A new force profile signal for a convex solution of muscle force estimation from electromyographic signals *

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***Abstract*— High-Density Surface Electromyography (HD-sEMG) is a non-invasive technique for measuring the electrical activity of a muscle with multiple, closely spaced electrodes. Estimation of muscle force is one of the applications of HD-sEMG. Usually, validating different EMG-Force models entails simple movements limited to laboratory settings. The validity of these models in more ecological conditions, requesting force production over a wide frequency band, remains unknown. In this study, we, therefore, compare the results of force prediction using four different types of input force profiles that can be representative of daily life activities, and we investigate whether the crest factor of these different input signals affects force prediction. For predicting the force from sEMG signals, we used our real-time and convex methods. HD-sEMG signals were recorded with 144 channels from the biceps brachii, brachioradialis, and triceps (long, lateral, and medial head) muscles of 24 healthy subjects during random signal, random phase, Schroeder phase, and minimum crest factor (crestmin) signal. The correlation and coefficient of determination (R^2) between measured and predicted forces were calculated for the different force feedback profiles. The crestmin signal showed significantly better results based on statistical tests (P-value < 0.05), with correlation and R^2 equal to 0.92±0.03 and 0.86±0.05, respectively. The results demonstrate that the crest factor of input signals is a crucial parameter that can impact the performance of EMG-Force models and must be considered during training.**

***Clinical Relevance*— This study demonstrates that lower crest factor multisine force profiles result in improved fitness for force prediction and can be used as an alternative to random signals.**

I. Introduction

High-density surface electromyography (HD-sEMG) is a technique used to measure the electrical activity of muscles at a high spatial resolution. It involves using multiple electrodes on the skin surface to capture muscle activity. The high number of electrodes allows for a more detailed and accurate analysis of the muscle activity, providing information about the distribution of muscle activity, muscle coordination, and muscle fatigue [1-4]. This technique is commonly used in clinical settings, research studies, and sports medicine to assess muscle function and evaluate the effectiveness of rehabilitation programs [5]. Additionally, HD-sEMG can be used to develop and evaluate prosthetic devices. It is also used to measure the force produced by the muscle [6], known as the EMG-force problem [7]. This method involves placing electrodes on the skin surface above the muscle of interest and measuring the voltage fluctuations resulting from changes in muscle excitation. The EMG-force relationship can be used to study muscle force production, muscle fatigue, and muscle adaptation in response to different types of training. It can also help control prosthetic devices and optimize movement patterns in sports science and ergonomics research [1, 2, 8].

Data recording for EMG-Force exercises follows specific protocols, usually based on the matching of a triangular input force (e.g., 0-20-0% MVC). The EMG-Force relationship is calculated based on this specific profile. Real-world tasks, however, hardly demand such a fixed force pattern, urging for a more ecological force profile if the EMG-Force relationship of more general validity is to be established. Studies using such types of evaluations are emerging [9]. When designing these types of exercises, it is essential to consider the design of the input force profile in a way that impacts the whole bandwidth of interest. In this regard, the crest factor must be considered when designing the input force profile.

In this article, we investigate the effect of the type of different force profiles on the fitness between the predicted force from HD-sEMG and the measured force exerted by young, healthy subjects. The results were evaluated with the proper statistical test and the importance, limitation, and future works were discussed.

II. Method and Materials

In this section, we describe the dataset and input force profiles, then present our method for predicting force from sEMG, followed by the validation parameters and statistical analysis used to validate results.

*Research supported by Spanish Innovation and Science Ministry from the project with ref PDC2021-120818-I00.

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A. Dataset

The data were recorded from 24 healthy right-handed subjects (10 men, 14 women). The experimental procedures considered in this study conformed with the Declaration of Helsinki and were approved by the Regional Ethics Committee.

