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EMG classification of hand and wrist force tasks using fractal algorithms

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***Abstract*—The hand has excellent functional, aesthetic and social importance. However, Parkinson's disease, stroke, and other myopathies can cause motor impairments. Patients require a rehabilitation program to follow their progress, and one of the tools used to do that is the electromyographic (EMG) signals. This article proposes using algorithms to characterize and classify EMG signals during force exercises for the wrist and forearm. Eight healthy subjects participated in this study. They performed seven exercises, making five trials for each one. Signal features were analyzed in different time windows using a genetic algorithm and machine learning techniques to select the window that maximizes the classification. Combining four electrodes, seven exercises, and 14 algorithms achieved a classification accuracy of 92.41% using the Multilayer Perceptron classifier. The study demonstrates a highly reliable method for classifying forearm and wrist exercises based on EMG signals, useful for exoskeletons or rehabilitation platforms. Future work will focus on implementing EMG signals to enhance motor rehabilitation therapy and provide findings that will help the scientific community investigate the combination of EEG signals for rehabilitation purposes.**

***Index Terms*—Multiclass, electromyographic signals, force tasks, wrist and forearm.**

I. INTRODUCTION

The hand allows us to execute daily activities, communicating and interacting with the environment. However, it can suffer various structural, mobility and sensitivity impairments due to trauma, disease or stroke. Hand motor recovery aims to improve hand function and mobility, prevent secondary complications, and favour the patient's social and occupational integration. Treatment may include various modalities, such as physiotherapy, occupational therapy, functional electrical stimulation, orthoses, exoskeletons, botulinum toxin and surgery, [1]–[3]. The use of EMG signals for measuring and evaluating rehabilitation therapy has increased [4]. An example that can be found in this type of therapy is the control of the position of a computer cursor through EMG signals, gradually rehabilitating the patient with support from a physical therapist [5]. The type of signal acquisition device in EMG is determinant since obtaining readings with an adequate resolution for its application in rehabilitation is necessary, [6]. The quality and resolution of the EMG signals can be improved considering the type of electrodes, invasive (needle) and noninvasive (surface), and the number of electrodes (high-resolution and low-resolution). However, surface and low-resolution electrodes are the most used due to the lower cost and practical implementation at the expense of low resolution. To tackle this, artificial intelligence algorithms are applied. The challenge is to increase the number of tasks commonly used for rehabilitation sessions and classify them with high accuracy. Different approaches have been focused on classifying EMG signals. Fang et al. used 16 electrodes and a bio-inspired Neural Networks to classify six hand gestures of wrist and forearm, obtaining 82% accuracy, [7]. Leone and their collaborators used six electrodes and Non-Linear Logistic Regression algorithm for seven classes for wrist and forearm, reaching 98% of accuracy [8]

In this article, we propose using algorithms based on fractal and typical statistical features to characterize the EMG signal during different exercises performed with the wrist and forearm and classify the movements according to their strength. Applications of this processing could benefit rehabilitation therapy from good classification, as sEMG signals can be used as sensors in systems such as exoskeletons.

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II. Methodology

A. Subjects

Eight healthy, right-handed subjects, consisting of four women and four men between the ages of 20 and 25, participated in the experiment. They were asked to sleep at least 7 hours the night before the experiment and were suggested to avoid consuming coffee, alcohol and drugs. The study complied with the Declaration of Helsinki, [9]. All subjects were provided information about the experiment and signed an informed consent form. Subjects were seated in a comfortable chair, and their right arm was wiped. Four superficial electrodes were placed on the skin near the following muscles: supinator, flexor carpi ulnaris, pronator teres, and extensor carpi ulnaris as shown in Figure 1.

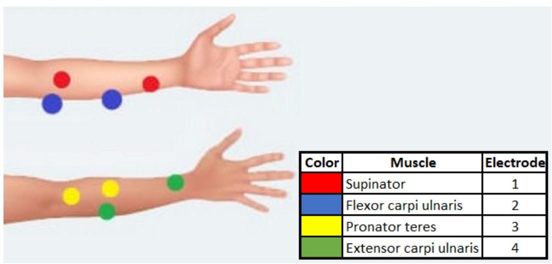

Fig. 1. Electrode placement used for the experiment.

B. Materiales

The electromyography (EMG) signal acquisition system consisted of an electronic card manufactured in the laboratory with a sampling frequency of 2000 Hz.

In addition, an experimental platform consisting of a desktop PC running Windows 10 64-bit, i7 processor, 16 GB RAM and an Nvidia GTX 750ti GPU, together with a monitor and speakers, was used.

Subsequently, the data obtained were processed through Matlab R2020b and WEKA 3.8.5 software.

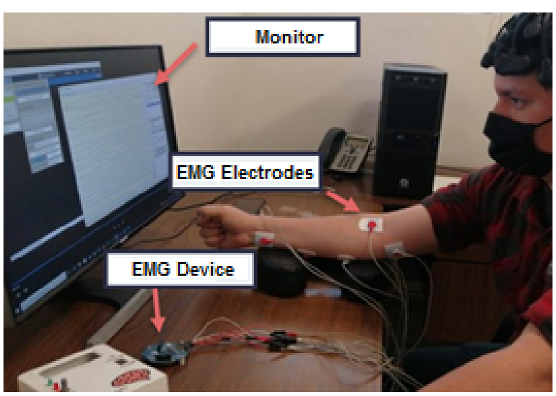

Fig. 2. Devices used in the experiment.

C. Task and procedure

Experiments were designed for 7 exercises: Abduction, Adduction, Pronation, Supination, Flexion, Extension and Circumduction. Each consisted of 11 steps, of which 6 were rest steps and 5 were test steps. The duration of each test step was 10 seconds, while each test step was 5 seconds. During rest, subjects were instructed to remain motionless and during the test steps were instructed to perform a repetition of the corresponding exercise. Each subject performed a total of 5 trials for each exercise. The sequence of the rest and test steps can be seen in Figure 3.

Time	10	5	10	5	10	5	10	5	10	5	10
Color	R	T	R	T	R	T	R	T	R	T	R
Total Time	10	15	25	30	40	45	55	60	70	75	85

Fig. 3. Timeline of the experiment showing where users started. R stands for rest and T stands for test.

D. sEMG signal analysis

Once the raw sEMG signal was obtained from each subject, the data analysis stages were carried out, which included signal preprocessing, extraction of relevant features, and classification of the signals. These stages are described below in Figure 4.

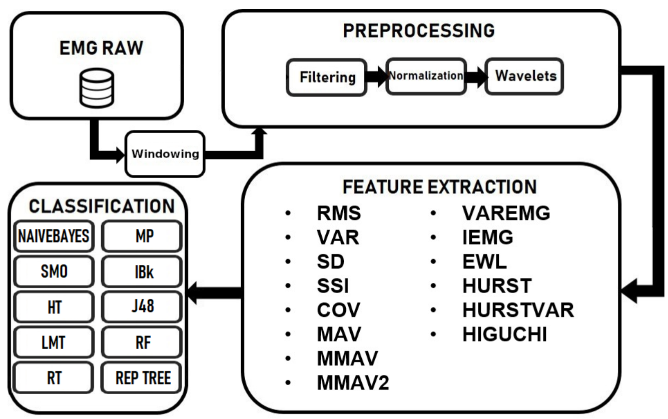

Fig. 4. Procedure: 1) Acquisition of raw sEMG signal: Measured with sEMG-based medical equipment; 2) Windowing: Extraction of data recorded during exercise (without rest); 3) Preprocessing: Filtering, normalization and wavelets; 4) Feature extraction: 14 algorithms for feature extraction; and 5) Classification: Selection of 10 classifiers in WEKA.

E. Pre-processing

An initial trimming of the intervals for each exercise was performed. Each initial time window consisted of 10 seconds of rest, followed by 5 seconds of exercise and then another 10 seconds of rest, resulting in 25-second windows, separating the measurement of each exercise and rest. See Figure 3.

Measurements were grouped according to the type of exercise, i.e., measurements of the same exercise for each electrode, person and repetition were grouped in the same class.

It was considered that, the exact instant of start and end of each exercise is unknown, which implies a tolerance of 1 second that for a 2000Hz sampling would represent considerably different results if not considered. To address this issue, it was decided to perform the processing in different time windows and compare the results according to the type of exercise to find the most appropriate time window.

A total of 23 time windows were determined, resulting from combinations of different time starts from 0.5 seconds before to 0.5 seconds after, with 0.1 second intervals, and exercise durations from 4.4 seconds to 6 seconds, with 0.2 second intervals.

Each measurement was processed at these 23 time intervals. First, a filter was applied and relevant features were amplified to remove noise present in the signals. Then, the signals were normalized to ensure a proper comparison between them. Finally, a frequency domain analysis was performed using the Wavelet transform. Details of the steps are given below:

1) *Filtering*: A sixth-order infinite impulse response (IIR) filter was applied to remove noise from the signals.
2) *Normalization*: All sEMG signals were normalized and rectified to ensure that the data were within a range greater than 0 and comparable between subjects.
3) *Wavelets*: Multiresolution wavelet analysis was used to obtain a time domain map and extract sEMG frequency components using the following equation:

$$W_f(a,b) = \langle f, \psi_{a,b} \rangle = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \psi \left(\frac{t-b}{a} \right) dt. \tag{1}$$

where a and b are dilation and translation parameters, respectively, $f(t)$ is the independent time variable. Four multiresolution levels with four coefficients were calculated. These provided the decomposition of the EMG signal at (20,150) Hz, although the ideal range is (150,350) