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Estimating different velocities in wrist movements from information contained in surface electromyography: Application of a machine learning technique

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Abstract

The study of surface electromyography (sEMG) has several approaches. It is used to classify upper and lower extremity movements by identifying the muscle groups that have been excited to generate movements. In general, movements have certain properties related to the type of movement, the force, and the speed at which they are performed. The hypothesis of this study is that information about different speeds is contained in sEMG signals. Participants performed wrist movements at different speeds, following verbal instructions to alternate between fast and slow movements. Our objective was to estimate whether there is information in the sEMG signal that can be associated with the different speed conditions; therefore, binary differencing (two classes) was chosen to test this. These two conditions (fast and slow) were used as classes for analysis and classification based on surface electromyography signals. The moving window method was used to extract sEMG envelopes at two different speeds performed by the test subjects. A linear discriminant analysis model was created to estimate the velocities with the resulting model. Finally, cross-validation was performed to estimate sensitivity (76.67%), specificity (91.2%), and accuracy (approximately 87%).

Keywords: Surface electromyography, Artificial intelligence, Linear discriminant analysis, Velocity in wrist movements

1. Introduction

Human movement constitutes one of the most complex and fascinating processes in physiology, resulting from close coordination between the nervous system, muscles, and joint structures. These movements, called "natural," range from every day, spontaneous gestures to specialized motor tasks requiring high levels of dexterity and precision [1], [2]. The upper extremities, particularly the hand, play a central role in this dynamic, being involved in manipulation, grasping, signaling, and interaction with the environment. This sophisticated motor capacity has been extensively studied by various disciplines, including biomechanics, neuroscience, and biomedical engineering [3], [4].

Understanding the mechanics underlying natural hand movements represents both a challenge and an opportunity for the design of rehabilitation systems, prosthetics, human-machine interfaces, and robotic assistance mechanisms. One of the main instruments used to assess these movements is surface electromyography (sEMG), which records muscle electrical activity through electrodes placed on the skin. This signal reflects the bioelectrical behavior of muscles during contraction, providing quantitative information on the intensity, duration, and rhythm of muscular effort [3]–[6].

The electromyographic signal not only serves to identify whether a muscle is active, but also allows for inferring fundamental biomechanical variables such as the force generated and the speed of movement [5], [7]–[14]. It has been shown that certain features extracted directly from the time domain of the signal, such as the root mean square (RMS), peak, and average, are correlated with the magnitude of muscular effort and the speed of movement [3], [14]–[16]. These temporal variables offer a direct and computationally efficient way to represent the muscle dynamics involved in different motor tasks [8], [17]–[20].

In recent years, sEMG signal analysis has been enhanced through the use of machine learning techniques, which allow the construction of models capable of recognizing patterns in muscle data and classifying them based on the type of movement or physiological condition [1], [5], [6], [11], [21], [22]. In particular, for classification tasks involving sEMG signals, linear discriminant analysis (LDA) has established itself as an effective and computationally inexpensive technique [9], [23]. This technique projects the data into a space where the separation between classes is maximal, which is ideal when working with features such as RMS or peak values in time domains [4], [24], [25].

This work presents an approach based on the classification of natural wrist movements based on the analysis of sEMG signals processed solely in the time domain. Six types of movements were studied: flexion, extension, pronation, supination, radial deviation, and ulnar deviation, each performed at two different speeds by a group of healthy subjects. The signals were segmented using a moving window technique, and representative features were extracted from each segment. These features were used as inputs for an LDA classification model, with the goal of identifying the speed at which each movement was executed. The main interest lies in demonstrating that it is possible to discriminate between two execution velocities of the same muscle movement using temporal sEMG, without resorting to more complex spectral representations. The underlying hypothesis is that differences in movement dynamics are sufficiently reflected in the morphology of the temporal signal, allowing a trained classifier to perform such discrimination with high accuracy.

This research not only seeks to provide empirical evidence on the relationship between movement velocity and the electromyographic signal but also aims to consolidate a simple and reproducible methodological approach for sEMG-based classification tasks. The feasibility of this type of approach can be very useful in the design of low-cost interactive systems, such as myoelectric prostheses, assistive interfaces, or rehabilitation tools, where differentiating between similar movements at different velocities can substantially improve functionality and user experience.

