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Differences in the force exerted during wrist movements are explained by a general mathematical model

C. L. Sandoval-Rodríguez[1-3*], C. J. Arizmendi -Pereira[2], D. M. Reyes-Bravo[2], O. Lengerke[1], R. Palacio[1], A. F. Jimenez-Quezada[1]

[1*] Unidades Tecnológicas de Santander, Bucaramanga, Colombia
[2] Universidad Autónoma de Bucaramanga, Bucaramanga, Colombia
[3] University of the Basque Country, Vizcaya, Spain

*Corresponding author E-mail: csandoval@correo.uts.edu.co

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Abstract

The goal of previous efforts has been to create hand prostheses with natural movements. Researchers have used tools to identify patterns in muscle signals associated with different hand movements. While many studies have successfully classified types of hand movements, it's important to analyze speed and strength to ensure that the resulting movements are natural. In this study, 16 healthy subjects were evaluated for (two) different forces and (six) hand movements using surface electromyographic (sEMG) records. A mixed effects model was used to examine the relationship between force and forearm sEMG signals. The results showed high R^2 values (median 0.9) and significant random effects, indicating that sEMG signals can explain variations in force signals during different hand movements by introducing the type of movement as part of the random effects of the model.

Keywords: General linear mixed effects model, Force signal, Surface electromyography, Wrist movement

1. Introduction

In recent years, surface electromyography (sEMG) has proven to be an effective tool for human-robot interaction, especially in force prediction and prosthetic control. sEMG signals, which capture the electrical activity generated by muscles, offer a non-invasive way to estimate grip forces, joint angles, and other critical variables [1]–[6]. Also, in previous research, the focus has been on electromechanical systems designed to replicate movements that closely resemble those of natural hands [7]–[11]. For applications requiring force estimation to aid in fatigue diagnosis [1], [12], [13] and for applications that require predicting movement dynamics, such as velocities and types of motion [3]–[6], [14]–[19]. Other studies have utilized electromyography signals to connect them with dynamic traits, such as strength, in order to assess a subject's muscle status and enhance the precision of strength predictions [19]–[22].

In [23], a model was created to establish a relationship between force and surface electromyography (sEMG), categorized into incremental and saturation zones. Each zone displayed different behaviors, and the models differed based on the type of movement. These zones are influenced by the number of motor cells recruited for the movement, which produces the sEMG. The type of movement also represents a difficulty in generalizing a model that allows predicting the force accomplished. Consequently, the type of movement affects the parameters of the model, particularly when constructing a general model. In our study, we introduce a general model that includes mixed effects to elucidate how relates strength and sEMG signal.

2. Methodology

2.1. Data collection

The six moments as shown in Figure 1: radial and ulnar deviation, and, flexion-extension, and pronation-supination, as described in [23],[24]. The dataset includes 96 recordings from six movements performed by 16 healthy subjects. For data acquisition, we used hardware for acquisition and Software for visualization as described in [23],[24]. To calculate the signal envelope, we applied a second-order Butterworth low-pass and a moving average of two samples with a 20 ms window, to sEMG. For force measurement, we employed a previously validated procedure [23]. The database does not contain the personal data of the participants.

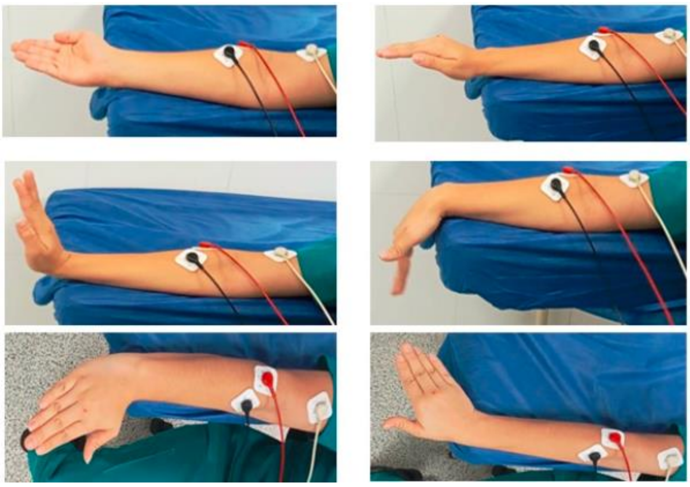

Figure 1. Studied movements; upper row: pron-supination; second row: flex-extension, bottom row: ulnar and radial deviation

