EMG-Driven Force Fields: Toward a Myoprocessor for 'Virtual Biomechanics'

Nicola Lotti(✉) and Vittorio Sanguineti

Department of Informatics, Bioengineering, Robotics and Systems Engineering, University of Genoa, Genoa, Italy
nicola.lotti@edu.unige.it

Abstract. Estimating the contributions of individual muscles during limb movements is crucial to understand motor system organization. In pathological conditions, identifying the roles of each individual muscles may provide a basis for devising personalized treatments. In a previous study we demonstrated how arm and muscle geometry can be estimated from isometric force data and used to reliably estimate isometric endpoint forces in various arm configurations. Here we use a Hill-type muscle model to predict muscle torques and equivalent endpoint forces during planar arm movements in real-time. In conjunction with a planar robot manipulandum, the model is then used to modify the directions of action of individual muscles or muscle groups.

1 Introduction

Muscle activity (EMG) has been often used as a control signal to operate a prosthesis. In isometric conditions, EMG activity may be assumed to reflect the force generated by that muscle [1]. The relation is much more complex during movements. For this reason, the task of building a myoprocessor – a computational module which is able of reliably estimating muscle torques from the recorded muscle activity and movement signals (kinematics, external forces) in real-time and during movements, has proven quite challenging. Recently, Durandau [2] used EMG activity in conjunction with movement kinematics and ground reaction forces to predict the torques generated by individual lower limb muscles in real-time, in a variety of lower-limb movements. Hasson [3] developed an upper limb myoprocessor with one degree of freedom (DoF) in order to study neuromuscular system adaptation. In a previous study [4] we estimated isometric endpoint forces in various arm configurations. Here we extend this work by estimating muscle torques and equivalent endpoint forces during movements. Our final aim is to use the myoprocessor, in conjunction with a planar robot manipulandum with two degrees of freedom, in order to generate force fields that mimic individual muscles or groups of muscles and to study the corresponding adaptation phenomena during movements.

This work is partly supported by a grant from the Italian Ministry of Education, University and Research – Research Projects of National Interest (PRIN 2015).

L. Masia et al. (Eds.): ICNR 2018, BIOSYSROB 21, pp. 1161–1165, 2019.
https://doi.org/10.1007/978-3-030-01845-0_232

2 Materials and Methods

2.1 Experimental Apparatus and Task

The subjects sat in front of a 40″ computer monitor placed vertically about 1 m away, at eye level. They grasped with their right hand the handle of a planar manipulandum with two degrees of freedom [5]. Torso and wrist were restrained. Seat position was adjusted so that, with the cursor pointing at the center of the workspace, the elbow and the shoulder joints were flexed about 90° and 45°. The robot handle included a support for the forearm to partly compensate for the effect of gravity. A Force/Torque sensor (Gamma 130-10, ATI Industrial Automation, USA), mounted on the robot handle, measured the interaction force between subject and robot. We recorded hand kinematics and the activity of eight muscles – see [4] for details. We designed a motor task which specifically aimed at model calibration (parameters identification) and test of the myo-processor. The task involves reaching movements through a sequence of seven targets, $x_{P1}, \ldots, x_{P7}$ evenly distributed within the whole arm workspace – see Fig. 1, left – and isometric force steps. During the isometric phase, the robot generated a position-dependent force (stiffness: 8 kN/m) directed toward each of the seven targets. Subjects were instructed to push against the force field to generate quasi-isometric force steps (amplitude: 25 N) in twelve directions. The target force was displayed as a white circle. The current force generated by the subject was depicted as a green arrow; see Fig. 1, right. Once the target force was reached, the target changed its color from white to red, and the subjects had to hold the force for 3 s, then the target circle disappeared. At this point, the subjects had to relax for 3 s, until a new force target appeared. The whole sequence (movement and force generation) was repeated for a total of 5 times.

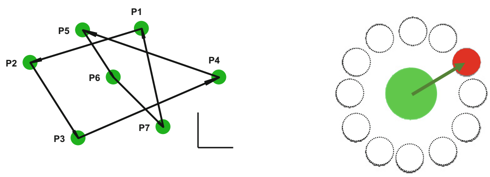

Fig. 1. Experimental protocol. Reaching movements through a sequence of seven targets (top; scale bar: 5 cm) and isometric force steps (25 N) centered around each target (bottom)

A total of four subjects (3 M + 1 F, age 25 ± 1) participated in this pilot study, all right-handed and with no previous history of neurological disorders.

2.2 Myoprocessor Model

The EMG activity, $U(t)$, was normalized with respect to minimum and maximum activation, calculated over the whole trial. We then calculated neural activation,

$n(t)$ as the output of a second-order low-pass filter: $\tau^2\ddot{n} + 2\tau\dot{n} + n = u$ with $\tau =$ 40 ms. The muscle model has the Lloyd/Thelen structure [6], with a contractile element (CE), a parallel element (PE) and a tendon element (TE). As simplifying assumption, we assumed a constant tendon length, i.e. $l_{TE} = l_{TE_0}$. The joint torque τ_m is calculated as

$$\tau_m = J_m(q)^T \cdot F_m \tag{1}$$

where q is arm configuration (shoulder and elbow angles), $J_m(q)$ (matrix of muscle moment arms) is the Jacobian of the vector of lengths of the muscle-tendon complex, $l_{MT}(q)$, and F_m is muscle force. We used a polynomial model to model the dependence of $J_m(q)$ on arm configuration [4].

2.3 Model Identification

To estimate the muscle parameters from the movement data we used a two-step procedure.

Muscle Geometric and 'Static' Parameters. We first focused on the isometric portion of the experiment. For each muscle we estimated the maximum activation, U_{max} as the maximum activation over all force directions and arm configurations. In isometric conditions, the endpoint force, F_h – i.e. the force exerted on the robot handle – reflects the muscle-generated torque:

$$\tau_m = J(q)^T F_h \tag{2}$$

where $J(q)$ is the Jacobian of the forward kinematics transformation $x = x(q)$, where x is hand position. We formulated the estimation procedure as a quadratic optimization problem:

$$\begin{cases} \min_p \sum_{i=1}^{7} \sum_{d=1}^{12} \sum_{t=1}^{T} \left[\tau_m(t) - J_m(q(t))^T \cdot F_m\right]^2 + \mu \left\|F_{max}\right\|^2 \\ J_m^{ij}(q) \cdot b_{ij} > 0 \quad i = 1 \ldots 2, j = 1 \ldots M \end{cases} \tag{3}$$

The additional constraints reflect the requirement that irrespective of the parameters values, moment arm of a given muscle with respect to a joint cannot change its sign. We set $b_{ij} = 1$ if muscle j is an extensor for joint i, and $b_{ij} = -1$ otherwise. The second part of the cost function penalizes solutions involving muscle co-contraction. The parameter vector p includes moment arm geometry, peak muscle force and all the static of muscle model parameters, i.e. $p = \{F_{max}, \ldots\}$.

Muscle Dynamic Parameters. To estimate the muscle dynamic parameters of the Hill-based Model we focused on the movement data. During movements the hand force measured by the force sensor, $F_h(t)$ reflects not only muscle torque τ_m, but also arm dynamics:

$$I(q)\ddot{q} + C(q, \dot{q}) = \tau_{dyn}(q, \dot{q}, \ddot{q}) = \tau_m - J(q)^T \cdot F_h \tag{4}$$

so that $\tau_m = J(q)^T \dot{F}_h + \tau_{dyn}$. We used a normative model of arm dynamics, whose parameters were determined from individual subjects' mass and arm geometry [7], in conjunction with measured joint rotations, angular velocities and accelerations to calculate the inverse dynamics, τ_{dyn} at each time instant. We then minimized the following cost function:

$$\min_p \sum_{r=1}^{4} \sum_{i=1}^{7} \sum_{t=1}^{T_{ir}} \left[J(q(t))^T \cdot F_h(t) + \tau_{dyn} - J_m(q(t))^T \cdot F_m \right]^2 \tag{5}$$

where $r = 1, \ldots, 4$ are the repetitions and $i = 1, \ldots, 7$ are the movements. The model parameters here describe, for each muscle, the dependence of CE force on shortening or lengthening speed, i.e. $p = \{A_h, B_h^{conc}, B_h^{ecc}\}$.

3 Results and Conclusions

Figure 2 shows, for the different movements, the measured and reconstructed joint torques for a typical subject. In most configurations, the model correctly captures the main features of the muscle biomechanics and control, with a coefficient of determination (R^2) ranging from 0.67 to 0.92 in isometric reconstruction and from 0.15 to 0.63 during movements. After parameter identification, we then simulated a EMG-driven force field which reproduced the equivalent endpoint force generated by one specific muscle (biceps short head). Model-generated forces turned out to be smooth and consistent with the biceps' expected directions of action. Although preliminar, this work is one step forward the implementation of a general myo-processor which is capable of estimating muscle torques in a variety of conditions.

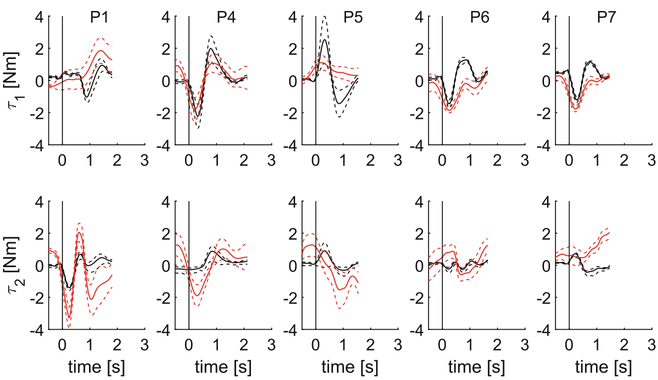

Fig. 2. Reconstruction of muscle torques during movement. Estimated (black) and reconstructed muscle torques (red) - mean ± SE - for a three specific movements, for a typical subject

References

1. Bueno, D.R., Montano, L.: Multijoint upper limb torque estimation from sEMG measurements. In: 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 7233–7236, July 2013
2. Durandau, G., Farina, D., Sartori, M.: Robust real-time musculoskeletal modeling driven by electromyograms. IEEE Trans. Biomed. Eng. **65**(3), 556–564 (2018)
3. Hasson, C.J.: An interactive simulator for imposing virtual musculoskeletal dynamics. IEEE Trans. Biomed. Eng. **65**(3), 539–549 (2018)
4. Lotti, N., Sanguineti, V.: Toward EMG-controlled force field generation for training and rehabilitation: from movement data to muscle geometry. In: 2017 International Conference on Rehabilitation Robotics (ICORR), pp. 90–95. IEEE (2017)
5. Casadio, M., Sanguineti, V., Morasso, P.G., Arrichiello, V.: Braccio di ferro: a new haptic workstation for neuromotor rehabilitation. Technol Health Care **14**(3), 123–142 (2006)
6. Thelen, D.G., Anderson, F.C., Delp, S.L.: Generating dynamic simulations of movement using computed muscle control. J. Biomech. **36**(3), 321–328 (2003)
7. Winter, D.A.: Biomechanics and Motor Control of Human Movement, 4th edn. Wiley, Hoboken (2009)