2. Materials and methods

We studied six movements into three pairs: radial and ulnar deviation; flexion-extension, and pronation-supination. In turn, the experimentation protocol was carried out as follows:

- Flexion-extension session: In this session, the subject is positioned with the elbow flexed at 90°, the hand pronated, and the shoulder abducted at 45°. The subject is asked to perform two repetitions of the flexion and extension movement, using a high and a low speed, as determined by the subject.
- Prone-supination session: In this session, the same procedure as above was applied, except for the subject's position: sitting with the elbow and shoulder flexed at 90° and the elbow immobilized, with the anterior side of the hand facing the center of the body (oriented toward a sagittal plane).

- Radioulnar deviation session: In this session, the previous procedures are repeated, but with elbow flexion at 90°, shoulder abduction at 45°, and hand pronation.

A break of approximately 5 minutes was taken between each session to avoid undesirable conditions (muscle fatigue) [7], [8], [11], [17], [19], [20], [26], [27]. This indicates that the average duration of each session was 6 minutes. The speed conditions (fast and slow) were defined based on verbal instructions given to participants to alternate wrist movements at the fastest and slowest speeds possible, respectively. It is important to note that direct speed measurement was not used to label the classes. sEMG envelopes were obtained to extract descriptors that could be associated with each speed. This process will be explained later. The sample consisted of 7 healthy volunteers (4 males, 3 females), aged between 18 and 25 years. This sample size was considered adequate for a pilot study aimed at evaluating the feasibility of the proposed method.

2.1. Data collection and signal processing

Data collection was performed using the PowerLab system in conjunction with a Bio Amp signal conditioning module, as described in [15], [28], [29]. To calculate the signal envelope, we applied a moving average of two samples with a 20 ms window. The moving window was applied with a size of 20 ms without overlap between consecutive windows. Figure 1 shows an example of a supination move. Figure 2 shows an example of different velocities.

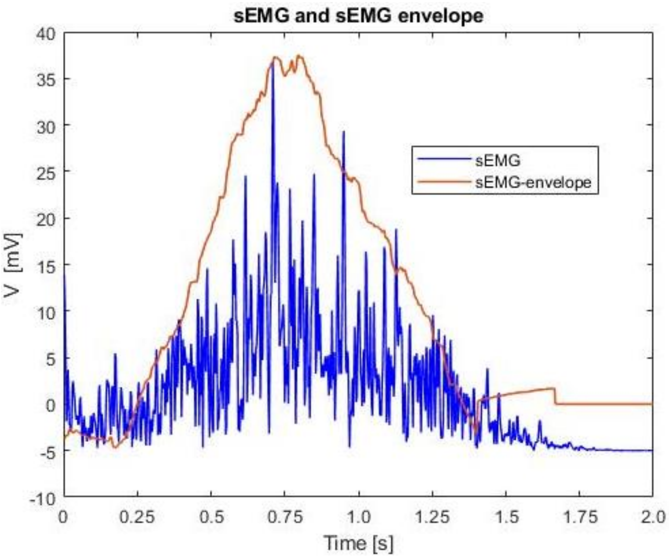

Figure 1. Result of the moving windowing process for calculating the sEMG envelope for the supination move

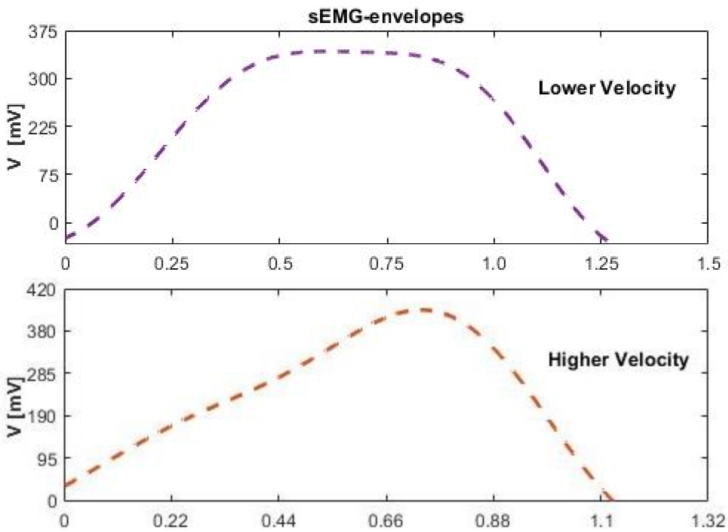

Figure 2. Example for different velocities

2.2. Feature extraction

The RMS characteristics and average value or DC value were extracted from the 84 records. According to the following equations.

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} X_i} \qquad (1)$$

$$DC = \frac{1}{N}\sum_{i=1}^{N} X_i \qquad (2)$$

2.3. Correlation between variables

To identify the dependence of the characteristics of each group (speed 1 and speed 2) on each other, the correlation between the RMS and DC characteristics for each group separately was evaluated using linear regression. It was assumed that the RMS and DC values are related to each other. The hypothesis is that if there is a good correlation, the characteristics can appropriately describe the phenomenon under study[1], [17], [21], [22], [30].