2.2. Modeling

We computed the median sEMG tone and the median force signal for each type of movement. Following this, we were introduced to a mathematical linear model (mixed-effects model -GLME), utilizing the tone from sEMG as direct or fixed effects and the various movement types as aleatory effects [25]. In the following equation, we can observe the model form linear.

$$Force = a * sEMG + int + mtm \qquad (1)$$

Where:
a= slope value
sEMG=Tone (sEMG envelope)
b=intercept
mtm=move type model (random effects)

3. Results

The results have four parts. The first part focuses on the characteristics of the data for the conception of the model. The second part presents the parameters and statistical results of the calculated model. The third part shows the results of a cross-validation where the linear model is obtained by a linear regression model for each type of movement. In this way, we obtained a model, which observed differences since the behavior is different in the different zones of the force response in each movement. Finally, it shows results from validation using the GLME model.

3.1. Features of GLME

Our GLME model uses 192 recordings (96 sEMG and 96 force) that correspond to the tone of the signals (envelope). These constitute the observations of the model. We incorporated a categorical variable into each observation about the type of movement (six) where the data have a statistical distribution of GAUSS bell. Table 1 shows a summary of these characteristics.

Table 1. Features of GLME

Features	Value
Observations	96
Fixed effects coefficients	1
Random effects coefficients	6
Distribution	Normal

3.2. Statistical results for GLME

Table 2 displays the findings. We observe that the aleatory and direct effects (movement type and sEMG) influence the outcome of the model (p-value < 0.05). Also, it observed that the intercept value is of low significance. In Figure 2, it is shown the measured force and estimated strength as a function of electromyographic signal and aleatory effects.

Table 2. Results of GLME

Name	Estimation	Square error (SE)	P value
Intercept	0.00012	0.095	0.9
sEMG	0.0075	0.044	<0.05
Random effects coefficients **(mtm)**		Std = $1.16 * 10^{-3}$ p-value <0.05	
Determination coefficient R^2		0.91	

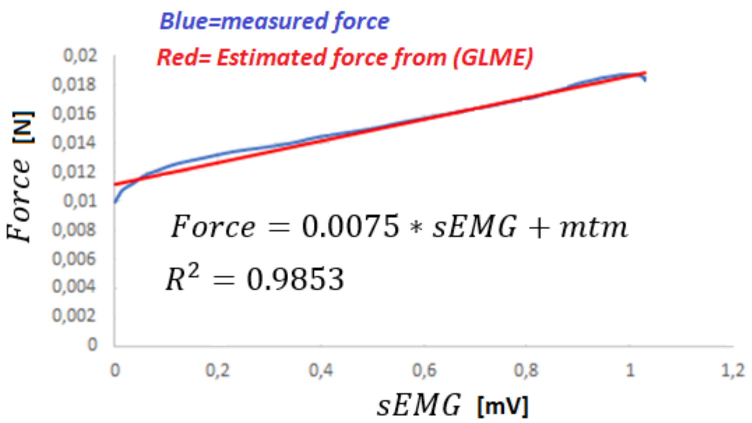

Figure 2. Force model GLME (excluding the intercept) compared to the measured force

Figure 2 shows that the force exerted depends on the electromyography signal but also the type of movement has a certain influence that cannot be neglected. In this way, when calculating the force from a linear model that is obtained for each movement, this model cannot be used to estimate force if the movement is different, see Figure 3.

