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Relationship between force signal and superficial electromyographic signals associated to hand movements

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ABSTRACT

The analysis of electromyographic signals is applied both to the diagnosis of pathologies and to the recognition of movement patterns. Variables such as force and speed of movement are factors that affect the characteristics of the signals of surface electromyography (SMEG). The naturalness of the movements of the hand are also associated with strength and speed. Current work assessment 96 records of SEMG -Force). The objective was to obtain a linear model that would allow the relation of the force signal with the tone of the forearm SEMG signals. The work results show models at the determination coefficient R^2 - median 0.78. The SEMG signal would contribute to the variation of the strength signal. However, there are appreciable differences in relation to the model in each type of hand movement.

Keywords: Forearm SEMG, Hand Movements, Force Signal, Linear Model

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1. Introduction

The relationship between SEMG signal and behavior of the muscle-skeletal force has been studied decisively in the last years. The studies use different alternatives for signal processing [1], [2] ,[3],[4]. On the other hand, to identify SEMG patterns associated with each movement, many authors have used fractal modeling and linear discriminant analysis. It should be clarified that it is first necessary to extract the characteristics of each movement.[5],[6],[7]. Temporary features to characterize SEMG signals as mobile windowing techniques have been used. In addition, characteristics in the frequency domain (Fast Fourier Transform-FFT) and wavelet processing are strongly used to obtain relevant information for each class or movement type .[8], [9],[10]. Other studies have incorporated the angular velocity of the hand and multichannel electrodes [11].[12]. The objective is to obtain models that allow controlling hand movements with little effort from the user.[13],[14],[15]. However, in order to control the movement naturally, it is necessary to evaluate variables such as force and speed in each movement.[16],[17],[18],[19]. Even though some study the characteristics associated with low complexity movements[20], [21], the deterministic relationship between the SEMG, force, and the velocity with which the hand moves is unknown.[22]. Nevertheless, many studies have reported information about the relationship between force and SEMG, but in other parts of the body [23],[1] [24], and other applications[25],[26],[27][28]. However, recognition systems exist, such as [29] and [30], but there the relationship between speed-SEMG and force -SEMG for uses associated with control ,not have been estimated [31].

The present work uses a previously validated methodology to measure force signals[32], and evaluate the relation of the SEMG signals to the force signals. We used the data acquisition system ML880 PowerLab and the ML135 Dual Bio Amp signal conditioner, and the LabChart graphical interface by ADINSTRUMENTS to see the data set. To calculate the SEMG signal tone, we use a filter Butterworth, a two-sample moving average, and a 20 ms window. Also, we use a linear regression model for each subject and each move type which allows seeing the relationship between both signals. The duration of both signals (SEMG-FORCE) was 4 s (average). The median determination coefficient R^2 was - 0.78, and the IQR was (0.62, 0.91) for different efforts (k1, k2) springs, which reflects low dispersion.

