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RESEARCH ARTICLE

Feature Set to sEMG Classification Obtained With Fisher Score

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ABSTRACT The best way to represent EMG signals for classification is a topic that has been widely studied due to the need to improve precision when identifying the type of movement being performed. However, by increasing the number of features when forming a matrix that represents the signals, the processing time increases since it not only involves calculating the features that are extracted from the signal but also the time that the classifier takes to answer. The central purpose of this research is to develop and validate a methodology that uses the Fisher Score to select a set of features in the classification of sEMG signals. This selected set is descriptive enough to achieve high levels of accuracy in detecting EMG signal patterns across multiple subjects. The analysis shows that using a variant of MAV, SSC, WAMP, RMS, and the maximum value together with the Shannon entropy and zero crossings of the Wavelet transform has an accuracy greater than 99%. Finally, a group of features is proposed to classify EMG signals that yield an accuracy greater than 98% and do not require more than 15 ms of processing time.

INDEX TERMS SVM, Fisher score, feature selection, sEMG, pattern recognition.

I. INTRODUCTION

Since it has become possible to measure the signals coming from the muscles, the so-called electromyographic (EMG) signals, their applications have increased, from monitoring health status to seeking to use the signals in devices such as prostheses that are fed back by them. The surface EMG (sEMG) signals are the most used to classify different types of movements due to their high correlation coefficient with them [1].

Generally, using electromyographic signals for movement classification requires a noise-free signal to achieve a correct classification. In this sense, several proposals offer filtering methods to improve the signal quality [2], [3]. However, since, in many cases, the quality of the signals is not optimal [4], it is necessary to use more than one feature to describe them. On the other hand, the choice of features to describe the signal directly influences the classification quality [5]. That is why this work offers a group of features for sEMG classification and suggests two more features that can be added to the group in case an improvement in precision is needed.

When there is a high number of features and/or channels (sensors) to describe the signal, it is said that it has a high dimensionality, which is not always recommended when classifying, so there are algorithms for its reduction [6], [7], [8]. In this sense, there are two main methods: feature selection algorithms and feature reduction algorithms. Feature reduction methods include independent component analysis, principal component analysis, linear discriminant analysis, and canonical correlation analysis.

On the other hand, feature selection algorithms aim to select a subset of features with the lowest internal similarity and the highest relevance [9] by eliminating redundant or irrelevant variables. However, eliminating all redundancy is not always possible [10]. These algorithms are classified into four different types: filter, wrapper, embedded methods, and hybrid methods.

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Filter methods have low computational costs. However, selected features do not achieve good classification performance as they can sometimes miss some critical assumptions about the underlying regression function linking input variables to the output [7], [8]. The best-known filters are Information Gain, Gain Ratio, Term Variance, Mutual Information, Gini Index, Laplacian Score, Relief-F, and Fisher Score, among others.

In contrast, the wrapping methods have a high computational cost and lose generality since a classifier is used and trained to select the optimal set of features, so it is not recommended to use them on a large scale [9]. Furthermore, finally, embedded methods consider the feature selection problem as part of a machine learning method; they incorporate the search and classification model into a single optimization model, which is usually faster than wrapper methods and slower than filter methods [11]. Some embedded methods are of the Structured sparsity-inducing type [12]. In contrast, others combine classification algorithms such as multiple filters to remove redundant features [13], [14], or are based on fuzzy sets designed for hierarchical classification [15], [16]. In [17], a metaheuristic signal selection algorithm is proposed using a Golden Ratio Optimization and Equilibrium Optimization algorithm. On the other hand, [18] applied genetic algorithms for the selection of 24 features in the time domain to classify five movements of the right upper extremity employing sEMG.

Hybrid methods combine filter and wrapper models. In [19], two methods are proposed that follow a two-stage procedure. In the first stage, a score and filter model are assigned, and the second stage selects the subset. The signal analysis involves time and frequency domain features, time-frequency analysis methods, power spectrum density, and higher-order spectra [20]. However, in this work, only 34 features in the time domain were considered for the initial analysis. On the other hand, [21] proposes a three-step classification scheme to address the between-subject search on sEMG signals generated by lower extremity movements. Independent component analysis decomposes the sEMG signals, time-domain discriminant features are extracted, and Fisher score is applied before using linear discriminant analysis.