Before placing the electrode grids, the skin over the targeted muscles on the right side was cleaned with an abrasive paste. An expert then determined the placement and orientation of the grids on each muscle. Efforts were made to include the innervation zone of the biceps and brachioradialis muscles in the recording area. HD-sEMG signals were recorded with 144 monopolar channels, with the reference strap electrode secured to the ipsilateral wrist. EMG signals from biceps brachii and triceps (long and lateral head) were recorded with a 64-channel electrode array, with 10 mm inter-electrode-distance (IED) (GR10MM0808, OT Bioelettronica, Turin, Italy), a 64-channel electrode array with 8 mm IED (GR08MM1305, OT Bioelettronica, Turin, Italy) respectively. Two arrays of 8 electrodes (5 mm IED; ELSCH008, OT Bioelettronica, Turin, Italy), one per muscle, were used to sample EMGs from the brachioradialis and the medial head of the triceps brachii. The location of the electrode array was selected based on SENIAM recommendations [10]. The sampling rate for force and EMG signals were set to 2048 Hz.

The proper hand position relative to the body was achieved by abducting the shoulder 90 degrees from the anatomic position and aligning the upper arm and forearm at a 90-degree angle. The subject's wrist was secured to the shaft attached to an isokinetic dynamometer (System 4 Pro, Biodex Medical System, Shirley, USA), which measured the force generated by the elbow. Fig 1 shows a picture of one of the subjects during signal recording.

This experiment considered four force profiles: random phase multisine, Schroeder phase multisine, minimal crest factor multisine (referred to as "creatmin"), and random signals. The force profile and the recorded force signal were displayed on a screen, and the subjects were asked to try to follow the profiles using 20% of their maximum voluntary contraction in flexion and extension. A rest period of 2-3 minutes was provided between each trial to avoid cumulative fatigue.

The force signal was filtered with a two-order Butterworth low-pass filter with a cutoff frequency of 20 Hz. Also, the powerline with its harmonics was filtered with a notch filter.

B. Force Profiles

In this study, we designed different multisine signals as input force profiles to equally excite all frequencies in the bandwidth of interest (0-5Hz), with varying crest factors to investigate its effect on EMG-force prediction. The formula used to create the multisine signals is:

$$u(t) = \sum_{k=1}^{F} A\cos(2\pi f_k t + \phi_k) \tag{1}$$

where k is the harmonic number, $A \in R$, ϕ_k is the phase and $f_k = l_k f_0, l_k \in N$, and F is the number of harmonics comprising the signal.

In this study, A was set to 1 to ensure all sine signals had equal energy and f_0 was set to 0.125. The random phase and Schroeder phase multisines were generated based on this formula. For the random phase mulitisine, the phase parameter was selected randomly from a uniform distribution $[0,2\pi]$. Schroeder phase mulitisine was generated by selecting the phase from $\phi_k = -k(k-1)\pi/\mathrm{F}$ [11].

Figure 1. Experimental recording of the signals in our study.

For the random force signal, samples were generated from a band-limited white Gaussian noise. The Crestmin force profile was generated based on approximating the non-differentiable Chebyshev (minimax) norm of a multisine signal [11]. Guillaume et al. [11] minimized the crest factor of a multisine signal by estimating the phase parameters using the Gauss-Newton Algorithm combined with Levenberg-Marquardt. The crest factor of a signal $x(t)$ can be represented as:

$$CF_x = \frac{l_\infty(x)}{l_2(x)} \tag{2}$$

$$l_\infty(x) = \max_{t \in [0,T]} |x(t)| \tag{3}$$

where $max|x(t)|$ is equal to the peak of the signal and $l_2(x)$ is the root mean square (RMS) of the signal.

C. Proposed Algorithm

Previously, we proposed an algorithm for predicting the force related to muscles from HD-sEMG [6]. The proposed convex method can accurately predict the produced force from the surface EMG signals.

The formula for predicting force from surface EMG is:

$$f(t) = w_0 + \sum_{i=1}^{M} \mathrm{w_i} \times \ln\left(\mathrm{sEMG}_i(\mathrm{t})\right) \tag{3}$$

$$t \in R, w \in R, M \in N$$

where $f(t)$ is the force generated by muscles, M is the number of muscles, $sEMG_i(t)$ is the representative envelope of the i muscle, and w_i is the weight of the i^{th} muscle. The sEMG envelope was estimated by low-pass filtering of the full-wave rectified sEMG signals. For each analyzed muscle, the sEMG envelope of one of the channels that were similar to others was considered as muscle sEMG envelope.