3.3. Cross-validation by each movement type

In Figure 3, you can see the force measured in a pronation movement compared to various estimates based on a model that relates force to surface electromyography (sEMG) signals. The graph illustrates the force measured during the pronation movement. As the line steadily rises, it stabilizes at approximately 0.03 N in just 2 seconds, indicating the muscle's active engagement and adaptive force modulation throughout the movement. The pronation model shown in the green line, which was calculated using the sEMG relationship, mirrors the measured force's pattern, demonstrating its precise predictive capabilities for force in this specific scenario. Conversely, the estimated forces from the extension, flexion, and ulnar deviation models (gray, yellow, and orange lines), which rely on a different approach, fall short of capturing the intricate dynamics of the pronation movement. This striking contrast highlights a crucial limitation; a single model is not adequate to explain and address the complexity of various movement types. This can be explained because the class of movement has not been taken into account to obtain all responses of the models. Therefore, when cross-validating, large differences are observed. By using a general mixed effects model, these differences are reduced, observing a better estimation of the force, see Figure 4 and Table 2.

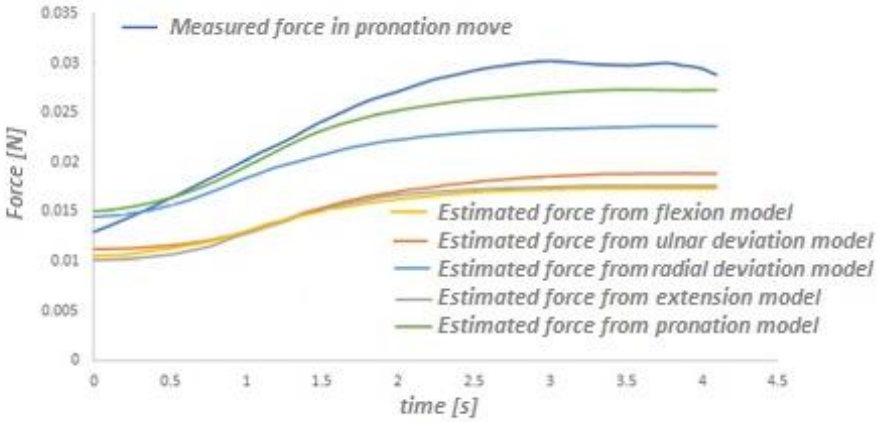

Figure 3. Cross-validation without taking into account the type of movement for the calculation of each model

3.4. Validation using GLME

The general model proposed in this work is the one described by Equation 1. Here, we have taken into account that there are variations in each type of movement (according to Figure 3). Consequently, the model obtained with the data in Table 2 and Figure 2 explains the changes in force as a function of sEMG and the type of movement. To assess the predictive capacity of GLME, we have performed tests with 96 records comparing the measured force with that estimated by the model, obtaining an approximate root mean square error of 6.44%. In Figure 4, you can see a comparison of force model GLME (excluding the intercept) with the measured force to an example of movement flexion.

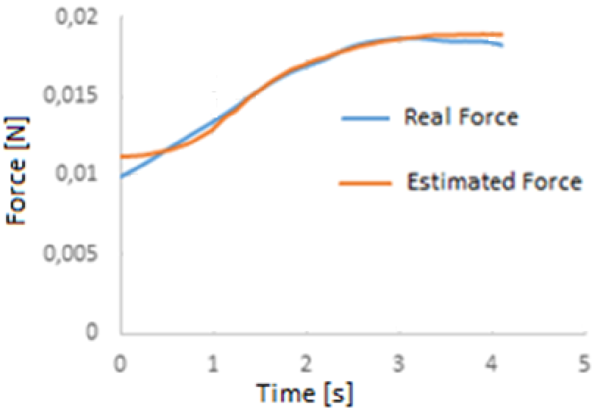

Figure 4. Comparison of the force model GLME (excluding the intercept) with the measured force (flexion movement)

4. Discussion

Previous studies have conducted research into strength prediction from electromyographic signals. Authors [6] and [20] focus on grip strength, [5], [12], [20], [21], [26], and [27] extend their approach to integrate both movement dynamics and gesture recognition and expert systems to classification moves. So [28] adds a novel perspective on the variability in force prediction during different muscle phases, raising questions about the ability of previous models to capture these temporal fluctuations. This approach may be crucial to improving accuracy in prosthesis control in real-world situations, where muscle dynamics are constantly changing. Some authors suggest that linear relationships may be adequate under certain conditions, but studies such as [28] highlight the nonlinear complexity of sEMG signals, especially during dynamic contractions. In contrast, our study addresses a linear mixed-effects model, in which a categorical variable such as movement class is weighted to assess its statistical significance, resulting in a more consistent prediction of force. This suggests that although linear models are simpler to implement, they may not be robust enough in complex situations.

However, in our work, we have studied six movements using a general mixed effects model, where results presented in Table 2 provide a clear insight into the influence of sEMG signals on force prediction and the importance of random effects arising from different types of muscle movements. The estimated intercept value was 0.00012, with a squared error value of 0.095 and a p-value of 0.9. This p-value indicates that the intercept is not statistically significant, indicating that the model cannot predict a relevant constant value of force when sEMG signals are null, in other words, it would not be relevant to include the intercept value in the model to adequately predict force from sEMG tone. In practical terms, this suggests that the constant component of force, without the influence of sEMG signals, is negligible for this model, which could also be interpreted as a validation that force variability is mainly linked to variations in the electromyographic signal. On the other hand, the sEMG parameter was 0.0075, with a squared standard error of 0.044 and a p-value < 0.05. It suggests that the increase in sEMG signals has a direct and considerable impact on the increase in muscle force, validating the use of sEMG as a robust predictor of the force generated by the muscle. The small standard error value reinforces the precision of this estimate.

The random effects are summarized in the table under the category random effects coefficients, with a standard deviation of 1.16 x 103 and a p-value < 0.05. These results are of particular interest because they highlight the influence of movement type as an important variability factor in the model. The low standard deviation indicates that, although there are differences between the different types of muscle movements, these variations are not excessively large. However, the p-value < 0.05 confirms that these random effects are significant, suggesting that each type of movement substantially influences the relationship between sEMG and force, justifying the inclusion of random effects in the model.

The high R^2 value (0.91) is an indicator of the quality of the model fit. This implies that the GLME model with random effects for different movements and the variable sEMG as a predictor provides an accurate and reliable description of the relationship between electromyographic signals and the generated force which contrasts with the results of [13], [29] and [28].

5. Conclusion

We demonstrate a linear relationship between the EMG and force signals in six moves (pronation, supination, flexion, extension, ulnar deviation, and cubital deviation). Our model includes sEMG, an additive random effect associated with movement class. Although the intercept is not statistically significant, including random effects related to different movement types significantly enhances the model’s accuracy, as evidenced by a high R^2 value. This approach captures the complexity of the force-sEMG relationship, particularly by accounting for variability introduced by distinct movements. When the movement type is included in the model, the relationship between force and sEMG signals becomes linear. Random effects associated with movement types greatly influence the model's outcome. The coefficient of determination improves when the intercept is excluded from the model.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

The contribution to the paper is as follows: C L Sandoval-Rodriguez, C J Arizmendi-Pereira: study conception and design; D M Reyes-Bravo, R Palacio, A F. Jimenez-Quezada: data collection; O Lengerke, C L Sandoval-Rodriguez, C J Arizmendi-Pereira, D M Reyes-Bravo: analysis and interpretation of results; C L Sandoval-Rodriguez, C J Arizmendi-Pereira, D M Reyes-Bravo: draft preparation. All authors approved the final version of the manuscript.

Ethical approval statement

Research ethics approval was obtained by the ethical approval to report this case obtained from * *Ethics Committee for Research, Bioethics and Scientific Integrity – CEI Resolución 02-474 de agosto 4 del año 2021/ FIN 11-15.*

Informed consent

Informed consent for the study was obtained from the subjects. The database does not contain the personal data of the participants.

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