Later, [22] presented a new method for recognizing movements of the lower extremities using the tuneable Q factor wavelet transform (TQWT) and Kraskov entropy (KrEn). sEMG signals from twenty subjects performing four different movements were recorded, the noise was removed using multiscale principal component analysis (MSPCA), and KrEn features were extracted from the subband signals obtained by TQWT. Subsequently, representative features were selected using the method of minimum redundancy and maximum relevance, and the highest classification was obtained using the linear discriminant analysis classifier.

In order to analyze which of the 34 features considered are the most useful to describe the signal, in this research work, the Fisher algorithm was considered because it assigns a weight to each one of them and leaves open the criteria in which they are eliminated features. This algorithm is based on differential geometry, from which Zhu proposed a Bayesian information geometry by combining information geometry with Bayesian decision theory [23], with which Fisher Score fixes.

Exploring a search space composed of 34 features represents a significant and meticulous effort in EMG signal research. Addressing such a broad set of features indicates exhaustive coverage, allowing the identification of features with lesser representation within the classifier. This breadth of exploration increases the likelihood of discovering unique interactions and patterns between features that might go undetected in a more restricted search space. Furthermore, working with such a wide variety strengthens the generality of the resulting model.

After analyzing the performance of each one of the features, a group of 5 features is proposed, and two more are indicated that can improve the precision if needed. The results are compared with the groups proposed in [24] and [25], which correspond to MAV + WL and WL + SHA, respectively.

The performance is tested through the precision of the selected group, using support vector machines, because they have a high potential for the classification of myoelectric signals, being able to recognize highly complex patterns [26].

In this paper, sEMG signals were recorded over four opposite muscles on the lower limb to compare the classification precision. The muscles selected to place the sensors were tibialis anterior (TA), gastrocnemius medials (GM), biceps femoris (BF), and vastus lateralis (VL), which present the better signal of the movement [27].

The present study stands out for its contribution to the field of sEMG signal classification, providing relevant contributions:

- Implementation of a group of features for the classification of lower extremity EMG signals using SVM, with high classification performance and computing time.
- Feature optimization: Using the Fisher algorithm, this work has provided a robust method for feature selection, minimizing redundancies and improving the accuracy of classifying sEMG signals.

The rest of the document is organized as follows. Section II reviews the theory necessary to understand the techniques used and a general description of support vector machines. Section III explains the order in which the experiments are performed and their results. The section IV concludes the work.

II. MATERIALS AND METHODS

This section shows the essential concepts applied in this work. Figure 1 shows the general flow diagram of the methodology followed in this work.

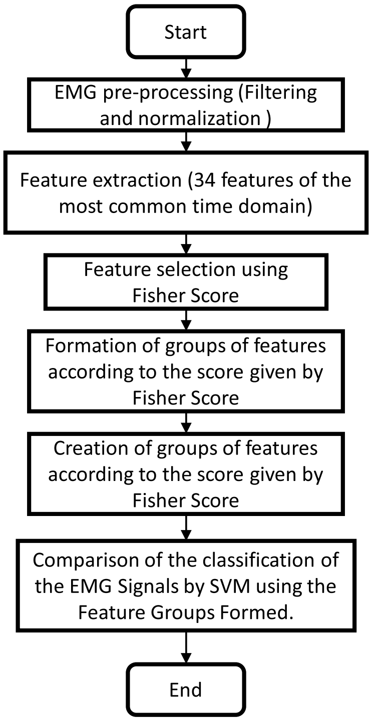

FIGURE 1. General flow diagram of the methodology followed in this work.

A. DATA BASE

The database described in this article was derived from work done by [28]. The consolidation of the information was carried out using MATLAB software.