2. Material and methods

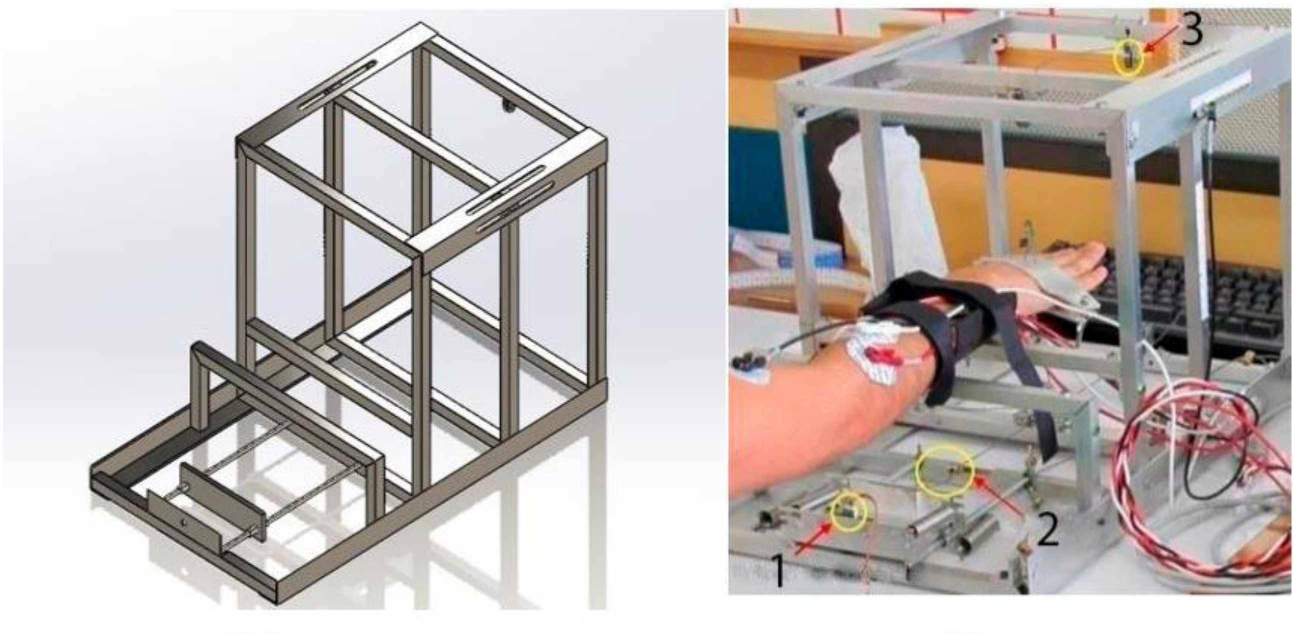
2.1. Data collection

The number of records was 96 (SEMG- force) from eight healthy subjects. Moves studied were: flexion-extension, ulnar deviation-radial deviation, prone-supination and two forces (low and high, We use the ML880 PowerLab data acquisition system and the ML135 Dual Bio Amp signal conditioner, and the LabChart graphical interface by ADINSTRUMENTS for the SEMG records. To record the force data, we use a previously tested system of data acquisition[32].

2.2. Force signals measurements

A set of instruments was necessary to obtain the force signal[32] and Hoke's law, according to equation 1, to force calculation. Transmission of moves was through cord steel (2 in Figure 1. B) and pulleys (3 in Figure 1. B) to spring with elastic constant k [32]. To record the spring's elongation (x(t), according to equation 1), we use a sensor distance (1 in Figure 1.B) and the resultant force signals (Figure 2) by multiplication as in equation 1. We use a DAQ of National instruments to record the force signal in each test employing the 250 Hz (sampling rate). Figure 1 shows the schematic design (Figure 1. A) and an example of the tests (Figure 1. B). We use a two-sample moving averaging and a 20 ms window to smooth the curve Force-time.

$$F(t) = k * x(t) \tag{1}$$



(A) (B)

