore, a valid model for the dynamic relation between surface EMG (an indirect measured of the muscle's neural input) and the torque should take the form of a Multiple-Input/Single-Output (MISO) system to account for the contributions of the different muscles. This paper presents a new method to accurately estimate the dynamic EMG/Torque relation when multiple muscles are active simultaneously. Using our method we found that flexor and extensor muscles at the ankle have different dynamic properties.**

I. INTRODUCTION

The characterization of the relation between the measured surface electromyogram (EMG) and the resulting force or torque has been an active topic of research for more than half a century [1]. A common approach to model this relation is to first extract the EMG envelope and then determine a static model between it and the torque. This method, although successful at predicting torque from EMG signal, involves complex filtering to extract the envelope from the raw data, and characterizes the actuator (*i.e* the muscle) solely by its gain, ignoring all but its steady state properties [2].

A more comprehensive approach is to characterize the EMG/Torque relation as a linear dynamic system non-parametrically by its impulse (or frequency) response, or parametrically by its transfer function. There is general agreement that under isometric conditions these dynamics can be modeled as a second-order, low-pass filter [1], [3].

While past studies have made important contributions regarding the dynamic characteristics of the muscle, they all identified a Single Input, Single Output (SISO) system assuming that only one agonist muscle was generating the torque and that the antagonist muscles remained inactive [1], [3]. However, usually several agonist muscles are involved in generating torque at a joint, and vigorous contractions may be accompanied by co-contractions of antagonist muscles [4].

In light of these observations, it is clear that an appropriate EMG/Torque model should account for the contributions of all the muscles involved and so it should take the form of a Multiple Input, Single Output (MISO) system.

Recently, we described a new Instrumental Variable (IV) based algorithm for the identification of MISO transfer function models [5]. The algorithm is based on the refined IV method [6] and a back-fit iteration [7].

This paper describes how this algorithm can be used to determine the dynamic relation between EMG and torque when multiple muscles are involve in the generation of torque.

This paper is organized as follows: Section II presents a simulation study which shows that the back-fit algorithm is robust to the multiplicative noise characteristic of EMG. It then compares three algorithms for the identification of MISO transfer function models and shows that our algorithm performs best. Section III demonstrates the application of the algorithm to experimental data acquired during agonist-antagonist contractions at the ankle. Section IV discusses results and outlines some possible applications.

II. SIMULATION STUDY

EMG signals are characterized by large multiplicative noise [2], which will cause some parametric identification techniques to estimate the EMG-torque dynamics incorrectly [8]. We have shown that our IV-based, back-fit algorithm gives un-biased results for high levels of additive output noise [5], but its behavior with multiplicative input noise was not studied. Nor has the performance of other MISO system identification techniques (*e.g.*, Matlab PEM [9]) have been examined for this scenario. Finally, it can be argued that if there is no co-contraction then the problem can be treated as a series of SISO identifications.

We though it important to investigate these questions via a simulation study.

A. Simulated model

The MISO transfer function model shown in Fig. 1 was simulated using Matlab at a sampling rate of 1 kHz for 120s. The inputs were $s_1(t)$ and $s_2(t)$ while $d_1(t)$ and $d_2(t)$ were nonnegative, stationary, colored, random sequences that were statistically independent of $s_1(t)$ and $s_2(t)$. The noise corrupted inputs were

$$u_i(t) = s_i(t)d_i(t).$$

*This work was supported by the Canadian Institutes of Health Research (CIHR) and the Natural Sciences and Engineering Research Council of Canada (NSERC).

[1]The authors are with the Biomedical Engineering Dept, McGill University. 3775, rue University, room 316 Montral, QC. H3A 2B4 Canada. Email: diego.guarinlopez at mail.mcgill.ca and robert.kearney at mcgill.ca

978-1-4244-7929-0/14/$26.00 ©2014 IEEE

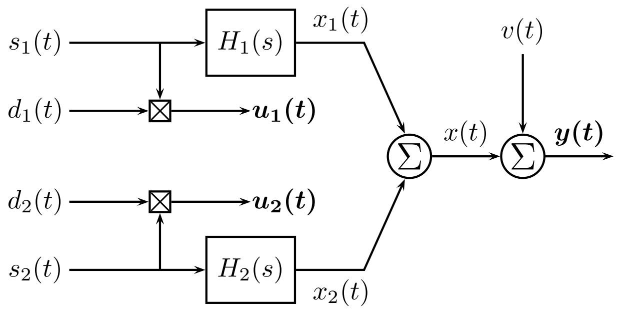

Fig. 1. Simulated model. The noise corrupted signals used for identification are in bold.

