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Input error analysis of an EMG-driven muscle model of the plantar flexors

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EMG is a useful tool for quantifying muscle forces and studying motor control strategies. However, the relationship between EMG and muscle force is not trivial, and depends in part on muscle dynamics. This work has the following objectives: the first, to find muscle excitations and partial joint torque contribution patterns in isometric plantar flexions, considering low and medium/high contractions. The second, to correlate such patterns with an EMG-driven muscle model error, indirectly assessed by the associate joint torques. Individual muscle contributions were calculated using the model driven by the measured EMG and compared to the total joint torque from dynamometric measurements. Thirteen young males performed a protocol with low and medium/high intensities contractions. Input functions were the normalized EMG of each *triceps surae* and *tibialis anterior* muscles. RMS error was calculated between the measured and estimated torque curves. The trends observed were: the order of individual muscle contributions to the total torque (SOL, GM, GL) was different from the order of the contraction intensities (GM, SOL, GL); the model was more accurate for medium/high contractions; the worst estimations occurred when excitation input signals found from EMG were underestimated. Possible causes for such errors and improvement suggestions are addressed.

Key words: *ankle joint, Hill-type muscle model, muscle synergies, triceps surae, EMG-driven models*

1. Introduction

Electromyography is a classical technique to study motor control strategies [1], [2]. Such signals can be measured non-invasively and provide highly valuable functional information about the muscle dynamic state, especially when they are associated with other experimental approaches, such as kinematics and dynamic measurements [3], [4]. If normalized EMG amplitudes are analyzed comparatively among muscles, they can provide a raw estimation of muscle force, and many inferences in the motor control field are usually performed based on such information [5].

Static and dynamic force-generating capabilities vary substantially among muscles and individuals. Thus, force estimations based on a direct relationship with EMG may mislead the interpretations about the actual role of the muscle, regarding its effective contribution to generating joint torque [7]. According to the same authors, EMG to force, torque or movement comprises four stages: activation dynamics, contraction dynamics, musculoskeletal geometry and multibody dynamics.

EMG-driven models can be used to improve muscle force predictability. Processed EMG is associated with the neural input $u(t)$ of the model and musculotendon force with output. By knowing muscle moment arms, joint torques can be estimated, more specifically, the individual contribution of each muscle to the total joint torque. Since the seminal works of HOF et al. [8], EMG-driven models have been used by several authors [7], [10] to solve a broad class of biomechanical problems. Some authors formulate the forward

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dynamics problem with EMG as inputs for upper limb [11] and lower limb [12]. Others use EMG associated with inverse dynamics as [9] and also with optimization [13], [14], as well as forward dynamics and optimization such as [15].

A formulation of muscle contraction dynamics has been proposed by MENEGALDO and OLIVEIRA [16] based on the classical nondimensional musculotendon actuator of ZAJAC [17]. We have added, following SCHUTTE et al. [18], parallel elastic and damping elements to the contractile part. Such a model resulted, for a specific testing protocol and using scale factors for some model parameters, in approximately 11% Root Mean Square Error (RMSE) for the prediction of submaximal plantar flexion isometric torques. However, torque estimation errors varied as much as 30% among the experimental subjects. Studying the sources of such errors is imperative to extend model accuracy and applicability.

Our analysis was performed over the *triceps surae* muscle group, which has several suitable characteristics: it is responsible for more than 90% of the plantar flexor torque, all the three components are easily assessable by surface EMG and have a high functional importance for daily activities and sport practice. Such muscle group has been extensively studied in the biomechanics modelling literature (e.g., [9], [15], [19]–[22]).

The objective of this work was to confront the observed model errors with the input EMG signals and suggest some directions to improve plantar flexion isometric torque prediction using the model.

2. Materials and methods

A group of 13 adult young male subjects (age: 18.6 ± 0.7 years, mass: 65.6 ± 6.0 kg and height: 173.9 ± 7.8 cm) was selected to participate in the study. The volunteers from the military personnel of the Physical Education School of the Brazilian Army, Rio de Janeiro, were engaged in a regular regimen of physical activity. All participants provided their written consent and did not report any history of osteomyoarticular injury to the right knee or ankle. The experiment was approved by the Federal University of Rio de Janeiro Ethical Committee (Proc. No. 031/07 HUCFF).

