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Cost function tuning improves muscle force estimation computed by static optimization during walking

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Abstract— **Muscle force estimation while a dynamic motor task is carried out still presents open questions. In particular, concerning locomotion, although the inverse dynamic based static optimization has been widely accepted as a suitable method to obtain reliable results, appropriate modifications of the object function may improve results. This paper was aimed at analyzing the sensitivity of estimated muscle forces when modifications of the objective function are adopted to better fit EMG signals of healthy subjects. A 7 links and 9 degrees of freedom biomechanical model accounting for 14 lower limb muscles, grouped in 9 equivalent actuators, was developed. Muscle forces were estimated by using the inverse dynamic based static optimization in which the performance criteria was the sum of muscle stresses raised to a certain *n* power. This exponent was gradually changed (from 2 to 100) and the agreement between force patterns and EMG signals was estimated by both the correlation coefficient and the Coactivation Index. Results suggested that force estimation can be improved by slightly modifying the cost function. In particular, with respect to adopted data, when the exponent belong to the interval between 2.75 and 4, estimated forces better captured general features of EMG signals. Concluding, a more reliable solution can be obtained by suitably tuning the cost function in order to fit EMG signals.**

I. Introduction

THE estimation of forces exerted by skeletal muscles while subjects carry out a motor task can provide suitable insights to clinicians in order to investigate reasons leading to abnormal patterns [2], to support surgical interventions [3], and to validate the estimation of intra-articular joint force supported by a prosthesis [4].

Currently, two main approaches are adopted: the forward dynamic and inverse dynamic based static optimization (see [5] for review). The former method consists in integrating along the time a system of differential equations describing the dynamic of body segments and accounting for the constitutive non-linear relationships undergoing muscle-tendon actuators reflecting architecture, activation, and contraction. The main advantage of this approach is that it predicts body movements, allowing a quite easy validation of the results. Moreover it considers the muscle contraction and activation dynamic which are difficult to incorporate in the static optimization framework, and takes muscle proprieties, such as the force-length and the force-velocity relationship into account. Nevertheless, its application is limited by the unknown initial state of the system, a relevant computational cost, and the complex model describing the system. The latter method consists in solving, frame by frame, the undetermined linear system described by the following equation (Eq. 1):

$$\begin{bmatrix} M_1 \\ M_2 \\ \vdots \\ M_n \end{bmatrix} = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,m} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n,1} & a_{n,2} & \cdots & a_{n,m} \end{bmatrix} \cdot \begin{bmatrix} F_1 \\ F_2 \\ \vdots \\ F_m \end{bmatrix} \quad (1)$$

where M_i is the moment resulting as overall effect of the many redundant actuators crossing the i^{th} joint, and $a^{i,j}$ is the moment arm of the j^{th} muscle crossing the i^{th} joint which related force is F_j. Equation 1 is solved by suitable optimization methods based on performance criteria which usually reflect the minimization of muscle efforts, muscle stress, and intra-articular contact force, or maximizing muscle endurance [6, 7]. The main advantage of this approach is that it is computationally cheaper than the forward dynamic based one and the model can be easily implemented. Conversely, its main disadvantage is the difficulty to identify the quantities which are supposed to be minimized during human movements. This limit becomes more binding when observed movements refer to pathological motor tasks because in this case muscle enrollment can usually reflect both poor motor control and/or compensative strategies.

Human locomotion is one of the motor tasks which has been widely investigated by means of both methodological techniques [5-9]. Although previous authors have shown that during locomotion many criteria are suppose to jointly contribute to drive muscle activity [6], literature agrees on the evidence that healthy human walking at self selected speed is carried out with the lowest energy consumption [10]. In this regard, muscle force estimation based on both inverse dynamic static optimization, constrained by the maximization of muscle endurance, and forward dynamic approach, leaded by the minimization of the metabolic cost, provide results practically equivalent [9].