Eight subjects were selected to construct the database: four men and four women. All participants are in good health, without overweight or amputations. Nine electrodes are placed on each person's right leg, two for each of the four muscles examined and an additional electrode for the reference. These electrodes are positioned at an distance of 2.5 cm from each other.

The specific electrode positions are:

- Vastus lateralis (VL) - 66% of muscle length.
- Tibialis anterior (TA) - 47.5% between the tip of the fibula and the medial malleolus.
- Gastrocnemius medialis (GM) - 38% of the muscle length from the medial side.
- Biceps femoris (BF) - Located at midway along the line between the ischial tuberosity and the lateral epicondyle of the tibia.
- Ground terminal - Inner side of the knee.

The subjects performed six different foot movements, repeated 20 times with 25-second intervals. With the state of relaxation included, there are seven movements to classify. These signals are sampled at a frequency of 1 kHz. The methodology of the experiment involved using the INA114 integrated circuit, followed by an amplification stage, filtering to eliminate 60 Hz frequencies, and, finally, an ADC conversion for digitization and storage on a PC. Table 1 shows the main features of the database.

TABLE 1. General features of the implemented database.

Feature	Value
Body member	Right leg
Participants	8 (four men and four women)
Sample rate	1 kHz
Signal duration	5 s
Relaxation time before starting the movement	1 s
Number of repetitions per movement	20
Number of channels	4 (TA, GM, BF, and VL)
Resolution	12 bits
Voltage amplitude	0 V-5V
Window time	250 ms

The 20 replicates are separated into two groups, making 560 samples for algorithm training and 560 for validation.

B. TIME DOMAIN FEATURE EXTRACTION

For the characterization of sEMG signals, a wide variety of features are available [29], [30], [31]. However, only 34 are used for the study, taking into account the ease and practicality of the calculation. Table 2 shows the features implemented for this study.

C. FISHER SCORE

The main idea of the Fisher Score algorithm for feature selection is similar to the principle of the support vector machine [32] since it consists of finding a subset of features in which the distances between data points of different classes are as large as possible. In contrast, those in the same class are as small as possible [10].

Given an input matrix $X \in \mathbb{R}^{d\times n}$, it is reduced to an output matrix $Z \in \mathbb{R}^{m\times n}$, where m is the number of features to be considered. The Fisher Score of each vector in the input matrix, corresponding to each feature, is calculated as follows:

$$F(X_i) = \frac{\sum_{j=1}^{c}\left(\mu_j^i - \mu^i\right)^2}{\sum_{j=1}^{c} n_j(\sigma_j^i)^2}, \tag{1}$$

where μ_i and σ_j correspond to the mean, and standard deviation of each vector and n_j is the size of the j-th class respectively in Z.

After calculating the Fisher Score for each feature, select the top m-ranked features with the highest scores.

D. NORMALIZATION

One of the normalization methods is the Z score, calculated through the formula

$$w_j^i = \frac{z_j^i - \mu_j^i}{\sigma_i}, \tag{2}$$

which gives the normalized value of each feature; in the same way as in Eq. (1), μ_i and σ_j correspond to the mean and standard deviation of each feature vector, respectively.

TABLE 2. Most common time-domain indicators in the classification of sEMG signals.

N°	Features	Abbr.	N°	Features	Abbr.
1	Average Amplitud Value	AAV	18	Fourth Temporal Moments	TM4
2	Mean Absolute Value	MAV	19	Fifth Temporal Moments	TM5
3	Modified Mean Absolute Value type 1	MAV1	20	Mean Absolute Value Slope	MAVSLP
4	Modified Mean Absolute Value type 2	MAV2	21	Maximum of Absolute Value	MaxAV
5	Simple Square Integral	SSI	22	Root Sum of Square Level	RSSQ
6	Data Variance	VAR	23	Skewness	SKEW
7	Zero Crossings	ZC	24	Kurtosis	KURT
8	Slope Sign Changes	SSC	25	Zero Crossings of Wavelet Coefficient	ZCWT
9	Waveform Length	WL	26	Energy of Wavelet Coefficient	EWT
10	Average Amplitude Change	AAC	27	Energy of Wavelet Packet Coefficient	EWP
11	Willson Amplitude	WAMP	28	Mean of Amplitude	MA
12	Root Mean Square Value	RMS	29	Shannon Entropy	SHA
13	Integrated EMG	IEMG	30	Third Order non-linear detector	VOR
14	Standard Deviation	STD	31	Difference of Absolute Standard Deviation	DASDV
15	Log-Detector	LOG	32	Maximum value	MAX
16	Myopulse Percentage Rate	MYOP	33	Minimum value	MIN
17	Third Temporal Moments	TM3	34	Difference between maximum and minimum value	MM