The subjects laid prone on a Norm/Cybex™ Dynamometer, with the knee extended and the ankle at neutral (90°) position (figure 1). Each volunteer was instructed to follow a protocol consisting of two 10-second sustained contraction steps of submaximal loads. Steps amplitude corresponded to 20 and 60% of the Maximum Voluntary Contraction (MVC) torque each, separated by a 10-second relaxing interval (see figure 2). A feedback display of the actual dynamometer torque on-line output was provided to the subject, who attempted to match it with a mask of the step protocol plotted on the computer screen. Such a mask was personalized for each subject, as a function of his measured MVC torque. The right foot was firmly fixed to the dynamometer foot adaptor. The experiments were preceded by a familiarization session, which consisted of submaximal plantar flexion contractions followed by one maximal effort and step protocol trials. Plantar flexion torque associated with a maximal voluntary contraction (MVC) was collected twice with two-minute rest between the trials. The highest value was selected as the maximum subject torque.

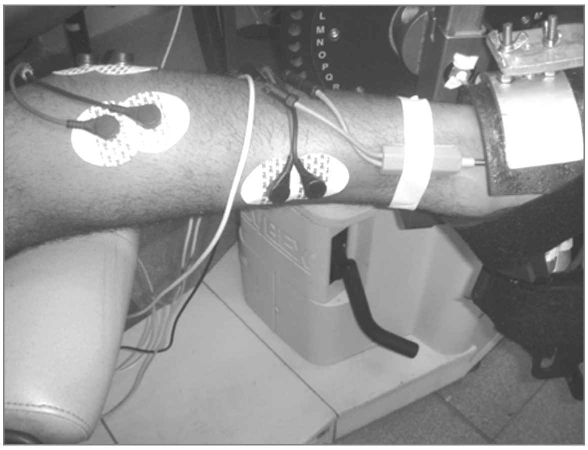

Fig. 1. EMG electrodes positioning and foot fixation on Cybex™ foot adaptor

Torque signal and surface EMG were synchronously collected (figure 1) using a electromyography (EMGSystem™, model EMG 800C, Brazil), with CMRR = 106 dB and analogical band-pass filter of 10–500 Hz, 2 kHz sampling rate, 16 bits A/D converter. Ag–AgCl pre-gelled electrodes were positioned on *gastrocnemius medialis* (GM), *gastrocnemius lateralis* (GL), *soleus* (SOL) and *tibialis anterior* (TA) muscles, according to SENIAM recommendations, after skin preparation [23]. Reference electrode was positioned on the left lateral malleolus. Raw EMG signal was initially band-pass filtered (15–350 Hz) to remove artifacts [2] and then rectified and low-pass filtered with a 2nd order Butterworth filter (2 Hz cut-off frequency). Input excitation signal $u(t)$ for the muscle model was found by normalizing the processed test protocol EMG by MVC EMG.

