Selection of sEMG-based Configuration for a Hand Gesture Recognition System

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***Abstract*—In recent decades, extensive research has been conducted on the analysis of Electromyography (EMG) signals, aiming to establish a novel communication pathway that utilizes the electrical activity generated by muscle contractions to control external devices. However, determining the optimal configuration for such systems in a given scenario remains as a challenging task. The challenges arise from two main factors: the growing number of available feature extraction methods and classification algorithms, and the necessity of designing control systems that prioritize user comfort, with considerations such as a reduced number of electrodes and fast reaction times. In this paper we propose a method to determine the most suitable configuration for an EMG system by considering three crucial parameters in control systems: reaction time, accuracy, and the required number of channels.**

***Index Terms*—Control systems, Electromyography, Hand gestures**

I. Introduction

Electromyography (EMG) is a widely used technique for evaluating and recording the electrical activity generated by skeletal muscles. This technique enables the analysis of EMG signals to detect abnormalities, assess muscle activation levels, and investigate the biomechanics of human or animal movements. To human-computer interaction, surface EMG (sEMG) has emerged as a valuable tool for designing interfaces that facilitates seamless interaction between humans and computers [1], [2].

The main objective of utilizing sEMG in Human-Machine Interfaces (HMI) is to accurately discern the user's intended actions by distinguishing between distinct electrical patterns generated by various muscle contractions [3]. This opens up new possibilities for creating user-friendly and efficient interfaces that cater to a diverse range of individuals and their unique needs.

Numerous studies have focused on evaluating the performance of feature extraction methods and classifier algorithms [4]. Many of these methods rely on well-known statistics such as standard deviation, root mean square, and mean absolute value, which are relatively straightforward to implement [5]. However, alternative approaches for signal characterization, such as wavelet analysis and principal component analysis have also been explored in previous studies [6]–[8]. For feature classification, the use of supervised and unsupervised algorithms to determine hand movements based on the extracted features has been widely studied. There is a wide range of options available [9], including Support Vector Machines (SVM) [10], and Linear and Quadratic Discriminant Analysis (LDA) [11], among others [12].

Although classifier accuracy is a primary concern in HMI, it is equally important to assess and optimize the time response of the system and consider user comfort to create a reliable and user-friendly system. The response time refers to the speed at which the HMI system can detect and interpret the user's intended movements based on the EMG signals. A fast response time is crucial for real-time applications to ensure smooth and seamless interaction between the user and the machine. Furthermore, comfortable and ergonomic interfaces can enhance the user experience and reduce fatigue or discomfort during prolonged use. Factors such as the number of electrodes, electrode placement, sensor size and weight, or the overall design of the interface play a significant role in ensuring user comfort.

In this work, a systematic approach to optimize the parameters involved in the training step of an sEMG-based HMI system is proposed. Our optimization methodology is focused on three key parameters:

- Utilization of a reduced number of sensors: It is crucial to minimize the number of sensors employed in the sEMG system. This reduces the overall complexity, cost, and potential discomfort for the user.
- Balance between accuracy and computational complexity. This can be achieved through the use of efficient feature extraction algorithms and classification methods.
- Detection of muscle movements using a reduced number of samples: this implies the use of robust feature extraction methods and machine learning algorithms that can effectively capture the essential information from EMG signals in a concise time frame. This reduces overall complexity, cost and reaction time.

This paper is organized as follows. Section II presents the review of the feature extraction methods and classification algorithms used in this paper. In this section, we also propose the procedure for selecting the most suitable configuration

Xunta de Galicia (grants ED431C 2020/15 and ED481B 2022/012), MCIN/AEI/10.13039/501100011033 and by the European Union NextGenerationEU/PRTR (grant TED2021-130240B-I00 (IVRY)). CITIC, as a center accredited for excellence within the Galician University System and a member of the CIGUS Network, receives subsidies from the Department of Education, Science, Universities, and Vocational Training of the Xunta de Galicia. Additionally, it is co-financed by the EU through the FEDER Galicia 2021-27 operational program (Ref. ED431G 2023/01).