E. SUPPORT VECTOR MACHINES

Vapnik & Corina 1995 introduced a theory based on constructing an optimal separation hyperplane in a feature space, which is usually of high dimension when the inputs are mapped using non-linear functions. This algorithm, called SVM, is often used to separate two types of objects; however, it can also be used as a multiclass classifier [33].

The training matrix is formed by the input values $(x_1, y_1), \ldots, (x_m, y_m) \in \mathbb{R}^N \times \{+1, -1\}$, where x_i is the value of each feature and y_i is the assigned label, according to the type of object to which the set of features that describes it corresponds, also called class.

When the data are not linearly separable, they can be linearly transformed by $\varphi \colon \mathbb{R}^N \to F$ according to Eq. (3).

$$w \cdot \varphi(x) + b = 0, \qquad w \in \mathbb{R}^N, \quad b \in \mathbb{R}^N \tag{3}$$

Then, the problem is reformulated as a problem to be solved through Quadratic Programming (QP) by building an optimal hyperplane with the maximum value of the separation margin and a maximum error ξ in the training algorithm, as seen in Eq. (4):

$$\min_{w,b} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m} \xi_i \tag{4}$$

subject to

$$y_i(w \cdot \varphi(x_i) + b) \geq 1 - \xi_i, \qquad i = 1, \ldots, m \tag{5}$$

From Eq. (4), called the cost function, the first term is considered as the maximum separation between the classes, and the second term indicates the upper limit for the errors in the training data. Finally, the constant $C \in [0, \infty)$ indicates a compensation between the misclassified samples of the training set and the separation of the rest of the samples with a maximum margin.

F. PERFORMANCE METRICS

The false positives and negatives obtained in the classification of the movements made by the system are used to calculate: the precision (PREC) Eq. (6), the sensitivity (SENS) Eq. (7), the specificity (SPEC) Eq. (8) and Positive Predictive Rate (PPR) Eq. (9). *TN* is the true negative case, *FN* is the false negative case, *TP* is the true positive case, and *FP* is the false positive case.

$$\text{PREC} = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

$$\text{SENS} = \frac{TP}{TP + FN} \tag{7}$$

$$\text{SPEC} = \frac{TN}{TN + FP} \tag{8}$$

$$\text{PPR} = \frac{TP}{TP + FP} \tag{9}$$

G. DATA PROCESSING

An ASUS brand laptop computer is used, with an Intel i7 processor, 8 GB of RAM, a 512 GB solid state hard drive, and a 64-bit Windows 10 operating system.

The MATLAB software is used with the LIBSVM version 3.2 library to process sEMG signals. This extension provides a module to apply SVM with various Kernels. For this work, a linear Kernel was produced. A C-SVC is implemented whose cost value C is '1'. On the other hand, a 60 Hz notch filter is used. The feature vectors are formed considering only a window of 250 ms from the start of the motion. The feature matrix is formed by calculating the 34 features of the seven movements of each of the four sensors. On the other hand, the Fisher Score feature selection algorithm is taken from the ASU Feature Selection Repository [32].

III. RESULTS AND DISCUSSION

Before using the Fisher Score, an individual evaluation of the precision obtained by each feature is carried out, and then different groups are formed with the features with the best results according fisher score.