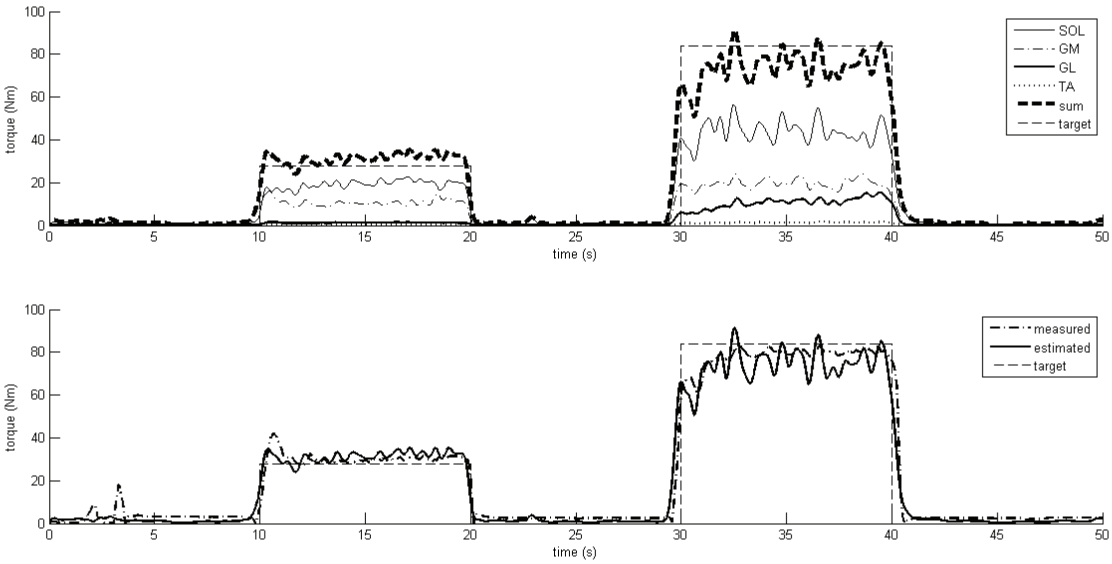

Fig. 2. Torque contribution curves from each muscle and total torque (sum), showing also the test protocol (target), for one example subject (above). Total torque generated by the model and measured by dynamometer (below). The thin dotted vertical lines represent the time limits (before and after the 20% and 60% MVC steps) used to calculate the RMSE. Individual muscle torque contributions: *soleus* (SOL), *gastrocnemius medialis* (GM), *gastrocnemius lateralis* (GL), *tibialis anterior* (TA)

The muscle model described in [16] was integrated using Matlab™ Ordinary Differential Equations "ode45" solver, with $u(t)$ as the input. The estimated torque output was found by the sum of each simulated muscle force multiplied by its respective ankle angle moment arm, using the polynomial equations from [24]. TA moment arm was considered negative, since it is a dorsiflexor. Muscle model parameters were taken from the "Both Legs with Muscles" model of OpenSim [25].

Differences between simulated torque and Cybex™ dynamometer measured torque was calculated as the normalized Root Mean Square Error (RMSE) between the two curves:

$$RMSE\,(\%) = \frac{1}{TM_{\max}} \sqrt{\frac{\sum_{i=1}^{N} \left(TM(i) - TS(i)\right)^2}{N}} \times 100\%\,, \tag{1}$$

where:

TM – the Cybex™ measured torque,

TS – the simulated torque,

N – the number of samples in the time series,

$TM_{\max}$ – the maximum dynamometer measured torque at MVC for each subject.

Each part of the experimental protocol comprising low (20% MVC) and medium/high (60% MVC) intensities was considered separately.

The group was then divided into two subgroups of poor- and good-torque estimation (PE and GE, respectively), and the Mann–Whitney U test was applied to assess significant changes of the individually estimated torque and excitation function of muscle. Linear regression and the Pearson coefficient correlation were applied to test the relationship between muscle excitation and model prediction error. Significant difference between means was set as a p value of 0.05 (Statistica 7.0 – StatSoft, Inc.).

3. Results

Torque curves estimated from the EMG-driven model and those measured by the dynamometer are shown in figure 2 for one example subject. Considering the total group, the $\%RMSE$ was significantly higher for the low intensity level compared to the medium/high one, showing a high coefficient of variation among the subjects (low: 23 ± 10.84%; medium/high: 18.15 ± 11.11%, $p = 0.046$).

In order to identify possible sources of model errors, the entire set of results were further divided into two groups, considering an error threshold of 20%, which is approximately the mean error value for both low and medium/high steps. Subjects were sorted according to their corresponding error values. The table presents the mean values (standard deviation) of each muscle contribution to the total joint torque. The individual muscle contributions to total torque presented similar patterns ($p > 0.05$ for all muscles and torques) in both PE and GE groups for the 20 and

Table. Mean ± standard deviation of the relative individual torque contribution to the total joint torque estimation, for low (20% MVC) and medium/high (60% MVC) contraction intensities. T_{max}: Maximum torque in the MVC test. GE: good estimations, PE: poor estimations

	%RMSE	SOL	GM	GL	TA	T_{max} (Nm)
Low GE ($N = 6$)	14.16 ± 3.99	55.48 ± 10.78	37.74 ± 6.96	8.96 ± 5.22	2.18 ± 1.17	107.83 ± 17.51
Low PE ($N = 7$)	30.61 ± 8.71	60.47 ± 14.06	33.45 ± 12.82	8.36 ± 3.12	2.28 ± 0.83	116.43 ± 14.60
Med/Hig GE ($N = 9$)	11.33 ± 1.98	58.29 ± 5.50	30.75 ± 4.24	13.59 ± 2.04	2.63 ± 0.91	107.44 ± 15.18
Med/Hig PE ($N = 4$)	33.50 ± 5.35	54.57 ± 10.40	35.02 ± 8.46	13.70 ± 3.33	3.29 ± 1.84	123.75 ± 12.53

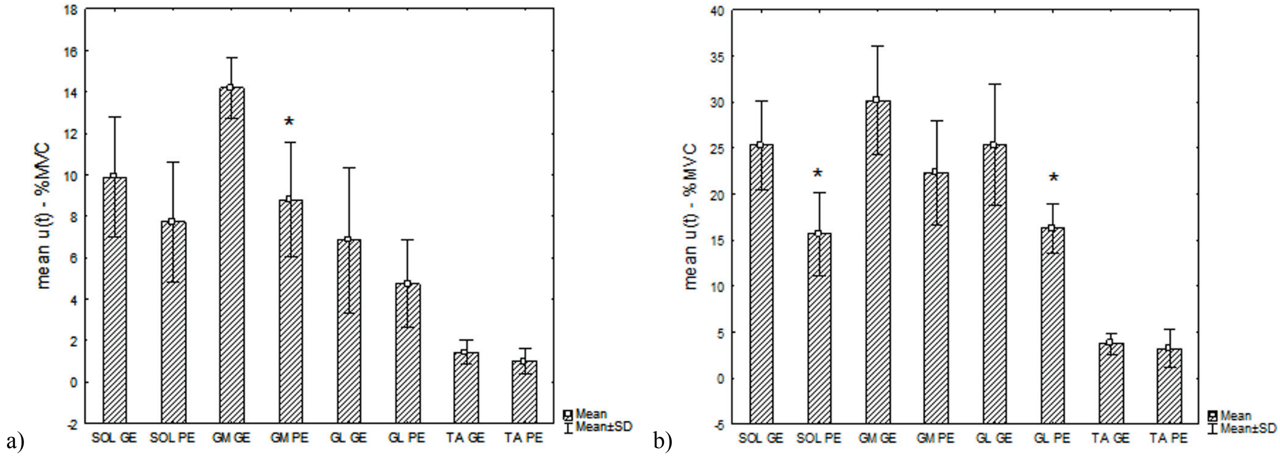

Fig. 3. Mean excitation $u(t)$. GE: Good Estimation; PE: Poor Estimation.
*$p < 0.05$ between GE and PE. *Soleus* (SOL), *gastrocnemius medialis* (GM) and *gastrocnemius lateralis* (GL).
For: a) 20% MVC contraction, b) 60% MVC contraction