Figure 1. A Schematic design. B example of a test

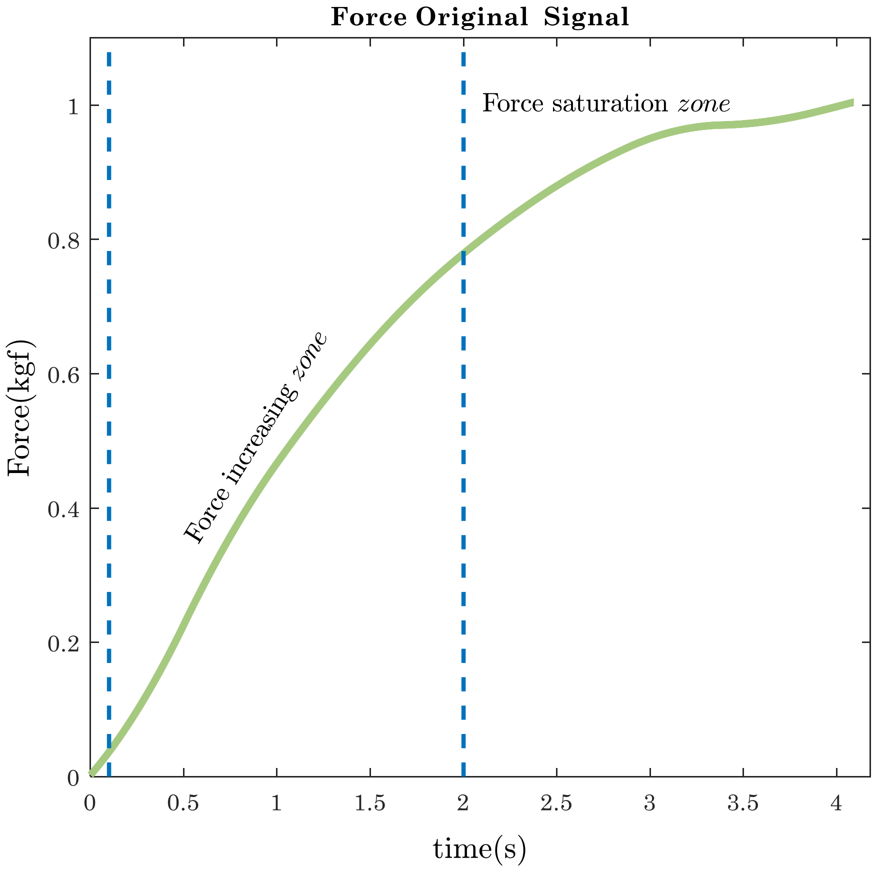


Figure 2. Resultant Force signal. Two Zones are depicted. A zone for increasing force: from 0 to 2 s approximately. And saturation zone (time> 2s)

Each subject was asked to perform the movement in two stages. First: Incrementally (as seen in the force increasing zone in Figure 2). Second: On a sustained basis during 2s (as seen in the force saturation zone Figure 2).

2.3. SEMG signal processing

Electromyographic signals have a non-stationary behavior. The nature of these signals is complex. However, it represents the performance from dynamics characteristics of the muscle-skeletal when a subject the making move[28]. In this sense, we use a combinate method for envelope extraction. First, a second-order low pass filter (Butterworth) was selected [14]. After, we use a two-sample moving averaging and a 20 ms window for obtaining the envelope (See the process in Figure3). Figure 4 shows an example of the results of this process. Left is the original SEMG signal (gray color). On the right side, you can see the envelope SEMG signal. Figure 4 (right side-green color) looks like the force signal (Figure 2). Also, you can see the same zones as the SEMG tone signal (envelop) and the force signal. We applied this process to all records.

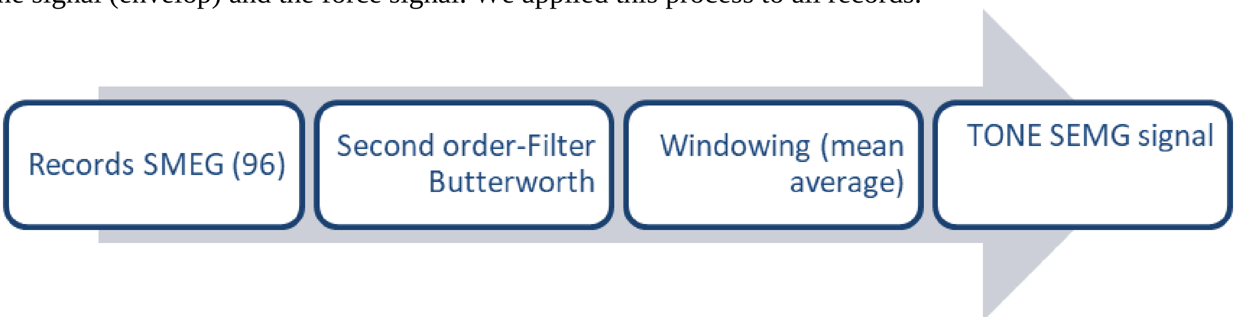


Figure 3. Process SEMG signal illustration.