2.4. Statistical analysis and distribution of characteristics in the study groups

As part of the statistical analysis of the features extracted from the electromyographic signals, boxplots were used to assess the distribution, dispersion, and presence of outliers in the data. This graphical tool allowed for a visual comparison of the differences between experimental conditions, particularly between movements executed at different speeds. Each diagram represents five descriptive statistics: minimum, first quartile (Q1), median (Q2), third quartile (Q3), and maximum, providing a clear view of the behavior of each feature based on the analyzed class. This visualization was essential for identifying the separation between groups and supporting the feasibility of classification based on the temporal properties of the signal, helping to validate the representativeness and discrimination of the variables selected for the machine learning model [12], [31].

2.5. Linear discriminant analysis

For the classification stage, linear discriminant analysis (LDA) was implemented, a supervised machine learning technique widely used in pattern recognition problems due to its low computational cost and effectiveness in contexts of high correlation between variables. While other classifiers, such as support vector machines or random forests, or artificial neural networks, could improve performance, their evaluation was left for future work. In this study, LDA was applied to discriminate between two running speeds associated with six wrist movements, based on features extracted from the time domain of sEMG signals. The selected features were the root mean square (RMS) and mean square (MSD) of the electromyographic signal envelopes obtained for each movement and speed. Each feature vector, composed of RMS and MD, was labeled with its corresponding class (speed 1 or speed 2) and used as input for the LDA model. The objective was to project the data into a linear subspace that maximizes the separation between classes, allowing for efficient and robust classification based solely on time domain information. Model validation was performed through confusion matrix analysis and performance metrics such as accuracy, sensitivity, and specificity.

3. Results

First, the results of the correlation analysis are presented. It is observed that the coefficients of determination (R square) are high, indicating a strong correlation between the characteristics studied (Table 1).

Table 1. Results of the correlation analysis

sEMG envelope	Model Results $RMS = a * DC + b$ (3)			
	a median IQR	b median IQR	R^2	RMSE %
Vel. 1 Low	1.146 (1.044, 1.248)	24.35 (4.584, 44.11)	0.9282	28.28
Vel. 2 High	1.033 (0.9922, 1.073)	2.171 (-4.54, 8.882)	0.9851	8.967

To observe the discriminatory power of the selected features, box plots were created (Figure 3). There is some overlap in the interquartiles for each class, although separation is better for the RMS than for the DC. Nevertheless, it was decided to combine the DC and RMS features to be applied in the LDA (Figure 4).

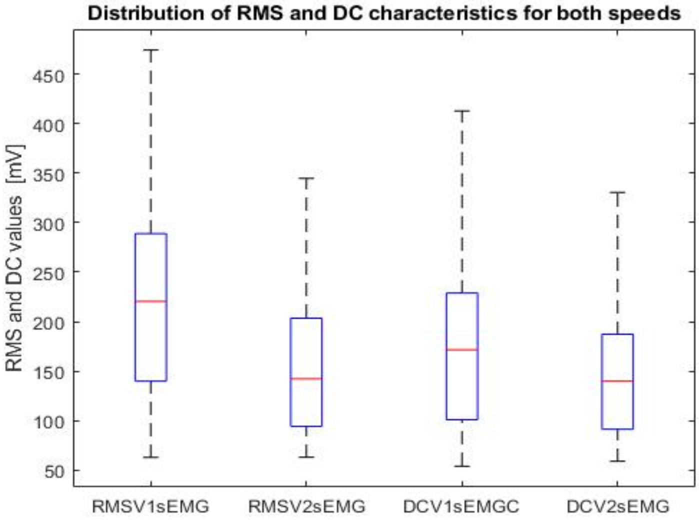

Figure 3. Boxplots of the characteristics for each speed

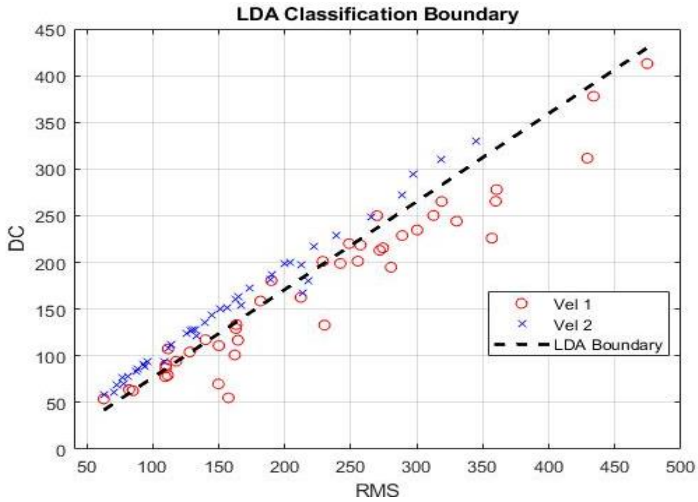

Figure 4. LDA for velocity classification

Once the validation stage was completed, metrics were calculated to estimate the supervised training process. The 95% confidence intervals were calculated using the Wilson method for the main metrics, obtaining: sensitivity 76.7% [CI: 59.1%–88.2%], specificity 91.2% [CI: 74.4%–96.5%], and accuracy 87.0% [CI: 70.3%–94.7%].

4. Discussion

There are studies focused on the study of biomechanics that highlight the use of sEMG to identify movement intention [18]. However, the evaluation of the speed with which the movements are performed is still under study [27]. On the other hand, the study of force is also a challenge [5], [17]. This study led to the discovery of an LDA model that can discriminate between two velocities. Although the classifier's performance is only fair, the results show that the model has a good ability to correctly identify the Vel 2 class (high specificity). However, it struggles to correctly identify all Vel 1 cases (lower sensitivity). The overall performance (87% accuracy) is acceptable, but could be improved by fine-tuning the model. In this context, velocity estimation has been largely achieved. Possible sources of error must be analyzed (Figure 5). This is an example of two different velocities for different movements. In this sense, very similar patterns are observed, which makes separation difficult, as was also observed in the box plots. There, an overlap of the interquartiles was observed, although not of the medians. This raises a question: Can movement velocity be estimated directly from sEMG? The evidence presented in this work shows that it is possible to differentiate at least between two velocities. Future work is proposed to evaluate the possible relationship between sEMG and velocity in each movement.

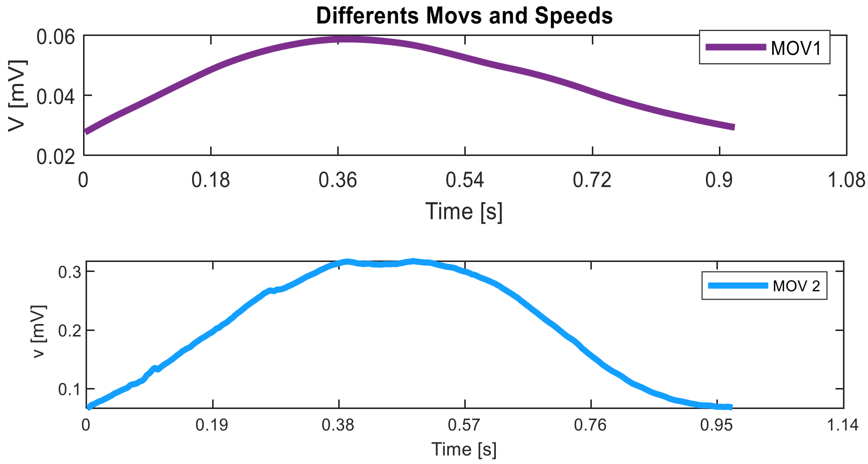

Figure 5. Comparison between two sEMG envelopes associated with two different movements and speeds

5. Conclusions

This study demonstrated that it is possible to estimate wrist movement velocity using surface electromyography (sEMG) signals processed in the time domain. By extracting simple features, such as root mean square (RMS) and mean square (DC), and using supervised learning techniques such as linear discriminant analysis (LDA), classification was achieved with 87% accuracy between two different execution velocities for six movement types.

Correlation analyses and box plots showed that both features exhibit high discriminative capacity, albeit with some overlap in their data distributions. This suggests that, while the model achieves acceptable performance, additional techniques or more complex features could be explored to improve the classifier's sensitivity, especially for the class corresponding to the lowest execution velocity.

Finally, the results support the hypothesis that the execution velocity of a movement is contained in the morphology of the electromyographic signal. This evidence contributes to the construction of simple, reproducible, and computationally inexpensive models applicable to devices such as prostheses, rehabilitation systems, or myoelectric interfaces that require dynamic interpretation of movement intent. Future research should evaluate this approach in more complex contexts and with more diverse populations to validate its clinical and industrial applicability.

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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Ethical approval statement

Research ethics approval was obtained the Ethical approval to report this case was obtained from * *Comité de Ética para la Investigación, Bioética e Integridad Científica – 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 personal data of the participants.

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