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Optimization of Input Parameters of an EMG-Force Model in Constant and Sinusoidal Force Contractions

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***Abstract*—In an electromyographic and muscle force (EMG-Force) model, the variability and uncertainty of the input muscle parameters increase the difficulty of assessing this type of model. In this study, a Monte Carlo method is used to evaluate the robustness and the sensitivity of an EMG-Force model, recently developed by our team, for two groups of simulations (constant and sinusoidal force contractions). Two existing criteria (EMG/force and force/force-variability relations) and a new criterion derived from this model (Root Mean Square error, $Error_{RMS}$, between the force command and the generated force) are used to extract relevant simulations and obtain the optimized parameter ranges in constant force contractions, while only the new criterion could be valuable in sinusoidal force contractions. The comparison of obtained results from the two groups of simulations has shown that the new criterion can replace the two existing criteria in constant and sinusoidal force contractions to give rise to stable optimized input parameter ranges for the studied EMG-Force model.**

Key words — EMG-Force model, Monte Carlo methods, Force/force-variability relation, constant and sinusoidal force contractions.

I. Introduction

Electromyography (EMG) and muscle force are considered as two critical tools in the assessment of skeletal muscle contraction because both of them reflect the level of muscle activation. However, as the EMG signal is influenced by many factors [1] and the muscle force cannot be measured directly [2], the EMG-Force models have become a principle method for studying the mechanisms of the relation between EMG and force in recent years. For this method, the selection of the input physiological parameter values is critical and it is important to obtain realistic simulated data that matches well with the experimental relationships. However, the variability and uncertainty of the parameters used in these models have increased the difficulty of assessing them. As the complete validation of these models needs to analyze multivariate interactions, multivariate Monte Carlo simulations have been used to explore the sensitivity of model predictions to uncertainty and variability in some physiological parameters [3]. In this study, two criteria corresponding to two experimental relations (EMG/force and force/force-variability) were chosen to indicate the relevant simulations in order to optimize the input parameter ranges. It is important to note, however, that these two criteria are only applicable in the isometric contraction with constant force.

In our study, we used the same Monte Carlo method to evaluate the robustness and the sensitivity of our recently developed EMG-Force model [4, 5] with two types of contraction force (constant and sinusoidal) by means of two previously noted criteria (EMG/force and force/force-variability relations) and a new criterion derived from our model (Root Mean Square error, $Error_{RMS}$, between the force command and the generated force). The simulated results are discussed following the type of contractions.

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II. Methods

A. EMG-Force Model

There are three principal components in the described model: 1) a recruitment pattern that gives the firing rate of each MU for a contraction force level, 2) the EMG signal simulation, based on the firing rate and the geometrical model of the spatial localization of each MU [4], and 3) the muscle force simulation, according to the firing rate and the generated force of each active MU [5].

1) MU recruitment pattern: An MU recruitment pattern (Fig. 1) provides the number of MUs activated and their firing rates in relation with the muscle force command P(t). P(t) represents the reaction force supplied to external loads [2]. It is defined by a percentage of the maximal voluntary contraction (MVC). We include in our muscle model two MU types, slow motor units (SMUs) and fast motor units (FMUs), with the same number of muscle fibers. Each MU type has its specific minimum and peak firing rates. As motoneurons innervating fast-twitch muscle fibers display shorter after-hyper-polarizations than those innervating slow twitch muscle fibers [6], both minimum and peak firing rates of the FMUs are modeled as higher than the ones of the SMUs. Once an MU is active, its firing rate increases almost linearly from the minimum firing rate (MFR) to the peak firing rate (PFR) with muscle force generation [7]. MUs are progressively recruited in an orderly sequence such that the SMUs are activated before the FMUs [8]. All MUs are recruited at a certain force level (RR), between 30% and 90% of maximal voluntary contraction force (MVC), according to muscle type [9]. The firing rate of all MUs attains their peak value (PFR) at 100% MVC. The recruitment threshold (RT) is the force level needed to recruit a new MU. RT_i of the i_{th} MU is modeled as follows [10]:

$$RT_i = e^{\frac{\ln RR}{N} i} \quad (1)$$

where RR is the recruitment range, i.e. the recruitment threshold of the last activated MU in a muscle (30% - 90% MVC in our test), N is the number of MUs, and i is an index identifying the MU.

2) EMG signal simulation: To simulate the surface EMG, the MUs are uniformly distributed within the muscle cross section. The muscle fibers are also located within each MU with a uniform distribution. In human muscles, the minimum firing rate generally ranges from 7 to 23 Hz, and peak firing rate from 14 to 50 Hz [7, 11]. Since the number of MUs and the number of fibers per MU vary in human muscles [12] and an MU can generally be considered to include 100 fibers [13], to evaluate the behavior of most muscles in our limited computational time simulations, the number of FMU and of SMU in a muscle are independently assigned and varied from 250 to 600, while the number of fibers per MU is assigned from 30 to 100. The Rosenfalck model is used to simulate individual fiber electric activity [14]. Muscle fiber conduction velocity is assigned as a Gaussian distribution with mean value 3 to 4 m/s [15] and standard deviation 0.5 m/s. For a given muscle, fast twitch fiber conduction velocity is greater than slow twitch fiber conduction velocity. The InterPulse Interval (IPI) of the motor unit firing is modeled as a Gaussian probability distribution function with a standard deviation between 10% and 30% of the mean IPI [16] (Table 1).

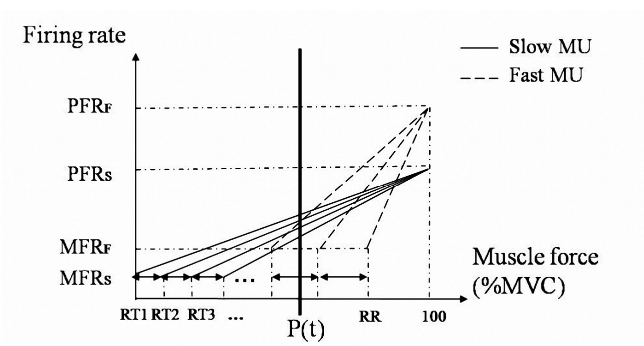

Fig. 1. MU recruitment pattern (PFR_F, MFR_F, PFR_S, MFR_S: peak and minimum firing rates of FMUs and SMUs respectively). In this schematic diagram, 4 SMUs (solid lines) and 1 FMU (dashed lines) are recruited at the muscle force level P(t).

According to the MU recruitment pattern, the action potential train of each MU is obtained for a given muscle contractions. Depending on the thickness of the volume conductor (muscle, fat and skin layers), these signals are filtered by spatial transfer function [17] and added to give a total potential distribution on the skin surface, called output plan [4]. The recorded EMG is finally obtained by filtering the output plan with an electrode transfer function [17].

3) Muscle force simulation: For each MU, we consider that the force generated by a single MU increases linearly with a positive slope α_i relative to its firing rate (FR_i) [5]. It is important to note that this modeling is a simplification of the experimental MU force-Firing rate relationship. Then, we obtain an output muscle force (F_m) which represents the sum of the active MU forces ($F_{MUi}= \alpha_i \cdot FR_i$). All α_i values can be also calculated with every recruitment threshold. When a measured muscle force P(t) is given, the number of active MUs and their firing rate are estimated by Fig. 1. Once all α_i values are known, the generated force by the muscle F_m is calculated.

B. *Monte Carlo Method*

Twelve muscular parameters were explored in our study to analyze their influence on the simulated output of the studied EMG-Force model. All the parameters are shown in Table 1 with their initial ranges. For each Monte Carlo simulation, a set of the parameter values were defined by random sampling from uniform distributions of each of the twelve parameters. Their initial ranges came from the experimental data as described in II.A.2. The simulated outputs (EMG and force signals) were computed at 1000 samples/s. To avoid carrying out many useless simulations and to save the computational cost, we adopted as in [3] a convergence test in our simulation for early simulation stopping.

C. *Simulation Procedure*

Two types of muscle force command were performed with the recent model and both commands began and ended with zero. One type of force was a 2 s command with three phases (0.3 s linear increase, 1.4 s constant and 0.3 s linear decrease). Four constant force levels (20%, 50%, 80% and 100% MVC) were simulated for each set of the parameters sampled from the initial ranges. The second force command was a 2 s sinusoidal command, i.e. the frequency of 0.5 Hz, with the maximum value of 20%, 50%, 80% and 100% MVC (Fig. 2).

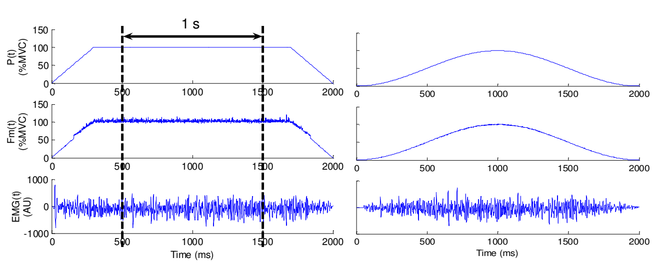

Fig. 2. Two types of force command (Left: constant command; Right: sinusoidal command; Upper: force command P(t); Middle: generated force $F_m(t)$; Bottom: generated EMG(t)).

Group 1 (Constant command): Force and full-wave rectified EMG were averaged over a 1 s window in the middle of the constant command, and SD of the force during this period was considered as the force variability. Convergence was declared when there was a change lower than 2% in the running mean and coefficient of variation of EMG amplitude and force for the last 20% of the simulations [3, 18]. Note that each Monte Carlo simulation required convergence for every one of the four command levels. Two criteria were chosen to indicate a reasonable match between simulated and experimental EMG/force relationship: a slope <1.05 in the regression line between EMG and force; and force/ force-variability relationship: a slope of log-log regression line between SD and mean force between 0.75 and 1.25 [3].

However, as these two criteria are issued from experimental data with constant-force contraction [3], they are only applicable to the constant force command. In order to simulate the isometric contractions with a non-constant force, we define a new criterion. In the studied EMG-force model [5], there are two considered muscle forces (normalized by a ratio of their respective MVC values): the force command (model input, P(t)) and the generated force (model output, $F_m(t)$). It is hypothesized that the generated force follows the force command. Thus, the similar degree (Root Mean Square error, $Error_{RMS}$) between these two forces could be considered as a new criterion. This new criterion is proposed to be used for non-constant force command. For that, the $Error_{RMS}$ value needs to be chosen so that most simulations meeting the new criterion are in the tolerance region determined by the two previous criteria (EMG/force and force/force variability relationships). This criterion is assessed by the success rate (the ratio of the number of the simulations satisfying the three criteria to the number of the simulations satisfying the new criterion).

Group 2 (Sinusoidal command): To evaluate the convergence of Monte Carlo simulations in the condition of sinusoidal force command, an adapted criterion is proposed. Indeed, a fully-rectified EMG signal was smoothed by a 4-order low-pass Butterworth filter with a cutoff frequency of 8 Hz to obtain its envelope [19]. Convergence was declared when there was a change lower than 1% in the running coefficient of multiple correlation (CMC) of the EMG envelope and the force for the last 20% of the simulations at all four command levels. The criterion $Error_{RMS}$ refined with Group 1 data, was used to verify whether the optimized ranges were well stabilized for the sinusoidal command.

III. Results

Simulation Group 1: The first Monte Carlo simulation series (Series 1) converged after 61 simulations. To ensure that most simulations chosen by the new criterion of the $Error_{RMS}$ lie within the tolerance region determined by the two previous criteria in each strategy, this new criterion was defined as the $Error_{RMS}$ values, computed from four command levels, lower than 3%. 18 simulations were selected based on this criterion, and all these 18 simulations met the three criteria (success rate: 18/18=100%) (Fig 2. upper). The second simulation series was then performed with the muscular parameter ranges optimized by these three criteria. Convergence was achieved after 169 simulations. There were 138 simulations chosen by the new criterion $Error_{RMS,}$ and 133 simulations met the three criteria (success rate: 133/138=96.4%) (Fig 2. bottom).

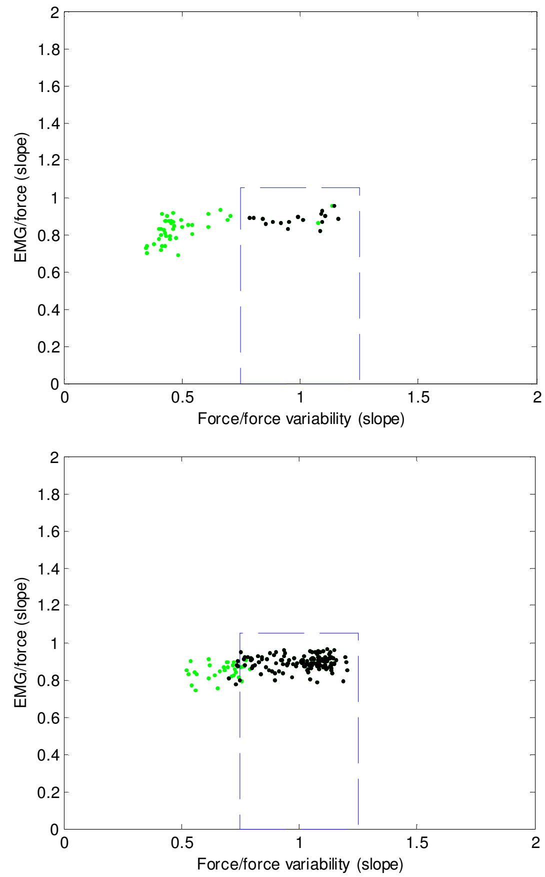

Fig 2. Two experimental criteria (EMG/force and force/force variability represented by a blue frame) in the simulation (Upper: Series 1; Bottom: Series 2; Black point: simulation selected by the criterion of the RMS error).

TABLE 1
INITIAL AND OPTIMIZED INPUT PARAMETER RANGES IN THE EMG-FORCE MODEL

Parameters	Initial	Optimized-Group1	Optimized-Group2
RR (%MVC)	30 – 90	71 – 89	72 – 89
Slow fiber CV(m/s)	3 – 4	3.0 – 3.8	3.0 – 3.8
Fast fiber CV(m/s)	3 – 4	3.0 – 4.0	3.1 – 4.0
SMUs number	250 - 600	250 - 590	250 - 590
FMUs number	250 - 600	250 - 570	250 - 540
Fibers number per MU	30 - 100	34 - 100	36 - 99
VC of IPI	0.1 – 0.3	0.1 – 0.3	0.1 – 0.3
Fiber length (cm)	4 – 16	6 – 16	6 – 15
MFR of SMU (Hz)	7 – 23	7 – 20	7 – 20
MFR of FMU (Hz)	7 – 23	8 – 23	9 – 23
PFR of SMU (Hz)	14 – 50	14 – 41	14 – 41
PFR of FMU (Hz)	14 – 50	27 – 48	27 – 48

RR = recruitment range, CV = conduction velocity, VC = variation coefficient, MFR = minimum firing rate, PFR = peak firing rate.

Simulation Group 2: The muscular parameter ranges optimized by Simulation Group 1 (2 series) were considered as the input ranges for Simulation Group 2. Convergence was achieved after 32 simulations. According to the new criterion, there were 29 selected simulations.

All twelve parameter ranges optimized after Group 1 and Group 2 are shown in Table 1. The optimized conduction velocity in the slow fiber is significantly slower than in the fast fiber after each group of simulations ($p<0.001$). There is no significant difference in all optimized parameters between Group 1 and Group 2 simulations (with p-value=0.05). The optimized ranges were not influenced by the modification of the contraction type, constant or sinusoidal force.

IV. Discussions and Conclusions

We have used a Monte Carlo method depicted in [3] to evaluate the robustness and the sensitivity of a recent EMG-force model [4, 5]. To differ from [3], a sinusoidal force command was evaluated in addition to a constant force command. For this purpose, new simulation convergence and selection criteria were proposed. For the constant force command, the new simulation selection criterion was used in addition to two previously used criteria [4, 18]. The obtained results demonstrate the accuracy of the new criterion in comparison to the existing ones. For the sinusoidal force command, the proposed criterion was able to select relevant input parameter ranges, by using the obtained ranges from simulations of Group 1 as initial values. We observed a good match between the two optimized groups of ranges. This match was confirmed by a statistical test (p-value=0.05). This indicates that the new criterion can be used for optimization of input parameter ranges for both constant and sinusoidal force commands. The new criterion was able to speed the optimization of the input parameters, because the simulations satisfying the new criterion almost met all three criteria in Simulation Group 1 (>95%).

We investigated in our study twelve input muscular parameters, which are known, for human experiments, as being able to influence the EMG and force production. We took into consideration the number and the conduction velocity of each MU type, the FMUs and the SMUs, because the effective parameter ranges of the two MU types often appear different from each other, for example the conduction velocity (Table 1). In particular, their contributions changed for different contraction types: for example, the range of the number of FMUs varied a little from the constant to the sinusoidal force command, while the range of the number of SMUs remained constant (Table 1). Among all twelve input muscular parameters, the MU recruitment ranges, as well as the peak firing rates of the SMUs and the FMUs, highly influenced our simulated results. This means that our model is sensitive to these parameters, which is in agreement with the results simulated by another EMG-force model [3]. However, as they vary according to the subject and to the muscle, it is also difficult to directly measure these parameters *in vivo*. In order to properly validate an EMG-force model by comparing it to the experimental results, it is important, as a first step, to completely optimize these input parameters so that stable ranges can be found for one or several command types. This was the primary goal of the proposed work.

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