According to previous findings, maximizing muscle endurance has been widely accepted to predict their related forces during healthy walking at self-selected pace [5, 7]. Noticeable, this criteria was traduced by Crowninshield and Brand [7] as minimizing an objective function consisting of

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TABLE I
MUSCLE PROPERTIES USED INTO THE MODEL

Actuators	Accounted muscle	PCSA [cm^2]	F_{max} [N]
IL	Iliacus, Psoas	49	800
RF	Rectus Femoris	43	780
VS	Vastus Medialis, Vastus Lateralis	131.3	3165
HA	Semimembranosus, Semitendinosus	87.2	2080
BS	Biceps Femoris (L), Biceps Femoris (S)	8.1	400
GA	Gastrocnemious medialis, Gastrocnemious lateralis	64.9	1605
GU	Gluteus maximus, 1st, 2nd, 3rd portions.	59.8	1300
TA	Tibialis anterior	16.9	600
SO	Soleus	186.7	2830

the sum of cubed muscle stresses. However, the authors also observed that when the objective function involves the sum of muscle stresses raised to a power between 2 and 5, an optimum solution is still predicted such that, although the power of 3 appeared to represent the consensus among values reported in literature, it is arguable that another similar value may be more appropriate [7].

A relevant issue concerning the inverse dynamic based static optimization is that muscle force patterns are generally compared to the electromyography (EMG) activity in order to validate results [5]. Nevertheless, it is well known that EMG signals are characterized by a significant inter-subjects variability [1]. Therefore, muscle force estimation based on the criteria proposed by Crowninshield and Brand [7] can be potentially improved, to better fit EMG signals, by a slight modification of the exponent of the cost function previously described. In other words, a suitable exponent of the objective function can be chosen within a range of values which both still guarantees an optimum solution, and better fits EMG activity. This choice will consequently allow to obtain a more reliable estimation of muscle forces.

The aim of this paper was to analyze the sensitivity of estimated muscle forces with respect to perturbations of the cost function suggested by Crowninshield and Brand [7]. In particular, we hypothesized that it is possible to improve the likelihood between force patterns and EMG activity and account for muscle coactivation, by slightly modifying the optimization criteria.

II. MATERIALS AND METHODS

A. Subjects

Five healthy young subjects, three males and two females, were enrolled for the study (age 33±8.1 ys, weight 65±9.3 kg, height 1.72±0.09 m). They did not show any evidences or known history of postural, musculo-skeletal or neurological disease, did not report any kind of pain or fall history, exhibited normal joints range of motion and muscle strength, and did not practice competitive sports. Before starting experimental sessions they provided informed consent. The protocol was designed in accordance with the Local Ethical Committee.

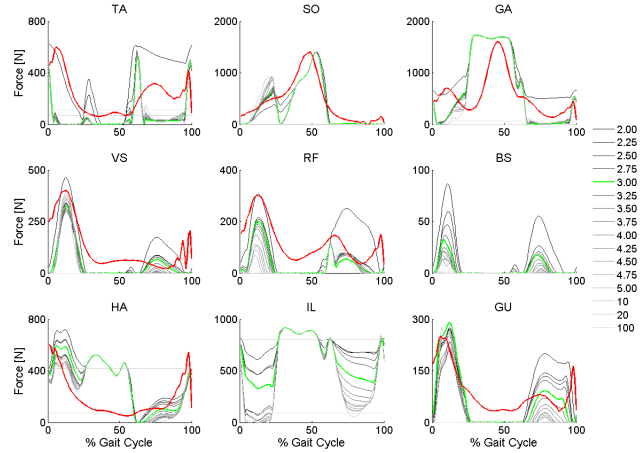

Fig. 1. This figure shows estimated muscle forces for all *n* values (gray scale). Data referring to *n=3* are highlighted in green. The EMG signals adopted as reference for the model validation, suitably scaled to provide a readable superimposition and extracted from literature [1] are represented in red.

B. Procedure

Subjects were asked to walk over ground, in a 15 m long room, at self selected speed, while five camera ELITE$_{PLUS}$ System (BTS, Milano, Italy) acquired the trajectory of twenty markers: 16 placed on anatomical landmarks (acromion-clavicular joints, anterior superior iliac spine, prominence of the greater trochanter external surface, lateral epicondyle of the femur, head of the fibula, lateral malleolus, fifth metatarsal head, for both the legs, seventh cervical vertebrae and middle point between the posterior superior iliac spines), and 4 on external bars mounted on both thigh and shank (in the middle point between their distal and proximal bone landmarks). Sampling frequency was 100 Hz. Ground reaction forces were also recorded by means of two force platforms (Kistler Instrumente AG, Winterthur, Switzerland, model 9286) embedded into the walkway. Sampling frequency was 1000 Hz.