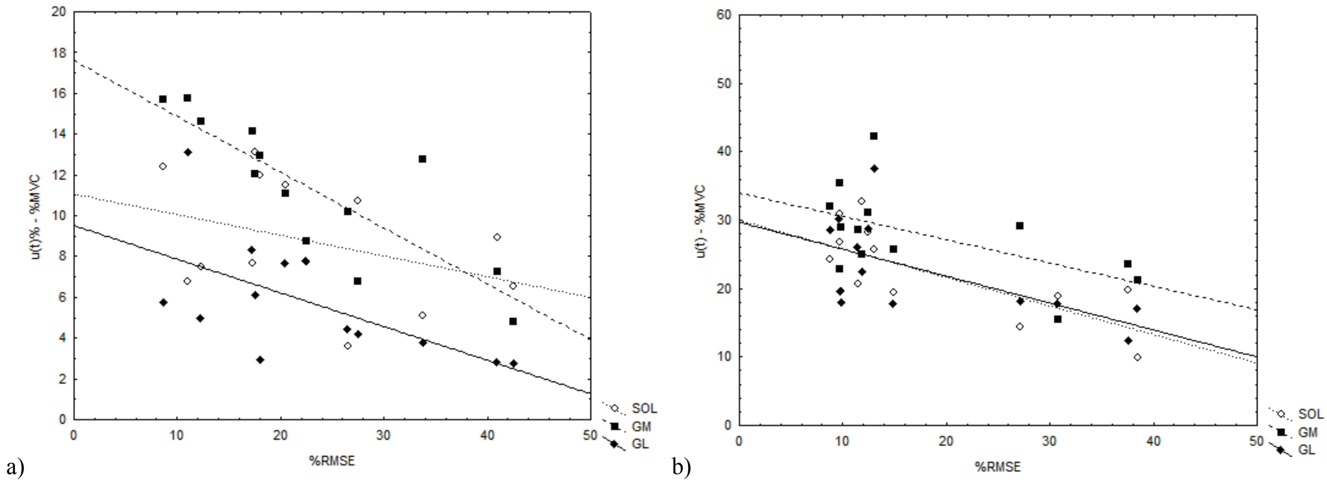

Fig. 4. Scatterplot and linear regression of the excitation $u(t)$ and %RMSE for:
a) 20% MVC contraction: *soleus* (SOL): $r = -0.37$, $p = 0.22$, *gastrocnemius medialis* (GM): $r = -0.84$, $p = 0.0003$, and *gastrocnemius lateralis* (GL): $r = -0.61$, $p = 0.0262$,
b) 60% MVC contraction: *soleus* (SOL): $r = -0.71$, $p = 0{,}0060$, *gastrocnemius medialis* (GM): $r = -0.56$, $- = 0.0464$, and *gastrocnemius lateralis* (GL): $r = -0.62$, $p = 0.0235$

60% MVC steps. The sharing contributions among the muscles, from the highest to the lowest, followed the order: SOL, GM, GL.

In figure 3, the mean values for the input excitation signal $u(t)$ are shown as a percentile of subject specific MVC for the PE and GE groups. The excitation levels present the differences between PE and GE groups for all muscles (significant for GM at 20% MVC step and for SOL and GL at 60% MVC step). In figure 4, the linear regression of the excitation $u(t)$ vs. %RMSE shows a significant inverse correlation for all the muscles in the 60% MVC case. In the 20% MVC step, GM and GL show the same trend.

4. Discussion

The results revealed a greater contribution of SOL muscle followed by the GM to the total torque, for both effort intensities. GL contributed less, although a significant increase from low to medium/high intensity level could be observed. The model estimated a small torque contribution of TA, showing that only a small amount of co-contraction was present in this task, in agreement with HOF [27]

The contributions from each muscle to total torque presented similar patterns in both PE and GE groups for the 20 and 60 %MVC steps. Muscle force share in the total torque always followed the sequence SOL, GM, GL and thus no relationship was found between torque sharing patterns and modelling errors. However, higher excitations were found in the GE group. It is important to emphasize that the relative error for the PE group, independently of the contraction intensity, was found in underestimation. Based on the correlation coefficients (figure 4), low excitation can be correlated with model accuracy reduction, suggesting that possibly an underestimation of $u(t)$ from the EMG and/or an overestimate of MVC may have occurred.

Inherent limitations of the superficial EMG technique have to be considered. EMG acquisition was based on bipolar configuration whose methodological problems have been extensively addressed in the literature. EMG signals constitute a summation of the motor units action potentials, occurring within the detection area of the electrode. Each motor unit action potential is biphasic or triphasic, and not strongly synchronized. Thus, constructive and destructive superimpositions occur, leading to a "natural" large variance of the EMG's linear envelope [1] that does not strictly represent fluctuations in muscle activation. Electrodes positioning with relation to the innervate zone can affect drastically the signal amplitude, as well as the conductor volume, which depends on the distance between the signal origin and the detection system, and varies among the anthropometric characteristics of each subject [1], [5].