$u_1(t)$ and $u_2(t)$ were not correlated, meaning no co-contraction. $x_1(t)$ and $x_2(t)$ were the responses of each sub-system to the excitation signals. The noise corrupted output was generated by

$$y(t) = x(t) + v(t),$$

where $x(t)$ is the sum of the output of each sub-system. The noise sequence $v(t)$ accounts for: i) unmodeled dynamics, ii) low-frequency physiological noise and iii) measurement noise. The ratio between $x(t)$ and $v(t)$ was 10dB. Finally, the transfer functions of the two sub-systems were

$$H_1(s) = 250\frac{26.75}{s^2 + 5.67s + 26.75}, \quad (1)$$

$$H_2(s) = -1100\frac{15.45}{s^2 + 5.96s + 15.45}. \quad (2)$$

These system chosen to have a dynamics similar to those reported for EMG-torque relation.

B. Discrete-Time Models

The system identification methods examined were designed for the estimation of discrete-time models. Therefore, before starting the identification, the continuous-time transfer functions were transformed to their discrete-time equivalents via a bi-linear transformation [5].

C. Identification algorithms

The three methods used to estimate the MISO transfer function models from the simulation data were:

1) *Matlab PEM*: The sub-systems were estimated simultaneously using a gradient descent algorithm that minimized the prediction error as described in [9, chap. 10].
2) *RIV individual*: The sub-system between each input and the total output was estimated sequentially using the refined instrumental variable (RIV) method described in [6, chap. 7].
3) *RIV Back-Fit*: First, an initial estimate of each input contribution to the output was computed. Then, the sub-system between each input and the output was estimated sequentially after removing the predicted responses to other inputs from the total output. This procedure was repeated until convergence [5].

D. Simulation Results

One hundred Monte Carlo trials, each with new noise sequences were simulated. Fig. 2 shows 30s segment of a typical simulation trial.

Fig. 3 presents the frequency responses estimated for the two systems by the three methods.

Fig. 3a-b show the estimates of $H_1(s)$ and $H_2(s)$ from *Matlab's PEM* algorithm. It is apparent that for some trials the estimates were consistent with the simulated model while for others the estimates were wrong. Fig. 3c-d shows the estimates obtained using the *RIV individual* algorithm. The estimates of $H_2(s)$ shown in Fig. 3d were quite accurate (although there was some bias). In contrast, as Fig. 3c shows, the estimates of $H_1(s)$ were not at all accurate, neither the dc gain nor the filter's break-frequency were estimated correctly. Finally, Fig. 3e-f shows that the estimates obtained with the *RIV Back-Fit* algorithm were always very accurate. The small differences that can be observed are s small given the presence of noise in both the input and the output.

III. Experimental Study

The subject lay supine in an experimental table with the left foot attached to the pedal of a stiff servo-controlled actuator by means of a custom made fiberglass boot. The leg was fixed rigidly by means of straps. The subject provided a written informed consent and the study was approved by the university's Research Ethics Board. The experiment lasted for 180s.

A. Experimental Methods

1) EMGs: Bipolar EMGs were recorded from Tibialis Anterior (TA), Soleus (SL), Gasctrocnemius Lateral (GL) and Medial (GM) muscles using surface electrodes (DELSYS DE-2.1) spaced 10 mm apart. The electrodes were attached

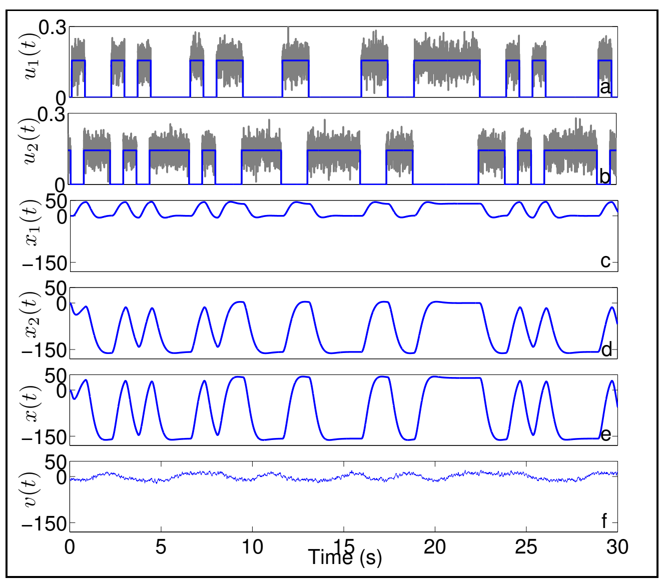

Fig. 2. Results of a typical simulation trial. a and b) Input signals ($s_1(t)$ and $s_2(t)$ in blue) and noise corrupted inputs ($u_1(t)$ and $u_2(t)$ in grey). c) Output of $H_1(s)$ ($x_1(t)$). d) Output of $H_2(s)$ ($x_2(t)$). e) Simulated noise-free output ($x(t)$). f) Noise signal added to the output ($v(t)$).