A. COMPREHENSIVE FEATURE EVALUATION: ANALYZING EACH FEATURE INDIVIDUALLY

Figure 2shows the number of times each feature is among the best three evaluated. Features that received seven votes

TABLE 3. Precision and processing time.

N°	Features	PREC	Time (ms)	N°	Features	PREC	Time (ms)
1	AAV	41.96%	2.177	18	TM4	41.61%	1.193
2	MAV	72.68%	1.331	19	TM5	34.23%	1.168
3	MAV1	71.07%	1.375	20	MAVSLP	47.68%	1.688
4	MAV2	69.82%	1.135	21	MaxAV	64.29%	1.269
5	SSI	60.18%	1.435	22	RSSQ	73.21%	1.437
6	VAR	60.18%	1.421	23	SKEW	38.21%	2.034
7	ZC	55.36%	1.489	24	KURT	54.11%	1.482
8	SSC	68.93%	1.451	25	ZCWT	61.61%	1.527
9	WL	69.29%	1.129	26	EWT	40.18%	1.297
10	AAC	69.29%	1.239	27	EWP	35.89%	1.935
11	WAMP	63.93%	1.108	28	MA	34.64%	1.888
12	RMS	73.21%	1.183	29	SHA	67.50%	2.752
13	IEMG	72.68%	1.234	30	VOR	52.29%	1.209
14	STD	41.78%	1.156	31	DASDV	60.00%	1.040
15	LOG	71.79%	1.187	32	MAX	65.36%	1.192
16	MYOP	52.32%	1.901	33	MIN	65.54%	1.271
17	TM3	46.07%	1.442	34	MM	66.61%	1.430

or less are omitted. Precision and processing time for each of the features of is shown in Table 3. It is observed that those of group 1 could have better results in precision.

B. FEATURE SELECTION USING FISHER SCORE

The feature matrix is used as input to the Fisher selection algorithm. Subsequently, ten repetitions of each subject are randomly chosen for each experiment to form the training matrix, and the remaining ten are used for validation. This procedure is performed ten times to obtain the evaluation parameters.

In the methodological development of the study, the Fisher Score was used to select features. This technique produced slightly different results in each experimental run. A scoring mechanism was adopted to address this variability and ensure consistent feature selection: each time a feature was ranked in the top three by the Fisher Score, it was assigned a point. This systematic accumulation of points over multiple iterations provided a measure of consistency and relevance for each feature. Figure 2 illustrates the features that consistently emerged as the most salient, having been selected at least seven times within the top three positions.

Subsequently, the selected features were categorized into three groups for analysis. The first group consisted of the three features with the highest number of points, thus reflecting their prominence in selection frequency. The second group included those features with intermediate scores, specifically those that accumulated 12 to 14 points. The third group considered the remaining features that reached a minimum of seven points. This classification allowed a detailed analysis of the predictive power of the features and their relative importance in the effectiveness of the model.

The precision and processing time for each of the feature are shown in Table 3. According to these, the groups are as follows: for group 1, the feature best evaluated are SSC and WAMP and MAV2, remaining in a second group, with a similar range of votes to WL, RMS, RSSQ, ZCWT and MAX.

TABLE 4. Performance by initial classification by groups.

Feature	SPE	SEN	ACC	PPR
Group 1	95.78%	75.08%	92.71%	74.48%
Group 2	97.79%	86.68%	96.19%	86.66%
Group 3	97.80%	86.76%	96.22%	86.77%

TABLE 5. The processing time required for the calculation of each of the features.

Features	Time (ms)
MAV2	1.1351
SSC	1.4513
WAMP	1.1057
RMS	1.1837
RSSQ	1.1437
ZCWT	1.5270
SHA	2.7528
MAX	1.1923

TABLE 6. The performance of the features best evaluated by Fisher score.

Features	SPEC	SENS	PREC	PPR
RMS+RSSQ+MAV+IEMG	96.2%	77.9%	93.6%	77.6%
RMS+RSSQ+MAV+IEMG+LOG+MAV1	96.6%	80.1%	94.1%	79.4%
RMS+RSSQ+MAV+IEMG+LOG+MAV2	97.0%	82.2%	94.8%	81.8%

Finally, in the third group are AAV, MAV, AAC, IEMG, LOG, MaxAV, SHA and MIN.