Triceps surae shows a pinnate fiber arrangement, which can possibly hinder the interpretation of surface EMG signals recorded from these muscles. Thus, the one-channel bipolar surface EMG may not represent actual excitation $u(t)$ for the muscle as a whole, as hypothesized by the model. It assumes a single input for each muscle, when excitation actually has a spatial distribution over the muscle surface [22], [28], [29]. Multiple, spatially distributed EMG channels collect independent information from separate sources and map myoelectric activity over a wide superficial area. Such a method would thus increase the reliability of the muscle excitation measurements. STAUDENMANN et al. [5] report up to 30% improvement of force estimation for the *triceps brachii* during three different contractions levels, without using muscle mechanical models. Our group has shown in a previous study, by using a similar plantar flexion protocol, that High Density (HD) EMG reduced the torque estimation error by approximately 16% for the medium/high effort [30]. On the other hand, reliable detection of surface EMG from several electrodes, closely separated from each other, represents a difficult technical problem. Complexity of the analysis increases considerably, since the recording signal has two spatial and one temporal dimension [31].

The reliability of the maximal voluntary isometric (MVC) test can be another source of model prediction errors. The difficulty in fixing the foot for reliable plantar flexion maximal torque acquisition is reported by many authors. Joint angular displacement can reach, in extremes cases, 20° of plantar flexion [32]. If the joint extends, the muscles from *triceps surae* shorten [32], [33] and the force at maximum excitation deviates further from the optimal length, which occurs about 20° of dorsiflexion, in static conditions (simulated with Opensim). MAGNUSSON et al. [34] suggested considering ankle rotation for correcting the Achilles tendon displacement during MVC tests to avoid overestimated strain values. Weaker than MVC torques are produced when the step test protocol is applied (20 and 60% MVC). If the heel keeps contact with the dynamometer foot apparatus, this comparatively advantageous situation will demand less neural effort. Thus, the modelled relationship between normalized $u(t)$ and force fails due to an unreliable normalization. With this potential problem in mind, we firmly fixed the subject's foot to the dynamometer foot adaptor. A custom-made rear heel u-shape apparatus was used to constrain the undesirable plantar flexion during MVC (figure 1). Heel linear displacement was assessed during MVC by a simple apparatus consisting of a pointer tightly fastened to the foot rear and a ruler that remained fixed, filmed by a video camera. The mean (standard deviation) displacement value of 1.92 ± 0.85 cm was recorded. It is possible that for some subjects, the foot positioning precaution resulted not completely worthy.

The two-step protocol allows evaluating the behaviour of the model in the rise, fall and sustentation of the force level, as well as the existence of unexpected delays, which should be more difficult to verify in the case of ramp tests [22]. The fact of using isometric contractions reduces the trend to produce artifacts in the EMG signal, keeps the task more uniform among the subjects and does not present problems regarding the integration of multibody differential equations, where small errors in moment estimation become serious when joint positions are found by integration [7].

In this paper, no optimization was used, since one of the objectives of study was to address the error characteristics. We believe that more reliable models allow reducing the number of variable parameters and narrowing the constraints of the optimization problem, keeping it more physiologically meaningful.

Any biomechanical model has numerous sources of errors in special non-modelled physiological or mechanical phenomena and the lack of model parameters reliability. However, it can be suggested that some experimental errors can aggravate such model limitations, namely: using processed single channel surface EMG to estimate model excitation and unreliable normalization from MVC EMG. Some directions to improve model predictability can be pointed out, such as:

a) Use multi-channel EMG.

b) Test other formulations of linear or non-linear activation dynamics, or use more sophisticated muscle models suitable to simulate low intensity contractions, such as WINTERS model [35].

c) Obtaining more reliable and subject-specific model parameters [36].

In this paper, the isometric plantar flexor torques generated by normal young male subjects and measured by a dynamometer were compared with the resultant torque estimated using an EMG-driven Hill-type muscle model. Model predictability was better for medium/high (60% MVC) when compared to low contractions (20% MVC) and the order of the partial contributions to the total torque was, from highest to lowest, as follows: SOL, GM and GL. Such an order was not followed when analyzing muscle excitations. Input errors related to processing surface EMG in the estimation of model excitation and unreliable normalization from MVC EMG can be pointed as possible causes for the observed error levels.

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References

[1] FARINA D., MERLETTI R., ENOKA R., *The extraction of neural strategies from the surface EMG*, Journal of Applied Physiology, 2004, 96, 1486–1495.

[2] MERLETTI R., PARKER P., *Electromyography: Physiology, Engineering and Noninvasive Applications*, Wiley, IEEE Engineering in Medical and Biology Society, 2004.