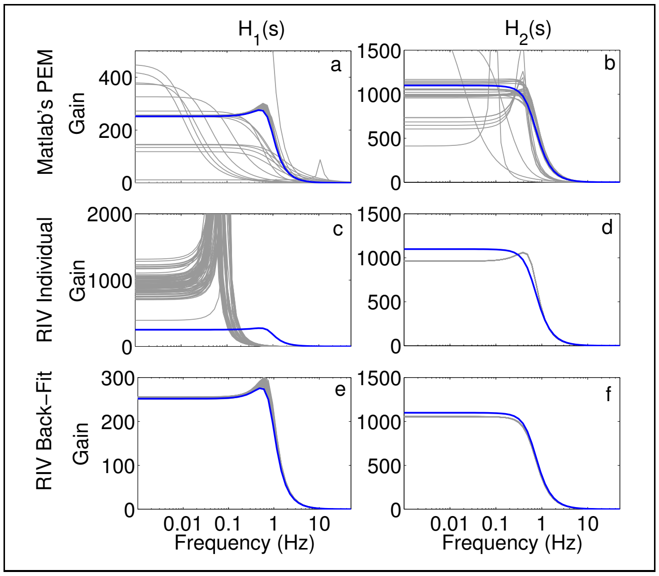

Fig. 3. Frequency response of the simulated systems (blue) along with the results of the 100 Monte Carlo simulations using different identification algorithms (grey). a and b) Systems estimated at the same time using Matlab PEM algorithm. c and d) Systems estimated sequentially using the RIV algorithm. e and f) Systems estimated using the RIV Back-Fit algorithm.

to the belly of each muscle after shaving and cleaning the skin.

The electrode output were connected to differential pre-amplifiers with a gain of 100, a common mode rejection of 100 dB, an input impedance of 300 MΩ and a frequency response from 0 to 15 kHz. This pre-amplified output was high-pass filtered (two-pole Butterworth, 10 Hz cutoff) and sampled at 1 kHz by a 16-bit A/D converter. The digital signal was full wave-rectified, low-pass filtered (eight-pole Bessel, 45 Hz cutoff) and decimated at 100 Hz for further processing.

2) Torque: Ankle torque was measured with a very stiff torque transducer (5000 Nm/rad) that connected the actuator pedal to the hydraulic motor. The torque signal was sampled and decimated in the same way as the EMGs.

3) Paradigm: The maximum voluntary contraction (MVC) both in plantarflexion and dorsiflexion was determined at the start of the experiment. The maximum contraction level that the subject was asked to generate was limited to 30% of the MVC to avoid fatigue and to reduce crosstalk between TA and SL [10].

The subject was provided with a display of a tracking command and low-pass filtered ankle torque. The subject was instructed to track the command signal by modulating the activity of its ankle muscles; the command signal was a Pseudo Random Binary Sequence (PRBS) which required the subject to generate torques to dorsiflex and plantarflex the ankle shown in Fig. 4a. Fig 4b shows the torque generated by the subject. Fig 4e-c show the EMG activity of the TA, GL and SL muscles. Each experimental trial lasted for 180s.

B. Experimental Results

1) Evaluation of EMG Crosstalk: Crosstalk was evaluated by computing the cross-correlation coefficient between different EMG signals at lags spanning ±0.5s [2]. The computed correlation coefficient between GL and GM muscles was large indicating either crosstalk or co-activation. Consequently, GM was not considered for further analysis. The correlation coefficient between the remaining muscles was no larger than that observed for two random signals with characteristics similar to the EMGs, indicating the absence of crosstalk.

2) Model Identification: The RIV Back-Fit algorithm was used to estimate dynamic EMG/Torque relation. The first 120s of the trial were used for model identification and the remaining 60s for validation. Fig. 5 shows the frequency response of the estimated parametric models relating the EMG from TA, SL and GL to torque (this non-parametric representation of the models was chosen to facilitate the visualization of the results). In addition, Fig. 6 presents the estimated torque using identification and validation data along with each muscle contribution to the total torque.

There was strong agreement between the model predictions and the measured data as evidenced by inspection and by the Variance Accounted For (VAF) [7] between the measured and predicted torques; this was greater than 97% both for identification and validation data.