C. Musculoskeletal model

A planar biomechanical model accounting for nine degrees of freedom was developed for each subject while walking. The body model accounted for seven links (feet, shanks, thighs and head-arms-trunk) which length and inertial proprieties were estimated in accordance with literature [11]. Hip and ankle joints were modeled as hinges and located respectively in accordance with Bell and colleagues [12] and at the lateral malleolus. The knee joint was modeled as described by [13], assuming 8.2 degrees as backward slope of the tibial plateau.

The model included 14 muscle grouped in 9 actuators (iliopsoas, IL, rectus femoris, RF, vasti, VS, hamstring, HA, biceps femoris short head, BS, gastrocnemious, GA, gluteus, GU, tibialis anterior, TA, soleus, SO) which features (Physiological Cross Sectional Area, PCSA, and Maximum Isometric Force, F_{max}) were extracted from literature [14] and are reported in Table I. Local coordinates of muscle origins and insertions were obtained by digitizing the model

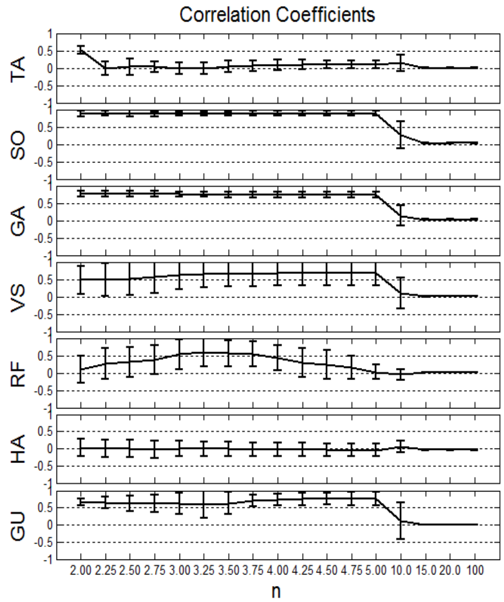

Fig. 2. The figure shows average and standard deviation (error bar) of the correlation coefficient between force patterns and EMG signals for all n values.

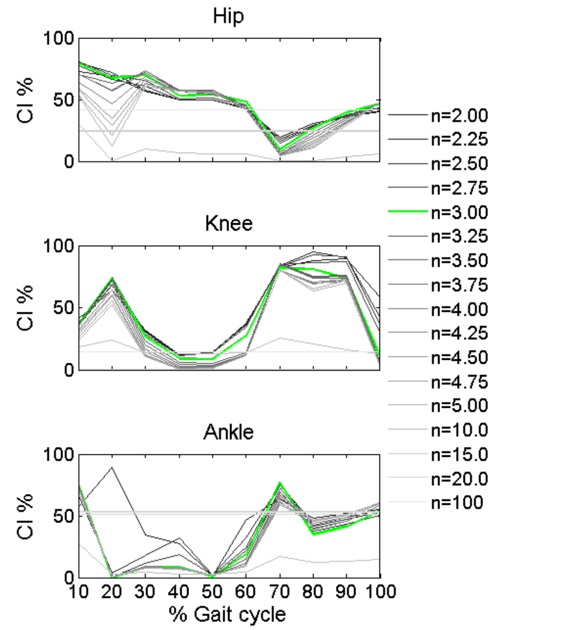

Fig. 3. The figure shows the average across all subjects of the CI for muscle crossing hip, knee and ankle. Data referring to $n=3$ are highlighted in green. Standard deviations are not reported to make reading easier.

developed by Nagano and colleagues [15].

D. Estimation of muscle forces

Angular excursions and joint moment were firstly computed in accordance with [11]. Then, muscle forces were estimated by solving the static optimization problem [5, 7] consisting in minimizing the cost function:

$$\Phi = \sum_{i=1}^{n} \left(\frac{F_i}{PCSA_i} \right)^n \qquad (2)$$

subjected to the constraints:

$$M_j = \sum_{i=1}^{9} d_{i,j} \cdot F_{i,j}; \qquad j = 1,2,3; \qquad (3)$$

$$0 \le F_i \le F_{\max_i}; \qquad i = 1,2,...,9; \qquad (4)$$

where F_i is the force of the i^{th} muscle, M_j is the moment at the j^{th} leg joint, $d_{i,j}$ is the moment arm of the i^{th} muscle crossing the j^{th} joint, and F_{maxi} is the Maximum Isometric Force for the i^{th} equivalent actuator.