[3] ISHIKAWA I., NIEMELII E., KOMI, *Interaction between fascicle and tendinous tissues in short-contact stretch-shortening cycle exercise with varying eccentric intensities*, Journal of Applied Physiology, 2005, 99, 217–223.

[4] WAKELING J.M., *The recruitment of different compartments within a muscle depends on the mechanics of the movement*, Biology Letters, 2009, 5, 30–34.

[5] STAUDENMANN D., KINGMA I., STEGEMAN D.F., van DIEEN J.H., *Towards optimal multi-channel EMG electrode configurations in muscle force estimation: a high-density EMG study*, Journal of Electromyography and Kinesiology, 2005, 15, 1–11.

[6] TROIANO A., NADDEO F., SOSSO E., CAMAROTA G., MERLETTI R., MESIN L., *EMG signal and perceived exertion scale*, Gait and Posture, 2008, 28, 179–186.

[7] BUCHANAN T., LLOYD D.G., MANAL K., BESIER T.F., *Neuromusculoskeletal modelling: Estimation of muscle forces and joint moments and movements of neural command*, Journal of Applied Physiology, 2004, 20, 367–395.

[8] HOF A.L., PRONK C.N.A., van BEST J.A., *Comparison between EMG to force processing and kinetic analysis for the calf muscle moment in walking and stepping*, Journal of Biomechanics, 1987, 20, 167–178.

[9] HOF A.L., van den BERG J., *EMG to force processing II: Estimation of parameters of the Hill muscle model for the human triceps surae by means of a calfergometer*, Journal of Biomechanics, 1981, 14, 759–761.

[10] ERDEMIR A., MCLEAN S., HERZOG W., van den BOGERT A.J., *Model-based estimation of muscle forces exerted during movements*, Clinical Biomechanics, 2007, 22, 131–154.

[11] KOO T.K., MAK A.F., *Feasibility of using EMG driven neuromusculoskeletal model for prediction of dynamic movement of the elbow*, Journal of Electromyography and Kinesiology, 2005, 15, 12–26.

[12] PIAZZA S.J., DELP S.L., *The influence of muscles on knee flexion during the swing phase of gait*. Journal of Biomechanics, 1996, 29, 723–733.

[13] LANGENDERFER J., LASCALZA S., MELL A., CARPENTER J.E., KUHN J.E., HUGHES R.E., *An EMG-driven model of the upper extremity and estimation of long head biceps force*, Computational Biology and Medicine, 2005, 35, 25–39.

[14] LLOYD D.G., BESIER T.F., *An EMG-driven musculoskeletal model to estimate muscle forces and knee joint moments in vivo*, Journal of Biomechanics, 2003, 36, 765–776.

[15] BARRET R.S., BESIER T.F., LLOYD D.G., *Individual muscle contributions to the swing phase of gait: An EMG-based forward dynamics modelling approach*, Simulation Modelling Practice and Theory, 2007, 15, 1146–1155.

[16] MENEGALDO L.L., OLIVEIRA L.F., *Effect of muscle model parameter scaling for isometric plantar flexion torque prediction*, Journal of Biomechanics, 2009, 42, 15, 2597–2601.

[17] ZAJAC F.E., *Muscle and tendon: Properties, models, scaling, and application to biomechanics and motor control*, CRC Critical Reviews in Biomedical Engineering, 1989, 17, 359–411.

[18] SCHUTTE L.M., RODGERS M.M., ZAJAC F.E., *Improving the efficacy of electrical simulation-induced leg cycle ergometry: an analysis based on a dynamic musculoskeletal model*, IEEE Transactions on Rehabilitation Engineering, 1993, 1, 109–125.

[19] ARNT A.N., KOMI, BRUGGEMANN G., LUKKARINIEMI J., *Individual muscle contributions to the Achilles tendon force*, Clinical Biomechanics, 1998, 13, 532–541.

[20] DELP S.L., LOAN J.P., ROY M.G., ZAJAC F.E., TOPP E.L., ROSEN J.M., *An interactive graphics-based model of the lower extremity to study orthopedic surgical procedures*, IEEE Transactions on Biomedical Engineering, 1990, 37, 757–767.