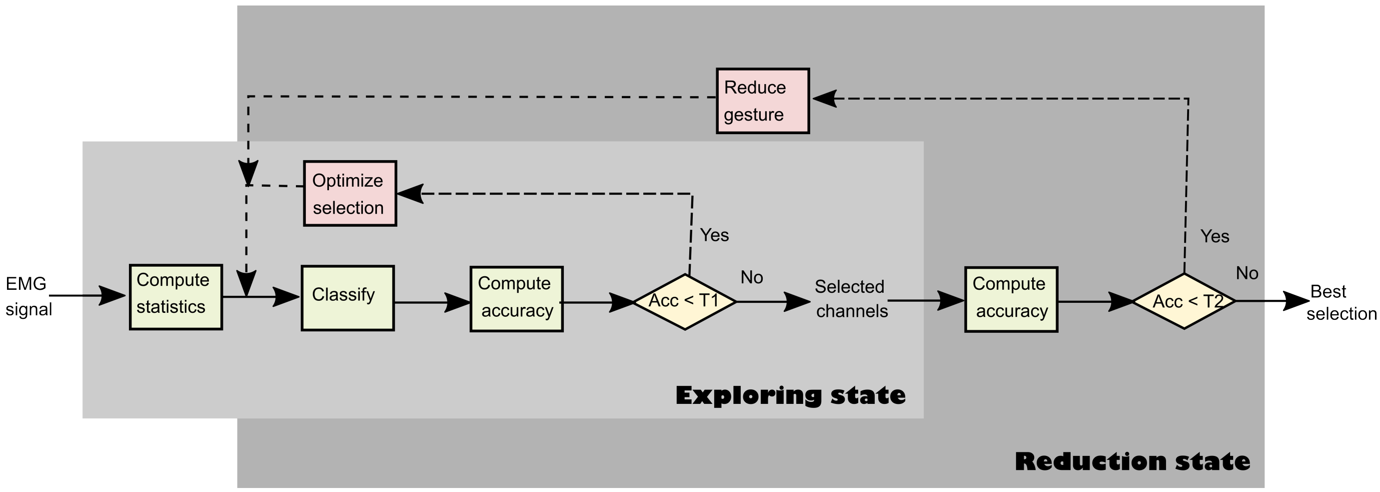

Fig. 1. Proposed system. First, the most suitable combination of feature extraction method and classification algorithm that achieves a higher accuracy than threshold $T1$ is computed in the exploring stage. Then, the reduction step is performed if the desired accuracy is not reached, i.e., is is lower than threshold $T2$.

of the sEMG-based HMI system. Section III presents the results obtained from a series of tests conducted to evaluate the performance and effectiveness of the proposed system. The results are then analyzed and interpreted in Section IV, providing insights into the strengths, limitations, and potential areas for system improvement. Finally, in Section V, the paper concludes with the most significant and relevant conclusions derived from this work.

II. Methods

Fig. 1 plots the diagram of the proposed system. The method for selecting the most suitable configuration of an sEMG-based HMI system involves two key stages:

- Exploring Stage. In this stage, features are computed from the raw EMG data using various methods. These extracted features are then processed by different classification algorithms. A selection criterion based on comparing the accuracy with a threshold is employed to determine the best feature extraction method for each classifier and the minimum number of channels required for accurate gesture recognition.
- Reduction Stage. Once the best configuration from the exploring stage (i.e., the most suitable combination of feature extraction method and classifier algorithm) is obtained, the system analyzes whether this configuration achieves the desired accuracy. If the desired accuracy is not attained, a reduction in the number of hand gestures to be detected is implemented, and the accuracy is computed again.

A. Feature Extraction

Feature selection methods have garnered significant attention in the classification field. Numerous studies have focused on developing and evaluating various techniques to identify the most informative and discriminative features for improving classification performance. In our study, we consider seven different statistics to extract features from the raw data, some of which have been used in previous works [13]–[15].