However, as seen in Table4, the feature of group 1 do not have the best results in precision. On the contrary groups 2 and 3 exhibiting better performance.

On the other hand, processing time is an essential factor when evaluating the performance of an algorithm. Table 5 shows the processing time required for the calculation of each of the features.

In a search for better performance, extended groups were formed, according to Table 6, which shows the performance of the four best-evaluated characteristics when used together, and two more proposals annexing the fifth and sixth, and with the fifth and seventh. It is observed that even using the six features with the highest precision cannot achieve a precision more significant than 85%.

C. TOWARD THE BEST FEATURE COMBINATION

In order to obtain the best group for a higher PPR, it is decided to combine the features of group 1. Later, two from group 2 and one from group 3 are combined to avoid information redundancy.

The contribution of each feature to the classification precision can also vary according to the available information. Due to this, what works for a person may not be the correct for another, so proposing a group of features that works for one subject does not guarantee that it works for another, as seen in Figure 3, where W4 (woman four) has the lowest results with any group, up to almost 20% difference, and M1 (man one) has an almost perfect result with any of them.

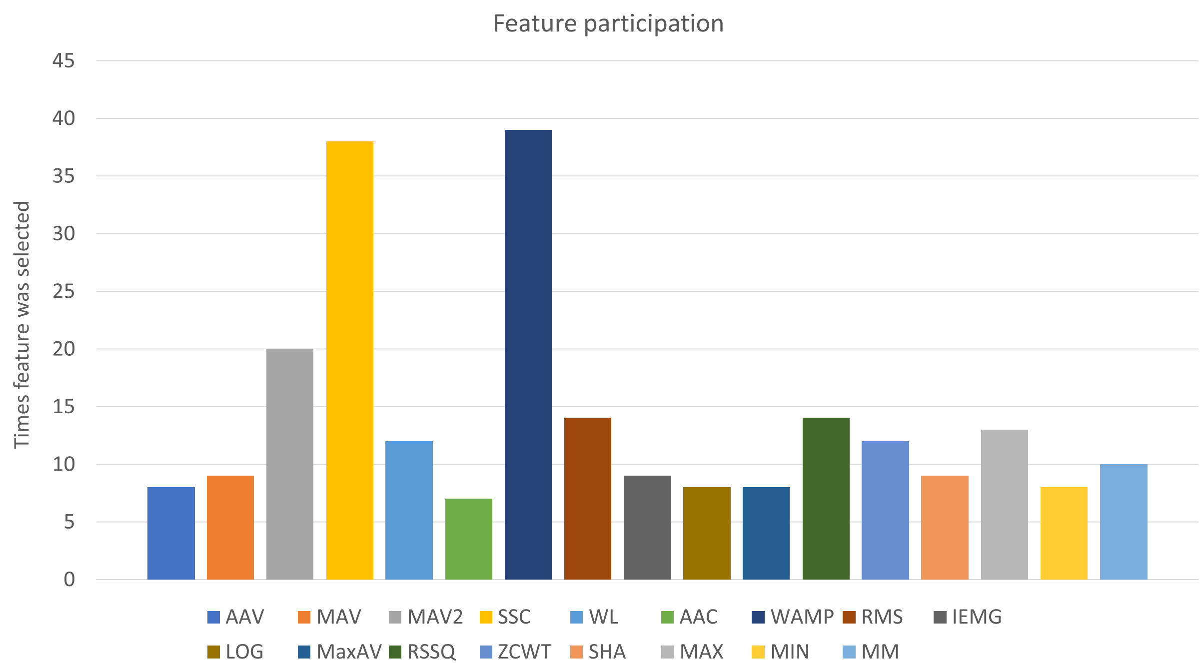

FIGURE 2. Participation of each trait selected by the Fisher Score breeder.

TABLE 7. Comparison of performance metrics for feature combinations in classification.