[21] LEGRENEUR, MORLON B., van HOECKE J., *Simulation of in situ soleus isometric force output as a function of neural excitation*, Journal of Biomechanics, 1996, 29, 1455–1462.

[22] STAUDENMANN D., KINGMA I., DAFFERTSHOFER A., STEGEMAN D.F., van DIEEN J.H., *Heterogeneity of muscle activation in relation to force direction: A multi-channel surface electromyography study on the triceps surae muscle*, Journal of Electromyography and Kinesiology, 2009, 19, 882–895.

[23] FRERIKS B., HERMENS H.J., DISSELHORST-KLUG C., RAU G., *The recommendations for signal processing methods for surface electromyography* [in:] Hermens H.J., Freriks B., Merletti R., Stegeman D., Blok J., Rau G., Disselhorst-Klug C., Hâag G. Enschede, *European recommendations for surface electromyography – SENIAM Project*, Ed: Roessingh Research and Development, 1999.

[24] MENEGALDO L.L., FLEURY A.T., WEBER H.I., *Moment arms and musculotendon lengths estimation for a three-dimensional lower-limb model*, Journal of Biomechanics, 2004, 37, 1447–1453.

[25] DELP S.L., ANDERSON F.C., ARNOLD A.S., LOAN HABIB A., JOHN C., GUENDELMAN E., THELEN D.G., *OpenSim: Open-source software to create and analyze dynamic simulations of movement*, IEEE Transactions on Biomedical Engineering, 2007, 54, 1940–1950.

[26] WARD S.R., ENG C.M., SMALLWOOD L.H., LIEBER R.L., *Are current measurements of lower extremity muscle architecture accurate*? Clinical Orthopaedics and Related Research, 2009, 467, 1074–1082.

[27] HOF A.L., *The relationship between electromyogram and muscle force*, Sportverletzun Sportschaden, 1997, 11, 79–86.

[28] KINUGASA R., KAWAKAMI Y., FUKUNAGA T., *Muscle activation and its distribution within human triceps surae muscles*, Journal of Applied Physiology, 2005, 99, 1149–1156.

[29] VIEIRA T.M.M., MERLETTI R., *Trade-off and coactivation between gastrocnemii during a quiet standing test: preliminary results*, XVIII Congress of the International Society of Electrophysiology and Kinesiology, Niagara Falls, Proceedings ISEK, 2008.

[30] OLIVEIRA L.F., VIEIRA T.M., MENEGALDO L.L., MERLETTI R.M., *Can the use of a high density EMG system improve a biomechanical model for predicting ankle plantar flexors force*? XXII Congress of the International Society of Biomechanics, Capetown, South Africa, Proceedings of ISB2009, 2009.

[31] MERLETTI R., HOLOBAR A., FARINA D., *Analysis of motor units with high-density electromyography*, Journal of Electromyography and Kinesiology, 2008, 18, 879–890.

[32] KARAMANIDIS K., STAFILIDIS S., DEMONTE G., MOREY-KLAPSING G., BRUGGEMANN G., ARAMPATZIS A., *Inevitable joint angular rotation affects muscle architecture during isometric contraction*, Journal of Electromyography and Kinesiology, 2005, 15, 608–616.

[33] KAWAKAMI Y., ICHINOSE Y., FUKUNAGA T., *Architectural and functional features of human triceps surae muscles during contraction*, Journal of Applied Physiology, 1998, 85, 398–404.

[34] MAGNUSSON S., AAGAARD , ROSAGER S., DYHRE-POULSEN , KJAER M., *Load–displacement properties of the human triceps surae aponeurosis in vivo*, Journal of Physiology, 2001, 53, 277–288.

[35] WINTERS J.M., *Concepts in neuro-muscular modeling* [in:] Allard, Stokes I.A.F., Blanchi J., *Three-Dimensional Analysis of Human Movement*, Champaign, IL: Human Kinetics, 1995, 257–92.

[36] OLIVEIRA L.F., MENEGALDO L.M., *Individual-specific muscle maximum force estimation using ultrasound for ankle joint torque prediction using an EMG-driven Hill-type model*, Journal of Biomechanics, 2010, 43, 2816–2821.