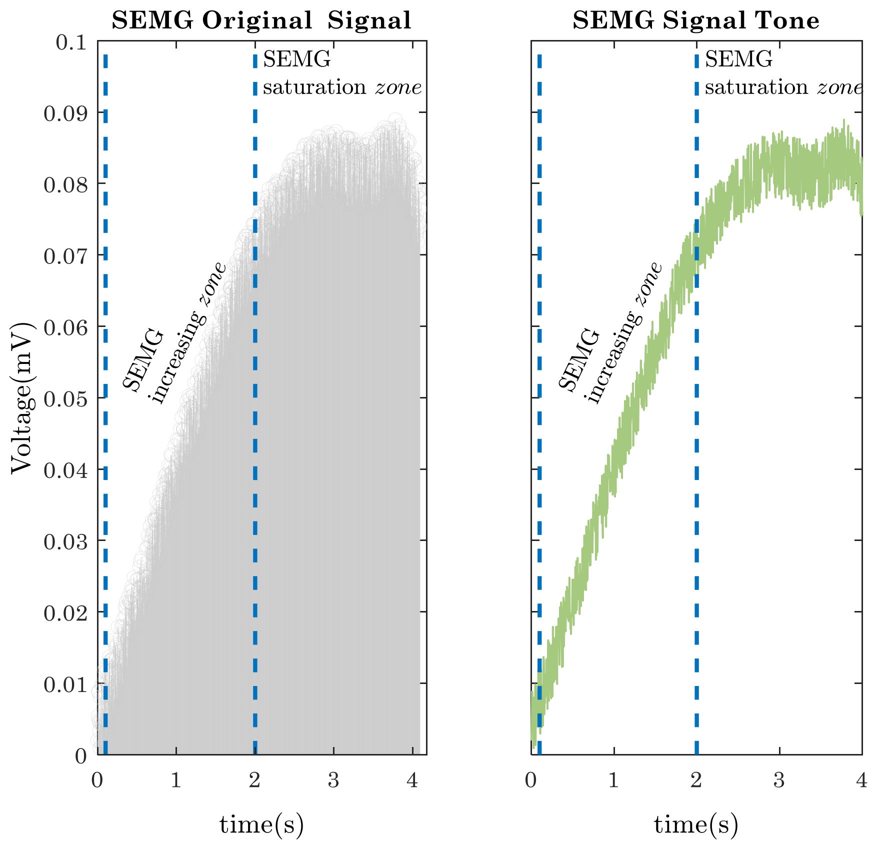


Figure 4. Left side original signal. right side envelop signal

2.4. Model calculation

We use a linear regression model to relate force signal and SEMG (tone). Biquadratic robustness was employed to fit the model. Estimation of model bondage was via a coefficient of determination R^2. The model is the form of equation 2:

$$F(t) = c * SEMG(t) + intercept \tag{2}$$

Where:

- F(t)= Is the force in the forearm applied in each move.
- c=Is the coefficient obtained in modeling process.
- SEMG(t)=Is the tone of SEMG signal.
- intercept=Is calculated in process of modelling

2.5. Statistical calculus

Results are reported as median IQR for each factor (c, intercept, R^2 and MSE). For each record (eight subjects and six hand moves and force levels,) a model has been calculated (96 models obtained). Figure 5 shows an example of the fit model (force-SEMG).

3. Results

Table 1 shows the demographic characteristics (age and sex) of database 1. The test duration was 384 s. The Elasticity constants were k1= 8.40 kgf/m (low force) and k2= 20.43 kgf/m. (high force). he characteristics demographic as age and sex of data base is shown in table 1. All probe duration was 384 s. Elasticity constants were k1= 8.40 kgf/m (low force) and k2= 20.43 kgf/m. (high force).

Table 1. Demographic characteristics

characteristic	Observed Value
Age (year) median IQR	22.5 (21.5, 24)
Sex (%)	Male (62.5), Female (37.5)

Each record has 1024 samples at 250 Hz off sampling rate. A model is calculated for each record (Force and SEMG). Table 2, shows the statistics for fit model.