It is possible to rewrite this formula in the matrix notation:

$$\begin{bmatrix} f[1] \\ \cdot \\ \vdots \\ \cdot \\ f[N] \end{bmatrix} = \begin{bmatrix} 1 & ln(sEMG_1[1]) & \cdots & ln(sEMG_M[1]) \\ \cdot & \cdot & \cdots & \cdot \\ \vdots & \vdots & \vdots & \vdots \\ \cdot & \cdot & \cdots & \cdot \\ 1 & ln(sEMG_1[N]) & \cdots & ln(sEMG_M[N]) \end{bmatrix} \begin{bmatrix} w_0 \\ w_1 \\ \vdots \\ \cdot \\ w_M \end{bmatrix} \quad (4)$$

The parameters of equation (4) could be estimated using the Least Square (LS) structure [6]. The parameters were estimated on 25% of the data, while 75% was used to test the model's goodness-of-fit with different force profiles.

D. Validation Parameters

We used the Pearson Correlation Coefficient (r) and the coefficient of determination (R^2) to validate the goodness-of-fit between the real force profile and the estimated version. The correlation can be calculated using the following formula:

$$\boldsymbol{r} = \frac{\sum_{i=1}^{N}(y_i-\bar{y})\times(\hat{y}_i-\hat{y}_m)}{\sqrt{\left(\sum_{i=1}^{N}(y_i-\bar{y})^2\right)\times\left(\sum_{i=1}^{N}(\hat{y}_i-\hat{y}_m)^2\right)}} \quad (5)$$

where, $\boldsymbol{y_i}$ is the measured force signal, $\boldsymbol{\hat{y}_i}$ is the estimated force signal, $\boldsymbol{\bar{y}}$ and $\boldsymbol{\hat{y}_m}$ are the average values of the measured and estimated force signals, respectively.

The coefficient of determination ($\boldsymbol{R^2}$) was calculated with the following:

$$\boldsymbol{R^2} = \boldsymbol{1} - \frac{\sum_{i=1}^{N}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{N}(y_i-\bar{y})} \quad (6)$$

E. Statistical Analysis

Continuous variables were reported as mean±std. The generalized Estimating Equation method [12] was used for modeling the effect of different force profiles on the goodness-of-fit of the predicted muscle force signal. The goodness-of-fit of the measured force compared with the force profile was used as a covariate. The Bonferroni correction was applied for pairwise comparison, and the adjusted P-value was then reported (adj. P). To identify the association between the crest factor and the force profile, and the measured and predicted force signals, the pearson's correlation coefficient was used—the level of statistical significance of P = 0.05. The statistical analysis was performed using IBM SPSS Statistics for Windows, version 22 (IBM Corp., Armonk, N.Y., USA).

III. RESULTS

The coefficient of determination (R^2) and correlation between the measured force and the predicted force, the measured force and force profile, and the crest factor of the input force profile are shown in Table 1.

TABLE I. FITNESS CRITERIA FOR DIFFERENT INPUT FORCE

Parameters	Different types of the input force profile			
	Crestmin	**Random Signal**	**Random Phase**	**Schroeder phase**
R Squared[a] (%)	86.17 ± 5.91	79.96 + 17.32	80.89 + 9.04	77.55 + 17.68
Correlation[a] (%)	92.77 ± 3.26	88.06 + 15.85	89.78 + 5.45	85.85 + 20.01
Crest factor profile	1.61 ± 0.013	2.88 ± 0.034	2.85 ± 0.028	1.92 ± 0.033
R Squared[b] (%)	61.2 ± 19.01	69.11 ± 14.14	65.60 ± 17.75	66.07 ± 18.05
Correlation[b] (%)	77.28 ± 12.81	82.69 ± 8.74	80.01 ± 12.85	80.36 ± 12.49

a. Between measured force and predicted force
b. Between measured force and profile force

The statistical test results showed that the entire multisine force profile was significantly (*adj.* $P < 0.05$) better than the random signal profile. Moreover, our study found a significantly low correlation between the goodness-of-fit of the predicted force signal and the crest factor of the force profile (r=-0.328, P=0.001). The Boxplot of the goodness-of-fit between the predicted and measured force signal (R^2) is shown in Fig.2 for different force profiles.

The sEMG envelope and the force signals of "crestmin" and random force profiles are shown in Fig. 3.