Neither of the other two methods described gave accurate models when applied to these data. Identification and validation VAF were equal to 0% for *Matlab's PEM* algorithm while the *RIV individual* algorithm resulted in VAF of 63% for identification and 60% for validation.

IV. DISCUSSION

This paper presents a methodology to estimate the contributions from multiple muscles to the torque generated around the ankle. This opens up new possibilities for the characterization of muscle dynamics during functional tasks that involve isometric contractions of agonist and antagonist muscles.

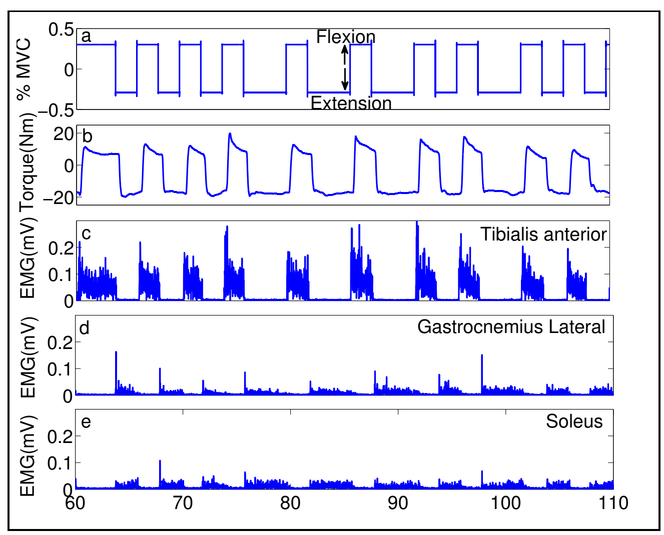

Fig. 4. a) Command signal as a function of %MVC both in dorsi and plantar flexion (0 indicates relaxation and the arrows indicate the activity that must be performed with the ankle to be able to track the command). b) Torque measured at the ankle. EMG activity measured at the belly of the c)TA, d) GL and e) SL muscles.

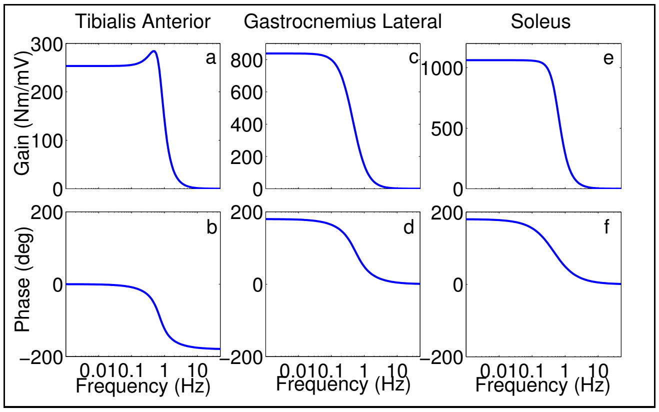

Fig. 5. Estimated frequency response (gain and phase) of the models that represent the activity of: a) Tibialis anterior muscles, b) Gastrocnemius Lateral and c) Soleus. The 180^o phase shift between flexor and extensors is due to the difference in the direction of the generated torque.

The simulation study showed that estimating the different sub-systems of the MISO model in a single step, either independently or simultaneously, gave biased results. This is likely because when estimating each sub-system the effective noise is not only the noise added to the output but the contribution(s) from other sub-system(s). The RIV back-fit algorithm deals with this by i) finding an initial estimate of each input contribution, ii) removing the contribution of other inputs when estimating each sub-systems and iii) iterating between the different steps to refine the estimates. The simulation study also showed that this strategy was valid with multiplicative noise at the input and additive noise at the output.

Application of this system identification method allowed us to estimate the dynamic EMG/Torque relation when several extensors (SL and GL) and a flexor (TA) muscles generated torque measured at the ankle; the excellent prediction ability demonstrated that the models were valid and the estimates accurate. Our results also showed that estimating each sub-system individually, without considering