Figure 5 shows the relationship between force signal and SEMG signal, and you could see the same two zones like in both Figure 2 and Figure 4. The relationship between FORCE-SEMG tone is clear. However, in distinct zones, behavior is different. The constant k2 requires high effort and the dispersion of data associated with it is high (see table 2). The Values of SEMG tone can see in the horizontal variable. Interval (0.04 to 0.105 mV) of SEMG tone corresponds to SEMG increasing zone. Interval (0 to 0.812 kgf) is force increasing zone. Behavior in the increasing FORCE/SEMG zone is linear. The higher values are the Force and SEMG saturation zone. Test in Figure 5 uses elasticity coefficient k2.

Table **2**. Results of fit and factors of the model

Characteristic	Observed Value	
	k2	k1
c, median IQR	10.23(8.43, 11.64)	11.36(8.87, 14.22)
Intercept, median IQR	-0.14(-0.49, 0.19)	-0.15(-0.30, -0.03)
R^2, median IQR	0.79 (0.65, 0.92)	0.78 (0.62, 0.91)
MSE (Estimated Force-Measured force) median IQR	0.17(0.14, 0.21)	0.18(0.15, 0.21)

In addition, Figure 6 shows the comparison between estimated force (blue line) and measured force (green line). The values are obtained using both the median of c and intercept and applied to the SEMG tone of a particular move (Extension), and the elasticity constant was k2. The mean square error MSE (Estimated force and measured force) is calculated for each record and reported in table 2.

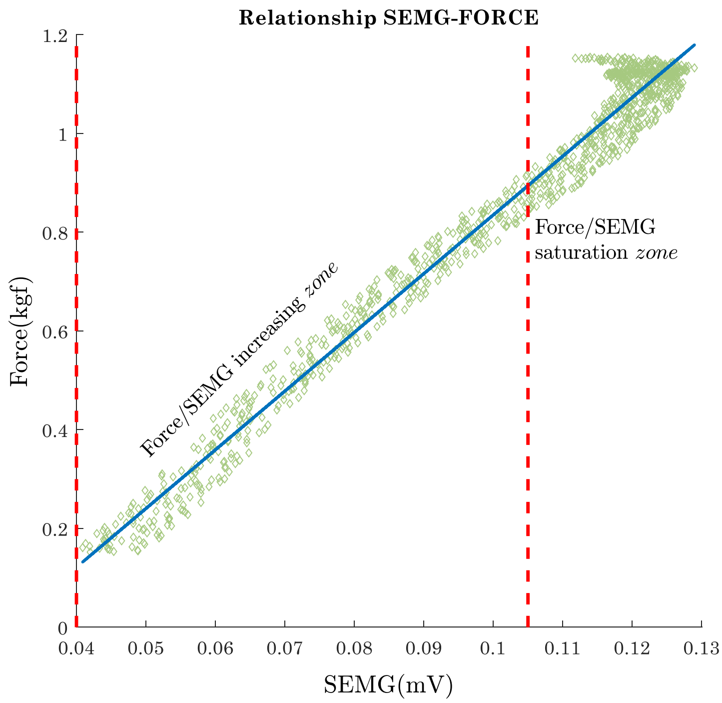


Figure 5. Example of fit model

On the other hand, Figure, 7-9 allow seeing the dispersion of factors corresponding to table 2. Figure 7. A shows the scatter on long over c coefficients from the model calculation for elasticity constant k1 for each move. In the B panel, you can see the dispersion over c to elasticity constant k2. In Figure 8, the intercepts data for k1 and k2. Finally, in Figure 9, the determination coefficient R2 to k1 and k2.

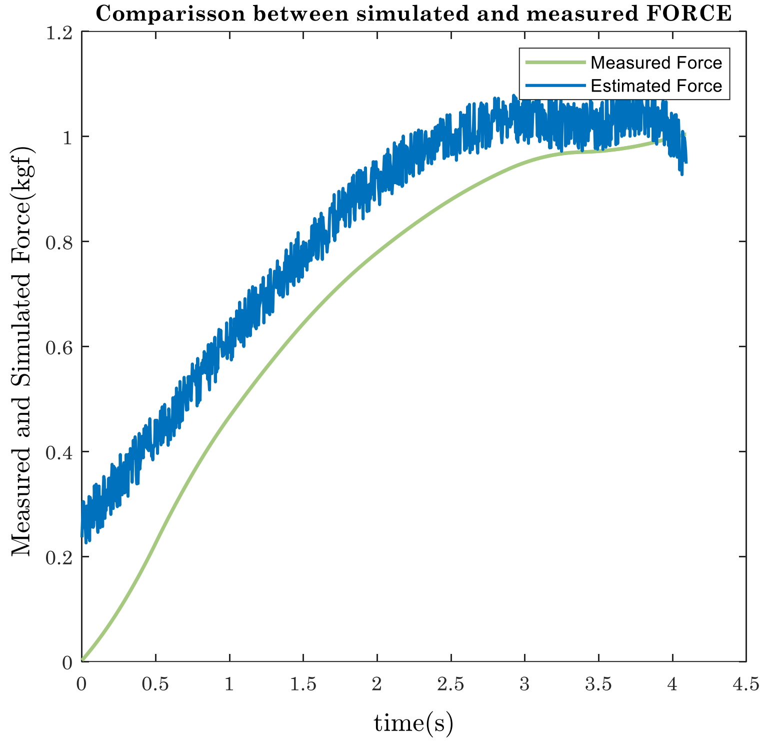


Figure 6. Example of comparison of measured force with the estimated force

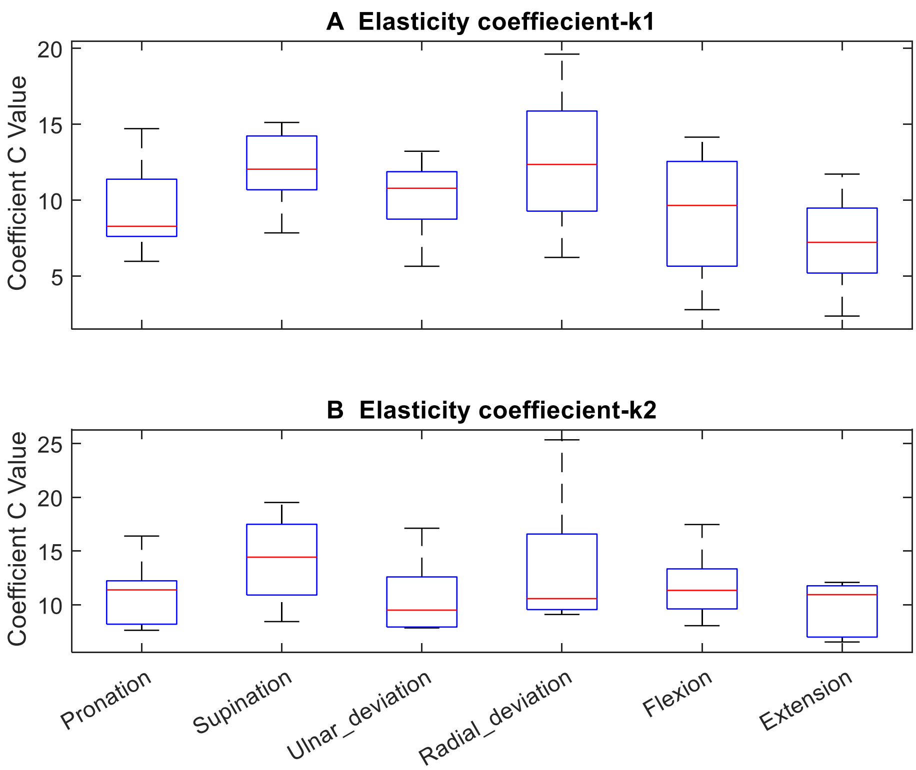


Figure 7. Dispersion in c coefficient to different hand moves. Panel A corresponds to k1-spring. Panel B corresponds to k2-spring

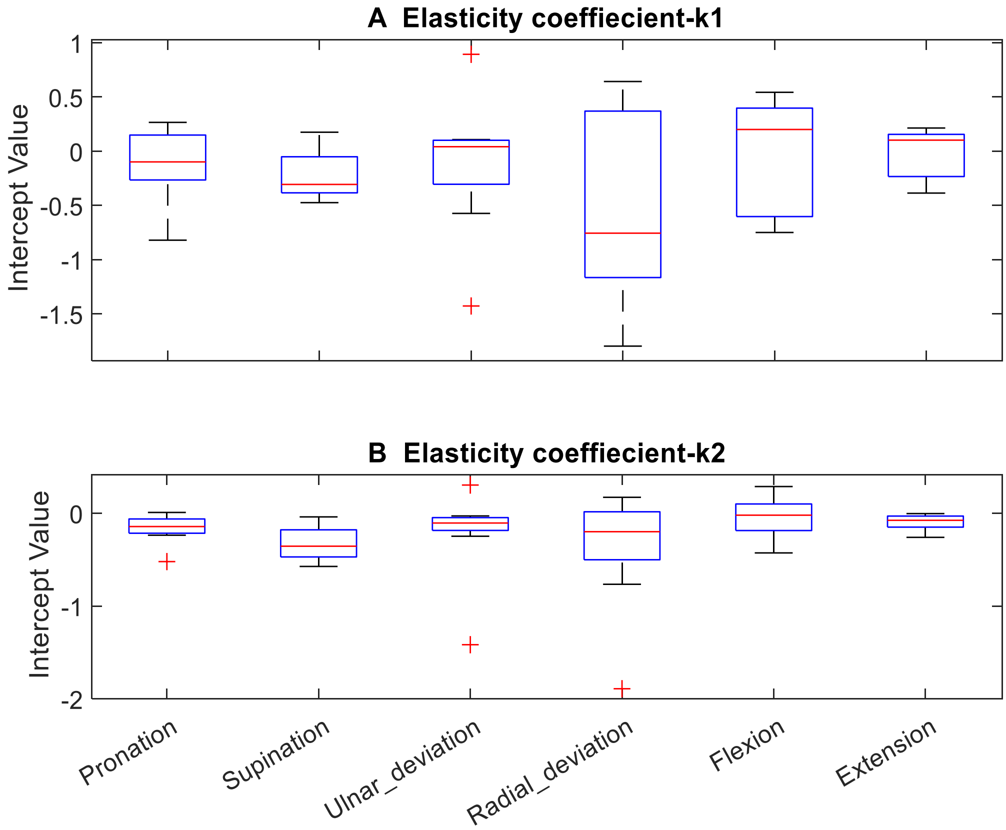


Figure 8. Dispersion in the intercept to different hand moves. Panel A corresponds to k1-spring. Panel B corresponds to k2-spring