As previously reported, $n=3$ has been widely accepted to predict muscle-tendon forces in healthy young subjects. In the present study, the optimization criteria was implemented by using seventeen different values of n: 2, 2.25, 2.50, …, 4.75, 5, 10, 15, 20, 100.

E. Validation of the model

In order to verify the degree of likelihood between estimated muscle forces and muscle activity [5], force patterns were compared to the EMG signals of the correspondent muscles reported by Winter [1], by using the correlation coefficient (ρ). Then, according to Peterson and Martin [16], the Coactivation Index (CI) was estimated at each joint by means of the following equation:

$$CI = 2 \cdot \left(\frac{\int \min\left(EMG_{ag}; EMG_{antag}\right) dt)}{\int EMG_{ag}\, dt + \int EMG_{antag}\, dt} \right) \cdot 100 \qquad (5)$$

where EMG signals for agonist (EMG_{ag}) and antagonist (EMG_{antag}) have been substituted with estimated forces normalized with respect to their related F_{max}. CI was calculated every 10% of gait cycle for each subject. The average CI across all subjects were computed for each n value.

The best solution was identified as that allowing the highest correlation coefficients between force patterns and EMG signals, and the greatest likelihood between coactivation reported in literature [16] and estimated CI.

Biomechanical model, estimation of muscle forces, and validation of the model have been computed by using custom Matlab (The MathWorks, Inc., Natick, MA, USA) scripts.

III. Results

Estimated muscle forces (Fig. 1) were in accordance with literature [7, 9] and were significantly affected by the exponent adopted in the cost function. In particular, when n increased force patterns appeared more variable, with a greater number of peaks, and a lower mean amplitude across the gait cycle.

The degree of likelihood between force patterns and EMG signals slightly changed among muscles and across n values (Fig. 2). However, it generally was higher (ρ>0.5) for the greater amount muscles when n belonged to the interval between 2.75 and 4, and fell down for n greater than 10.

According to the results (Figs. 1 and 2), force patterns related to SO, GA, VS, RF and GU where those more similar to EMG signals, whereas forces referring to TA and HS muscles appeared more dissimilar than their related desired references.

The CI (Fig. 3) referring to thigh muscles was higher during all the stance phase, especially during the loading response, compared to the swing phase. Instead for the knee and ankle joints, it was higher mainly during the swing phase (Fig. 3), with the exception of the knee during the early stance phase.

The CI related to all joints decreases when n increases, till $n = 10$. When n was greater than 10, since estimated muscle force amplitudes were very low than the expected ones, the CI remained almost constant during the whole gait cycle. Again, for n closed to a limited interval across 3.75, the CI was more similar to data reported in literature [16].

IV. Discussion

Muscle force estimation based on the inverse dynamic static optimization allows to obtain a suitable estimation of forces related to leg muscle of young subjects while walking [5, 9]. Moreover, since it involves small computational cost, it allows researchers to carry out the analysis of the sensitivity of the results in order to evaluate their robustness.

Usually inertial parameters and/or muscle-tendon ones are the subject of the analysis of the sensitivity of the estimated force. Nevertheless, Crowninshield and Brand [7] argued that also the cost function described by the equation 2, and in particular its exponent n, should be checked because a values different than 3 may be more appropriate with respect to the specific features of the observed subject [7].

The present paper shows a possible approach to improve muscle estimation based on the degree of likelihood between force patterns and EMG signals. In particular, our hypothesis was that slight modifications of the exponent of the cost function can increase the similarity between desired and estimated variables. From the best of our knowledge, this work is the first which investigates optimized solutions of the inverse dynamic problem, analyzing the likelihood between estimated forces and desired EMG signals. In particular, Crowninshield and Brand [7] highlighted that, although n=3 reflects a physiologically based criterion for force prediction in locomotion, the criteria is still respected with greater values of the exponent n. With the present study, we integrated previous results [7], showing that increasing excessively n, estimated forces can lack of a suitable likelihood with EMG signals.