Let x_m be the sample at the discrete instant m of the M-length signal x. We define the following statistics:

- Root Mean Square (RMS):

$$RMS = \sqrt{\frac{1}{M}\sum_{n=1}^{M}(x_n)^2}$$

- Variance (VAR):

$$VAR = \frac{1}{M}\sum_{n=1}^{M}\left(x_n - \left(\frac{1}{M}\sum_{n=1}^{M}x_n\right)\right)^2$$

- Simple Square Integral (SSI):

$$SSI = \sum_{n=1}^{M}(x_n)^2$$

- Difference Variance Value (DVARV):

$$DVARV = \sum_{n=1}^{M-1}(x_{n+1} - x_n)^2$$

- Log Difference Absolute Standard Mean Value (LDAMV):

$$LDAMV = \log\left(\sum_{n=1}^{M-1}|x_{n+1} - x_n|\right)$$

- Log Difference Absolute Standard Deviation Value (LDASDV):

$$LDASDV = \log\left(\sum_{n=1}^{M-1}(x_{n+1} - x_n)^2\right)$$

- Integrated EMG (IEMG):

$$IEMG = \sum_{n=1}^{M}|x_n|$$

B. Classification Algorithm

Four well-known classifiers were used and tested for analyzing the effects of the seven feature selection algorithms (see [16]):

- Gaussian Naive Bayes (GaussianNB) is a probabilistic classifier that applies Bayes' theorem with strong independence assumptions. It assumes that the presence or absence of a specific feature is unrelated to other features, given the class variable. This classifier simplifies computations and is efficient for high-dimensional data. It models class distributions using Gaussian distributions.
- Quadratic Discriminant Analysis (QDA) is a modified version of Linear Discriminant Analysis (LDA) that takes into account the assumption that the covariance matrix can vary for each class. This modification makes QDA a more flexible classifier when dealing with datasets where the covariance structures of different classes significantly differ.
- Decision Tree Classifier (TREE) utilizes a classification or regression decision tree as a predictive model for analyzing a set of features. It operates by partitioning the feature space based on certain conditions and drawing conclusions accordingly. In this work, a maximum depth of 5 is employed.
- k-Neighbors Classifier (KNN) is a classification strategy that assigns a class label to a test point based on the majority vote of its nearest neighbors. Each test point is classified by considering the class labels of its k nearest neighbors. In this work, the value of k is set to 3, meaning that the three closest neighbors of a test point will contribute to the final classification decision.

C. Sequential Feature Selector

In our study, we employ a Sequential Feature Selector (SFS) to carefully select a subset of features from our dataset based on their relevance to the target variable. This iterative algorithm evaluates the performance of the chosen classifier and different feature extraction methods for each channel. We implemented a forward selection, where we begin with an empty set of features and iteratively add features based on the specified evaluation metric, which in our case is accuracy. For this purpose, a K-fold cross-validation approach is used with $K = 5$. In order to reduce the computational load, a tolerance parameter determines if the inclusion of a new feature represents an improvement in the accuracy (we set $t = 0.05$ in our experiments).

The inclusion of SFS serves two primary purposes in our research. Firstly, it helps us to identify the most effective feature extraction-classification algorithms. Secondly, SFS allows us to reduce the number of channels used in our analysis. This not only helps in reducing computational complexity but also enhances interpretability by prioritizing the most relevant channels.

III. Experiment

A. Dataset

For experimental purposes, we use the dataset from the UCI-Machine Learning Repository [17]. For recording patterns, they used a MYO Thalmic bracelet worn on a user's forearm, and a PC with a Bluetooth receiver [18], [19]. The bracelet is equipped with eight sensors equally spaced around the forearm that simultaneously acquire myographic signals while subjects performed series of static hand gestures with a sampling frequency of 200 Hz. Due to the computational complexity derived from the SFS algorithm, we decided to employ a reduced number of subjects to test the proposed system. Hence, 8 randomly selected subjects were used in the experiments.

The subject performs two series, each of which consists of six (seven) basic gestures. Each gesture was performed for 3 seconds with a pause of 3 seconds between gestures. In this work, we marked as (0) hand at rest, (1) hand clenched in a fist, (2) wrist flexion, (3) wrist extension, (4) radial deviations and (5) ulnar deviations.

In the sequel, we present the mean and standard deviation (STD) of the results after performing cross-validation.

B. Results from Exploring Stage

The experiment involved conducting comparisons of classifiers using different window sizes, namely 256, 512, 768, and 1024. For each window size, the system computed statistics for eight channels, which were enumerated from 0 to 7. To determine the best combination, the SFS method was utilized.

Table I shows the results obtained for a window size of 256 samples, which is equivalent to $1.28\,\text{s}$. It is evident that for three statistics (RMS, LDAMV, and LDASDV), the highest accuracy is achieved using the QDA classifier. Conversely, for four statistics (VAR, SSI, DVARV, and IEMG), the KNN classifier yields the best accuracy. The number of selected channels varies depending on the specific feature selection process. Notably, the most favorable overall performance is observed when QDA is trained using LDASDV. In this particular case, the system achieves an accuracy of 0.794 ± 0.046, utilizing four channels (1, 3, 4 and 6).

Table II presents the results obtained for a window size of 512 samples. Comparing these results to those obtained with a window size of 256 samples, we observe an improvement in accuracy. However, it is important to note that the mean accuracy for all cases remains below 0.9. The best overall performance is achieved when QDA is trained using LDASDV. In this particular scenario, the system achieves an accuracy of 0.842 ± 0.069 by utilizing five channels (2, 3, 4, 5, 6). Notably, this configuration includes an additional channel compared to the setup with a window size of 256 samples.

The same strategy was employed for window sizes of 768 and 1024 samples. To summarize the overall process, Table III presents the configurations that yielded the best accuracy for each window size. It is noteworthy that the optimal configuration consistently involves the utilization of

TABLE I

RESULTS OBTAINED FROM EXPLORING STAGE FOR WINDOWS OF 256 SAMPLES: ACCURACY (MEAN $\pm$ STD) AND CHANNELS SELECTED FOR EACH STATISTIC AND CLASSIFICATION METHOD. THE SELECTION WITH THE BEST ACCURACY IS MARKED IN BOLD LETTERS.

Explored mehtods		Results	
Statistic	Classifier	Mean $\pm$ STD	Selected channels
RMS	GANB	0.533 ± 0.043	3, 6
	QDA	0.781 ± 0.050	1, 3, 4, 5, 6
	TREE	0.654 ± 0.064	2. 4. 6
	KNN	0.748 ± 0.053	1, 2, 4, 6
VAR	GANB	0.542 ± 0.044	3, 6
	QDA	0.542 ± 0.035	3, 6
	TREE	0.035	0
	KNN	0.634 ± 0.048	1, 4, 6
SSI	GANB	0.543 ± 0.046	3, 6
	QDA	0.543 ± 0.037	3, 6
	TREE	0.631 ± 0.025	0, 3, 4, 6
	KNN	0.633 ± 0.043	1, 4, 6
DVARV	GANB	0.544 ± 0.056	3, 6
	QDA	0.547 ± 0.050	3, 6
	TREE	0.167	0
	KNN	0.724 ± 0.025	0, 2, 3, 5, 6
LDAMV	GANB	0.707 ± 0.094	1, 3, 4, 6
	QDA	0.789 ± 0.047	1, 3, 4, 6
	TREE	0.571 ± 0.065	2, 6
	KNN	0.755 ± 0.030	0, 3, 4, 6
LDASDV	GANB	0.717 ± 0.090	1, 3, 4, 6
	QDA	0.794 ± 0.046	**1, 3, 4, 6**
	TREE	0.578 ± 0.053	2, 6
	KNN	0.751 ± 0.033	0, 3, 4, 6
IEMG	GANB	0.548 ± 0.041	3, 6
	QDA	0.724 ± 0.039	1, 3, 4, 6
	TREE	0.684 ± 0.053	1, 3, 4, 6
	KNN	0.768 ± 0.026	0, 1, 3, 4, 6

TABLE II

RESULTS OBTAINED FROM EXPLORING STAGE FOR WINDOWS OF 512 SAMPLES: ACCURACY (MEAN $\pm$ STD) AND CHANNELS SELECTED FOR EACH STATISTIC AND CLASSIFICATION METHOD. THE SELECTION WITH THE BEST ACCURACY IS MARKED IN BOLD LETTERS.

Explored mehtods		Results	
Statistic	Classifier	Mean $\pm$ STD	Selected channels
RMS	GANB	0.557 ± 0.049	3, 6
	QDA	0.817 ± 0.052	1, 3, 4, 5, 6
	TREE	0.628 ± 0.086	2, 4, 6
	KNN	0.770 ± 0.589	1, 2, 4, 6
VAR	GANB	0.554 ± 0.056	3, 6
	QDA	0.555 ± 0.038	3, 6
	TREE	0.167	0
	KNN	0.686 ± 0.058	1, 2, 4, 6
SSI	GANB	0.554 ± 0.056	3, 6
	QDA	0.555 ± 0.041	3, 6
	TREE	0.636 ± 0.063	3, 4, 6
	KNN	0.677 ± 0.076	1, 2, 4, 6
DVARV	GANB	0.55 ± 0.057	3, 6
	QDA	0.554 ± 0.049	3, 6
	TREE	0.167	0
	KNN	0.662 ± 0.03	0, 3, 6
LDAMV	GANB	0.712 ± 0.102	1, 3, 4, 6
	QDA	0.836 ± 0.065	2, 3, 4, 5, 6
	TREE	0.559 ± 0.071	2, 6
	KNN	0.783 ± 0.053	1, 3, 4, 6
LDASDV	GANB	0.725 ± 0.098	1, 3, 4, 6
	QDA	0.843 ± 0.069	**2, 3, 4, 5, 6**
	TREE	0.575 ± 0.08	2, 6
	KNN	0.796 ± 0.045	1, 3, 4, 6
IEMG	GANB	0.555 ± 0.043	3, 6
	QDA	0.807 ± 0.033	1, 2, 4, 6
	TREE	0.704 ± 0.047	1, 3, 4, 6
	KNN	0.765 ± 0.050	1, 2, 4, 6

the QDA classifier with either LDASDV statistics for window sizes of 256, 512, and 1024 samples, or LDAMV statistics for a window size of 768 samples. Interestingly, the increase in the number of samples only leads to improved performance when transitioning from 256 to 512 samples. However, it is important to mention that in all cases, the achieved accuracy remains below 0.9.

C. Results from Reduction Stage

Given that the accuracy achieved during the exploration stage remains below 0.9, the reduction stage is employed to identify a new configuration that involves classifying a reduced number of hand movements. Fig. 1 illustrates the process of systematically eliminating individual hand movements (from 0 to 5) and measuring the resulting classification accuracy. The best result is obtained, and this hand gesture is removed for the next iteration. The procedure continues until the accuracy reaches a value equal to or greater than 0.9, at which point it stops (i.e., we remove one additional movement at each iteration).

Table IV presents the results obtained for each configuration in the reduction stage. This table shows information on the achieved accuracy, the number of iterations required to reach the desired accuracy threshold (0.9), the selected channels, and the removed gesture. For the first iteration, the configuration LDAMV-QDA with 768 samples and LDASDV-QDA with 1024 samples achieve the desired accuracy by eliminating the hand gesture corresponding to ulnar deviation. Note also that the system proposes to use only four sensors. However, for LDASDV-QDA with 256 samples and 512 samples, we need to remove two hand gestures corresponding to radial deviations and ulnar deviations. This reduction of hand gestures allows us to use only three sensors.

TABLE III

BEST RESULTS OBTAINED FROM EXPLORING STAGE FOR WINDOWS OF 256, 512, 768 AND 1024 SAMPLES AND QDA CLASSIFIER: ACCURACY (MEAN $\pm$ STD) AND CHANNELS SELECTED FOR EACH WINDOW SIZE.