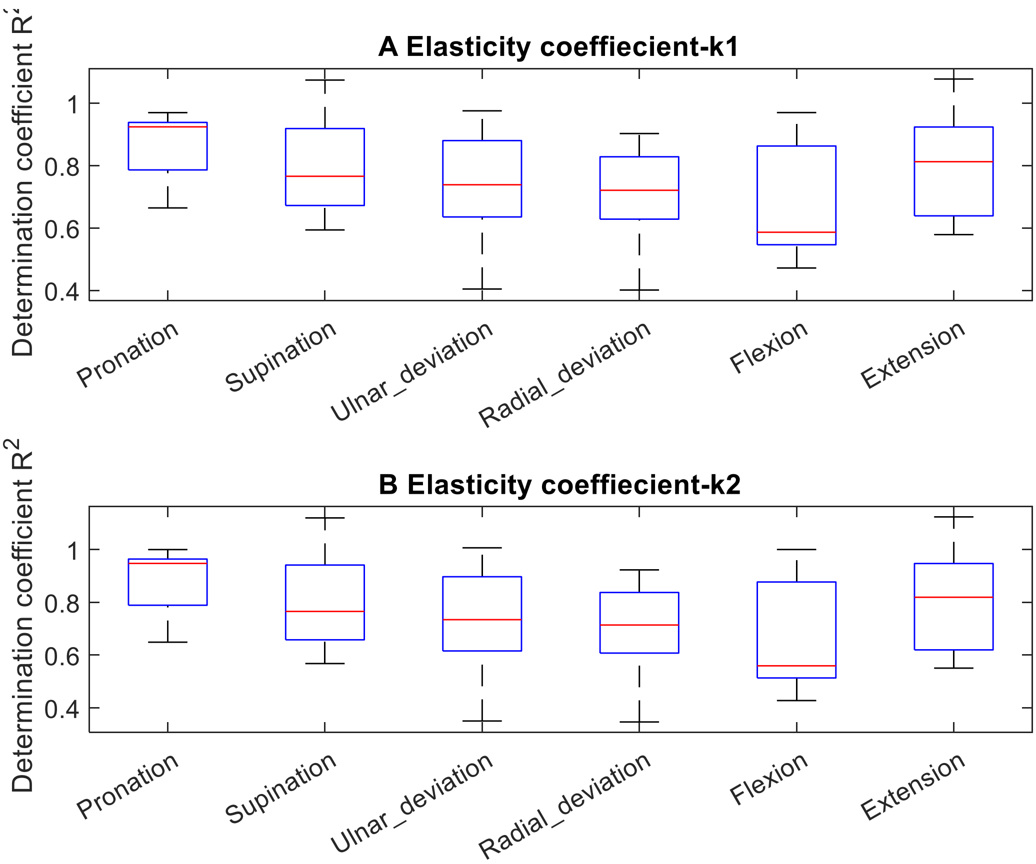


Figure 9. Dispersion in the determination coefficient R^2, to different hand moves. Panel A corresponds to k1-spring. Panel B corresponds to k2-spring

4. Discussion

It's known that the SEMG is a factor that explains the variation in force signal and behavior of the muscles in the body. Many works have studied these phenomena. Two examples focused on the legs movements to characterize the effort and muscle activity [24][23]. Other work shows the relationship between force and SEMG in the forearm as a heuristic model to predict the force signal [28] In our work, the relationship between the force signal and SEMG signal is from a deterministic model. Another study relates three variables: the force, SEMG, and the incidence of the angular position of the elbow in the movements: flex-extension of the forearm[33]. Another study has proposed a relationship nonlinear between force and SEMG[3]. In [32], the relationship between the force signal and SEMG in wrist movements was studied, but not the causes of possible variations in SEMG signals due to other factors. Our work proposed a linear relationship between the force and SEMG in wrist movements, and we reported a study of the possible causes of variation of SEMG.

The current work presents the variation in force signal as a function of SEMG signal in hand-wrist movements, with a linear relationship between both signals (see Figure 5 and equation 1). Table 2 shows that the intercept is a negligible value, and its dispersion is high (see Figure 8.) in each move. On all duration of force/SEMG signals, the relationship is not the same in both zones, due in the saturation zone (Figure 2 and Figure 4), the correlation is poor (see Figure 5). Also, it can reflect in the determination coefficient R^2 on all moves (see Table 2 and Figure 9). This affirmation suggests that estimation of force signal would make early (increasing zone) easily than in the saturation zone. The c coefficient of equation 1 has low variability in its median value (see Figure 7) in all moves and both types of efforts (k1, k2).

Finally, variations in force signal would explain by variations in SEMG signal. However, other factors that influence the changes on SEMG, like the movement's types (see Figure 9-the determination coefficient R^2 is not uniform behavior in all moves) and efforts (k1, k2); generalized linear model effects would be an option to study these phenomena. Also, the velocity in movements has an impact on variations of SEMG. Since that velocity signals are not available in the database, this is a limitation for current work. In addition, different efforts would produce distinct performance in the human body. In Figures7-9, you can see it. For example, with great effort (k2), the median R^2 is low compared to low effort (k1). Therefore, the median IQR of MSE is either high for all cases.

5. Conclusion

A model to predict the force in hand movements was developed. The relationship between the force signal and SEMG signal is strongly linear. Two zones (increasing and saturation) are different behaviors and would be studied separately. Factors such as hand movement types (pronation, supination, ulnar deviation, radial deviation, flexion, and extension), and different efforts(k1,k2), have an impact on modeling results (determination coefficient R2).

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