According to presented results, when n was lower than 3, estimated muscle forces generally appeared characterized by lower variability (Fig. 1) and involved greater coactivation (Fig. 3). Conversely, when n was greater than 3 estimated muscle coactivation decreased. Moreover, the likelihood between force patterns and muscle activity assumed higher values when n was slightly greater than 3 (Fig. 2) but disappeared when n was strongly different than 3. These findings highlighted that, from one hand values more appropriate of the exponent of the object function should be carefully checked because it can improve force estimation. From the other hand, the best value belongs to an interval, around 3, which still guarantees an optimized solution.

We would like also to remark that the best solution individuated by our analysis is mainly related to published EMG signals which can be considered a standard data set [1]. However a more suitable solution would have been obtained if the experimental protocol would have accounted for recording of EMG signals of enrolled subjects.

V. Conclusion

A tuning of the cost function used in the inverse dynamic based static optimization improves estimated muscle forces. In particular we found that an optimum solution is still predicted when the power of the cost function ranges from 2.75 to 4. Therefore, to adopt the n exponent in this interval could be useful to customize the biomechanical model in order to represent different classes of subjects characterized by specific muscle activity or coactivation.

References

[1] D. A. Winter, *The biomechanics and motor control of human gait : normal, elderly and pathological*, 2nd ed. Waterloo, Ont.: University of Waterloo Press, 1991.

[2] J. S. Higginson, F. E. Zajac, R. R. Neptune, S. A. Kautz, and S. L. Delp, "Muscle contributions to support during gait in an individual with post-stroke hemiparesis," *J Biomech,* vol. 39, pp. 1769-77, 2006.

[3] S. L. Delp, J. P. Loan, M. G. Hoy, F. E. Zajac, E. L. Topp, and J. M. Rosen, "An interactive graphics-based model of the lower extremity to study orthopaedic surgical procedures," *IEEE Trans Biomed Eng,* vol. 37, pp. 757-67, Aug 1990.

[4] H. J. Kim, J. W. Fernandez, M. Akbarshahi, J. P. Walter, B. J. Fregly, and M. G. Pandy, "Evaluation of predicted knee-joint muscle forces during gait using an instrumented knee implant," *J Orthop Res,* vol. 27, pp. 1326-31, Oct 2009.

[5] A. Erdemir, S. McLean, W. Herzog, and A. J. van den Bogert, "Model-based estimation of muscle forces exerted during movements," *Clin Biomech,* vol. 22, pp. 131-54, Feb 2007.

[6] J. J. Collins, "The redundant nature of locomotor optimization laws," *J Biomech,* vol. 28, pp. 251-67, Mar 1995.

[7] R. D. Crowninshield and R. A. Brand, "A physiologically based criterion of muscle force prediction in locomotion," *J Biomech,* vol. 14, pp. 793-801, 1981.

[8] F. C. Anderson and M. G. Pandy, "Dynamic optimization of human walking," *J Biomech Eng,* vol. 123, pp. 381-90, Oct 2001.

[9] F. C. Anderson and M. G. Pandy, "Static and dynamic optimization solutions for gait are practically equivalent," *J Biomech,* vol. 34, pp. 153-61, Feb 2001.

[10] P. E. Martin, D. E. Rothstein, and D. D. Larish, "Effects of age and physical activity status on the speed-aerobic demand relationship of walking," *J Appl Physiol,* vol. 73, pp. 200-6, Jul 1992.

[11] D. A. Winter, *Biomechanics and Motor Control of Human Movement*. New York: Wiley, 1990.

[12] A. L. Bell, D. R. Pedersen, and R. A. Brand, "A comparison of the accuracy of several hip center location prediction methods," *J Biomech,* vol. 23, pp. 617-21, 1990.

[13] G. T. Yamaguchi and F. E. Zajac, "A planar model of the knee joint to characterize the knee extensor mechanism," *J Biomech,* vol. 22, pp. 1-10, 1989.

[14] S. Delp, "Surgery simulation: a computer graphic system to analyze and design musculoskeletal reconstructions of the lower limb," Stanfor University, 1990.

[15] A. Nagano, T. Komura, S. Yoshioka, and S. Fukashiro, "Contribution of non-extensor muscles of the leg to maximal-effort countermovement jumping," *Biomed Eng Online,* vol. 4, p. 52, 2005.

[16] D. S. Peterson and P. E. Martin, "Effects of age and walking speed on coactivation and cost of walking in healthy adults," *Gait Posture,* vol. 31, pp. 355-9, 2010.