Explored mehtods		Results	
Statistic	Win. size	Mean $\pm$ STD	Selected channels
LDASDV	256	$0,794 \pm 0,046$	1, 3, 4, 6
LDASDV	512	$0,843 \pm 0,069$	2, 3, 4, 5, 6
LDAMV	768	$0,839 \pm 0,070$	2, 3, 4, 5, 6
LDASDV	1024	$0,843 \pm 0,072$	2, 3, 4, 5, 6

IV. DISCUSSION

The experimental results demonstrate the effectiveness of our system in achieving an optimized configuration. There is redundancy within the EMG signal when eight channels are used. For example, we found that it is possible to detect three hand gestures using a cost-effective configuration with only 256 samples and three channels. However, when it comes to identify four hand gestures, it becomes necessary to utilize 768 samples and four channels. The final decision regarding the configuration should be based on application requirements.

TABLE IV

BEST RESULTS OBTAINED FOR WINDOWS OF 256, 512, 768 AND 1024 SAMPLES IN THE REDUCTION STAGE: ACCURACY (MEAN $\pm$ STD), CHANNELS SELECTED AND REMOVED HAND GESTURES FOR CONFIGURATIONS OBTAINED IN THE EXPLORING STAGE. CONFIGURATION 1: LDASDV-QDA; CONFIGURATION 2: LDAMV-QDA

Conf.	Win.	Iter.	Results		
			Mean $\pm$ STD	Channels	Removed ges.
1	256	1	0.869 ± 0.043	1, 3, 4, 6	5
		2	0.919 ± 0.041	0, 3, 4	5, 4
1	512	1	0.895 ± 0.036	1, 3, 4, 6	5
		2	0.939 ± 0.04	0, 3, 4	5, 4
2	768	1	0.900 ± 0.041	1, 3, 4, 6	5
1	1024	1	0.920 ± 0.023	1, 3, 4, 6	5

Furthermore, the results demonstrate that the QDA classifier method, in combination with either LDASDV or LDAMV feature extraction methods, is the one that works best on this dataset. However, it is important to note that our system is versatile and can explore various classification algorithms and feature extraction methods. This flexibility allows for experimentation and adaptation to different datasets and application scenarios.

V. CONCLUSIONS

We have proposed a systematic approach to optimize the parameters involved in the training step of an EMG-based HMI system. Our investigation focused on exploring various feature extraction techniques and evaluating different classification algorithms. By systematically evaluating these combinations, our goal was to identify the optimal configuration for each classifier, ultimately maximizing the accuracy of hand movement recognition.

In cases where the desired accuracy threshold was not achieved through the initial exploration, our system employed an additional analysis. By selectively removing certain hand gestures from the dataset, we assessed the impact on performance and accuracy. This step allowed us to further refine the system's configuration and determine the most suitable setup that would achieve the desired accuracy with the minimum number of sensors.

As a consequence, by carefully considering both accuracy and practical constraints, our approach aims to strike a balance between performance and usability in EMG-based HMI systems.

REFERENCES

[1] C. I. Christodoulou and C. S. Pattichis, "Unsupervised pattern recognition for the classification of EMG signals," *IEEE Transactions on Biomedical engineering*, vol. 46, no. 2, pp. 169–178, 1999.

[2] A. R. Mane, S. Biradar, and R. Shastri, "Review paper on feature extraction methods for EEG signal analysis," *Int. J. Emerg. Trend Eng. Basic Sci*, vol. 2, no. 1, pp. 545–552, 2015.

[3] G.-C. Chang, W.-J. Kang, J.-J. Luh, C.-K. Cheng, J.-S. Lai, J.-J. J. Chen, and T.-S. Kuo, "Real-time implementation of electromyogram pattern recognition as a control command of man-machine interface," *Medical engineering & physics*, vol. 18, no. 7, pp. 529–537, 1996.

[4] A. Turner, D. Shieff, A. Dwivedi, and M. Liarokapis, "Comparing machine learning methods and feature extraction techniques for the emg based decoding of human intention," in *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2021, pp. 4738–4743.

[5] A. Phinyomark, S. Hirunviriya, C. Limsakul, and P. Phukpattaranont, "Evaluation of emg feature extraction for hand movement recognition based on euclidean distance and standard deviation," in *ECTI-CON2010: The 2010 ECTI International Confernce on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology*, 2010, pp. 856–860.

[6] A. Phinyomark, C. Limsakul, and P. Phukpattaranont, "Application of wavelet analysis in emg feature extraction for pattern classification," *Measurement Science Review*, vol. 11, no. 2, pp. 45–52, 2011. [Online]. Available: https://doi.org/10.2478/v10048-011-0009-y

[7] J. Rafiee, M. Rafiee, F. Yavari, and M. Schoen, "Feature extraction of forearm emg signals for prosthetics," *Expert Systems with Applications*, vol. 38, no. 4, pp. 4058–4067, 2011.

[8] X. Zhang and M. Zhang, "Study on the methods of feature extraction based on electromyographic signal classification," *Medical & Biological Engineering & Computing*, vol. 61, no. 7, pp. 1773–1781, 2023.

[9] Y. Omama, C. Haddad, M. Machaalany, A. Hamoudi, M. Hajj-Hassan, M. A. Ali, and L. Hamawy, "Surface emg classification of basic hand movement," in *2019 Fifth International Conference on Advances in Biomedical Engineering (ICABME)*, 2019, pp. 1–4.

[10] M.-F. Lucas, A. Gaufriau, S. Pascual, C. Doncarli, and D. Farina, "Multi-channel surface emg classification using support vector machines and signal-based wavelet optimization," *Biomedical Signal Processing and Control*, vol. 3, no. 2, pp. 169–174, 2008, surface Electromyography.

[11] B. Saeed, S. O. Gilani, Z. u. Rehman, M. Jamil, A. Waris, and M. N. Khan, "Comparative analysis of classifiers for emg signals," in *2019 IEEE Canadian Conference of Electrical and Computer Engineering (CCECE)*, 2019, pp. 1–5.

[12] V. M. Gallón, S. M. Vélez, J. Ramírez, and F. Bolaños, "Comparison of machine learning algorithms and feature extraction techniques for the automatic detection of surface emg activation timing," *Biomedical Signal Processing and Control*, vol. 94, p. 106266, 2024.

[13] D. Tkach, H. Huang, and T. A. Kuiken, "Study of stability of time-domain features for electromyographic pattern recognition," *NeuroEngineering Rehabil.*, vol. 21, 2010.

[14] A. Phinyomark, F. Quaine, S. Charbonnier, C. Serviere, F. Tarpin-Bernard, and Y. Laurillau, "Feature extraction of the first difference of EMG time series for EMG pattern recognition," *Computer Methods and Programs in Biomedicine*, vol. 117, no. 2, pp. 247–256, 2014.

[15] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for EMG signal classification," *Expert Systems with Applications*, vol. 39, no. 8, pp. 7420–7431, 2012.

[16] E. Keogh, *Instance-Based Learning*. Boston, MA: Springer US, 2017, pp. 672–673.

[17] S. Lobov, N. Krilova, I. Kastalskiy, V. Kazantsev, and V. Makarov, "Latent factors limiting the performance of sEMG-interfaces," *Sensors*, vol. 18, no. 4, p. 1122, Apr 2018.

[18] C. Tepe and M. C. Demir, "The effects of the number of channels and gyroscopic data on the classification performance in emg data acquired by myo armband," *Journal of Computational Science*, vol. 51, p. 101348, 2021.

[19] H. A. Javaid, M. I. Tiwana, A. Alsanad, J. Iqbal, M. T. Riaz, S. Ahmad, and F. A. Almisned, "Classification of hand movements using myo armband on an embedded platform," *Electronics*, vol. 10, no. 11, p. 1322, 2021.