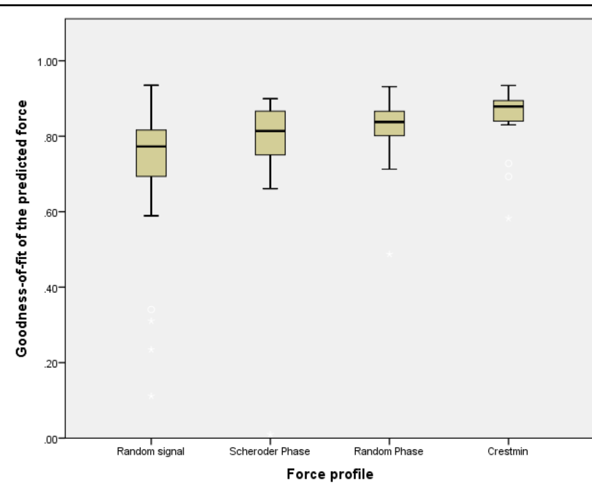

Figure 2. The Boxplot of goodness-of-fit between predicted force and different measured input force profile.

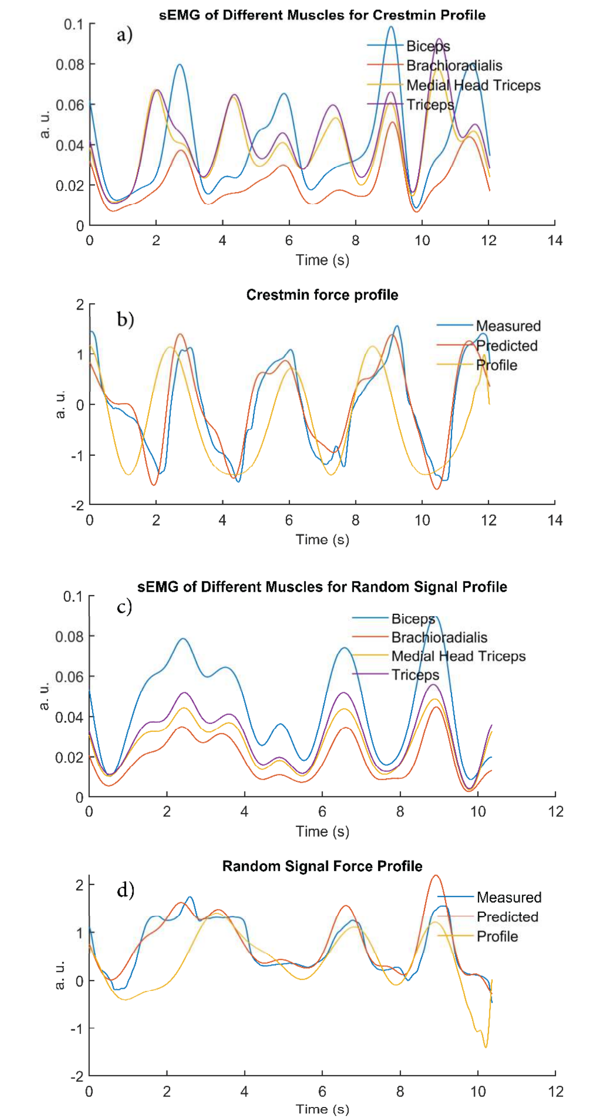

Figure 3. a) The envelope of different muscles in the "crestmin" force profile. b) Measured force and predicted force and input force profile for the "crestmin" input force profile. c) The envelope of different muscles in the random signal force profile. d) Measured force and predicted force and input force profile for the random signal input force profile.

IV. CONCLUSION

This study investigates the relationship between the crest factor and input force profile in the EMG-Force relationship. The EMG-Force prediction models in the literature were frequently tested using a swaying protocol or random signal as input force. Although selecting random signals as a dynamic scenario for testing the model's robustness is popular, this study demonstrates that other signals meet this criterion and can be used as input force. Statistical tests indicate that different multisines (signals with a minimum crest factor, random phase, and Schroeder phase) provide significantly better results than random signals for fitting the predicted force. This shows that to improve force prediction results, training the models using force profiles with lower crest factors is necessary. However, this study also has its limitations. We used a representative channel to calculate the envelope of the sEMG signals, but this representative channel can be selected more optimally by combining the information from different channels, and this step can be done in future studies. Also, to increase the generalizability of results, future studies should use dynamic exercises with different maximum voluntary contractions and collect data from more subjects.

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