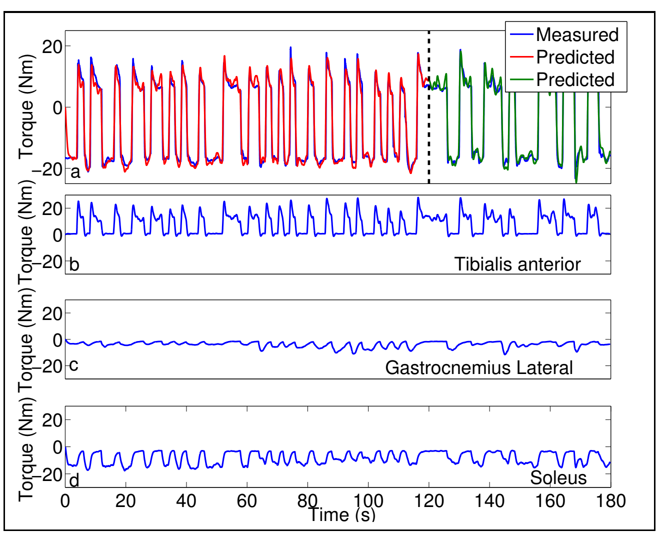

Fig. 6. a) Measured torque (blue line) along with the predicted torque during the identification (red line) and validation (green line) stages. b, c and d) Estimated contribution form TA, GL and SL muscles to the total torque.

the influence of the other inputs gave models with very poor prediction ability. The significance of these results is that even though co-activation of agonist and antagonist muscles can be reduced experimentally, by for example asking the subject to perform only flexions or extensions of the joint, the performance of the task will most likely involve the activation of several muscles. Consequently, estimating the sub-systems individually (or estimating only one sub-system as is common practice) will result in incorrect estimates due to the large levels of colored noise (*i.e.* the unmodeled dynamics in addition to the measurement noise).

In addition, we confirmed that, as indicated in the literature [1], [3], a second order linear system is an appropriate model for the EMG/Torque relation during isometric contractions .

From the estimated frequency responses presented in Fig. 5, we found that the bandwidth of the model that represents the dynamics of the TA muscle was larger than the other muscles (0.9 Hz for TA versus 0.5 Hz for SL and 0.3 Hz for GL). The gain curves for each muscle also show important differences, indicating that the muscles have different properties. The differences are particular noticeable between the flexor and extensor muscles. For example, the steady state gain of extensors (GL and SL) was larger than that of the flexor (TA). This might be due to the difference in strength between the flexor and extensor muscles but given that the EMG are measured in the skin it also might be related to the attenuation of the EMG signals.

The information that can be extracted from the muscles' frequency responses and/or transfer function may be potentially useful in characterizing neuromuscular diseases.

References

[1] G. L. Gottlieb and G. C. Agarwal, "Dynamic relationship between isometric muscle tension and the electromyogram in man," *J. of app. physiology*, vol. 30, no. 3, pp. 345–351, 1971.

[2] E. A. Clancy and N. Hogan, "Relating agonist-antagonist electromyograms to joint torque during isometric, quasi-isotonic, nonfatiguing contractions," *IEEE Trans. on Biomedical Eng.*, vol. 44, no. 10, pp. 1024–1028, 1997.

[3] W. F. Genadry, R. E. Kearney, and I. W. Hunter, "Dynamic relationship between emg and torque at the human ankle: variation with contraction level and modulation," *Medical and Biological Eng. and Comp.*, vol. 26, no. 5, pp. 489–496, 1988.

[4] K. N. An, W. P. Cooney, E. Y. Chao, L. J. Askew, and J. R. Daube, "Determination of forces in extensor pollicis longus and flexor pollicis longus of the thumb," *J. of Applied Physiology*, vol. 54, no. 3, pp. 714–719, 1983.

[5] D. L. Guarin, K. Jalaleddini, and R. E. Kearney, "Identification of a parametric, discrete-time model of ankle stiffness," in *Eng. in Medicine and Biology Society (EMBC), 2013 Annual Int. Conf. of the IEEE*, 2013, pp. 5065 – 5070.

[6] P. C. Young, *Recursive Estimation and Time-Series Analysis*. Berlin: Springer, 2011.

[7] R. E. Kearney, R. B. Stein, and L. Parameswaran, "Identification of intrinsic and reflex contributions to human ankle stiffness dynamics," *IEEE Trans. on Biomedical Eng.*, vol. 44, no. 6, pp. 493 – 504, 1997.

[8] P. J. Lago and N. B. Jones, "Parameter estimation of system dynamics with modulation - type noise. application to the modelling of the dynamic relationship between the emg and force transients in muscle," in *IEE Proceedings D*, vol. 131, no. 6. IET, 1984, pp. 221–228.

[9] L. Ljung, *System Identification - Theory For the User*, 2nd ed. Upper Saddle River, N.J.: Prentice Hall, 1999.

[10] C. J. De Luca and R. Merletti, "Surface myoelectric signal crosstalk among muscles of the leg," *Electroencephalography and clinical Neurophysiology*, vol. 69, no. 6, pp. 568–575, 1988.