Features	SPEC	SENS	PREC	PPR
MAV2+SSC+WAMP (Group 1)	98.4%	90.1%	97.2%	90.1%
Group 1+RMS	98.6%	91.5%	97.6%	91.4%
Group 1+RMS+RSSQ	98.8%	92.7%	97.9%	92.7%
Group 1+RMS+MAX	99.1%	94.3%	98.4%	94.3%
Group 1+RMS+ZCWT	99.3%	95.8%	98.8%	95.8%
Group 1+RMS+SHA+MAX	99.6%	97.5%	99.3%	97.5%
Group 1+RMS+SHA+ZCWT	100%	98.0%	99.0%	98.0%

Table 7 illustrates the results obtained with the classification with different combinations of features of group 1 and some of group 2.

It is observed that a precision of 98% is obtained when using different features of group 2, which indicates that several offer excellent precision results without the need to include them all, even when one from group 3 is added.

On the other hand, the processing time varies according to the way each one of them is calculated. The average classification times for each group are shown in Table 8. The time does not increase considerably from 3 to 6 features, so it is only essential to consider the time it takes to calculate each feature.

When the processing time for the calculation of the features and the training time is added, there is a variation of more than 2.6 ms when using six features, compared to the use of five, and the time is doubled if compared to the use of three, so it is important to consider the set of features to be used.

TABLE 8. Processing time for group classification.

Features	Time (ms)
MAV2+SSC+WAMP	1.5497
MAV2+SSC+WAMP+RMS	1.6437
MAV2+SSC+WAMP+RMS+RSSQ	1.7969
MAV2+SSC+WAMP+RMS+MAX	1.9448
MAV2+SSC+WAMP+RMS+ZCWT	2.1120
MAV2+SSC+WAMP+RMS+SHA+MAX	1.7559
MAV2+SSC+WAMP+RMS+SHA+ZCWT	1.9613

TABLE 9. Classification metrics for the selected set of features with respect to previous work.

Features	SPEC	SENS	PREC	PPR
SSC + WAMP	97.8%	86.8%	96.2%	86.8%
WL + SHA	97.8%	86.7%	96.2%	86.7%
MAV + WL	95.8%	75.1%	92.7%	74.5%

D. COMPARISON WITH OTHER PROPOSED GROUPS

Finally, a comparison is made with other proposed groups in [24] and [25], which correspond to MAV + WL and WL + SHA, respectively. The comparison compares the two features with the highest number of occurrences in Figure 2. The results are shown in Table 9.

The two minimum features suggested for the classification of sEMG signals in this work (SSC + WAMP) are slightly higher than those suggested in [24], so it can be estimated that the performance is the same. On the other hand, as shown in Table 10, the computation time of the features is very different, SSC + WAMP only takes 0.01220 ms, while WL + SHA 0.01521 ms, which delays the response time of the classifier. This time could be significant if real-time EMG signal classification applications are considered.

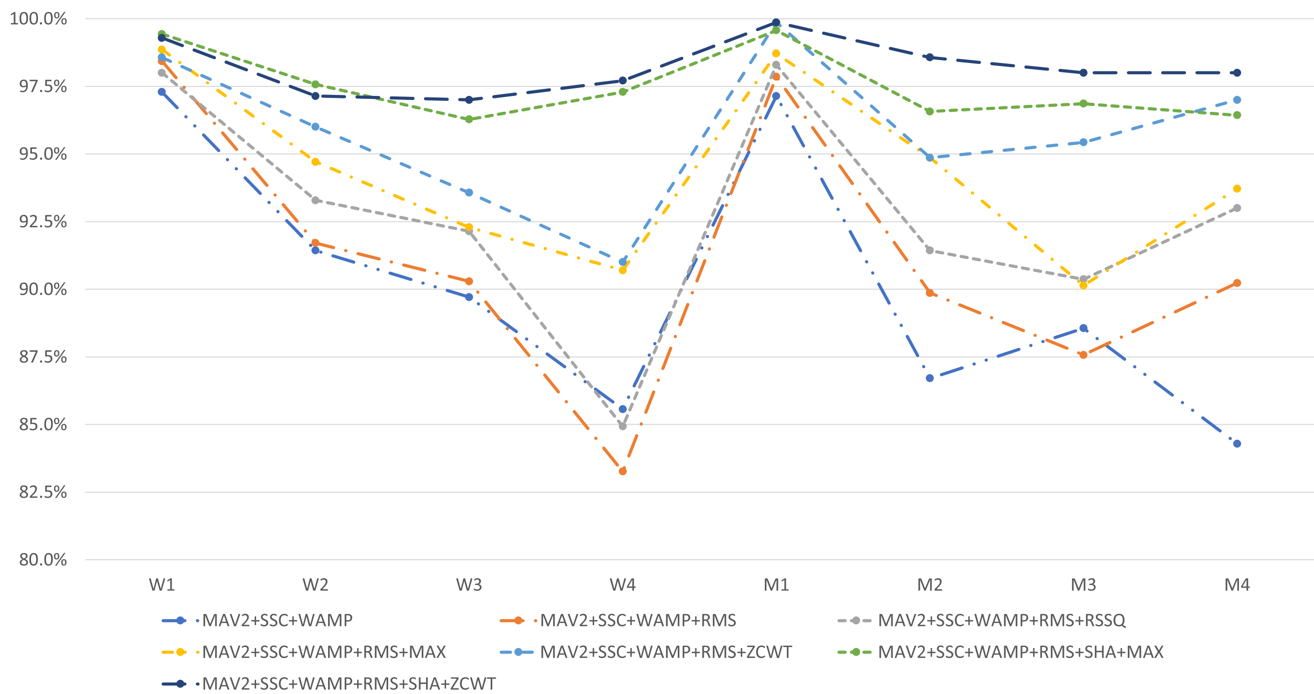

FIGURE 3. Precision obtained by group, where W represents the women in the database and M represents the men.

TABLE 10. Calculation times for the evaluation of the most efficient EMG signal features.

Feature	Time (ms)
MAV	0.0085
MAV2	0.1861
SSC	0.0068
WL	0.0061
WAMP	0.0053
RMS	0.0003
RSSQ	0.0060
ZCWT	1.2551
SHA	10.015
MAX	0.0068

The calculation time to obtain a classification greater than 94% using the features MAV2 + SSC + WAMP + RMS + MAX takes approximately 0.20 ms. On the contrary, to reach a classification of 98%, the time increases by 10 ms since it is necessary to calculate an additional feature, SHA.

IV. CONCLUSION

Data analysis in tables 6 and 7 reveals that combining the functions with the best individual performance does not always lead to the highest precision. This finding suggests that, in some instances, there may be non-linear or complementary interactions between the features that must be considered to obtain the best performance in the study system.

A strategy based on grouping features with outstanding scores when evaluated together and in multiple iterations is suggested to improve the accuracy of the predictions. This methodology permitted identifying a set of characteristics that exhibit a precision of 98%. These results indicate that synergistically combining specific attributes yields substantially better performance than using them separately. However, questions remain to be explored, such as interpreting the observed interactions between features and the reasons behind their joint contribution to accuracy.

Future research must deepen the analysis of these interactions to obtain a more complete understanding of the underlying mechanisms. Furthermore, the potential of applying deep learning techniques could be explored. The results of this study highlight the importance of considering the synergistic combination of traits rather than simply selecting the ones with the best individual performance. The proposed methodology has proven to be highly effective. It requires a set of features with exceptionally high precision and identifying two key features whose sum leads to near-perfect precision.

Finally, the observation of variations in performance among the subjects, as presented in Figure 3, indicates the need to deepen the study of the behavior of the SEMG signals. These differences highlight how the unique factors of each individual can influence the classification results. It is recognized that the analysis of these variations must be a critical approach in future investigations. This understanding is crucial to improve the precision of classification models and increase the applicability of findings and practical solutions in the scientific community.

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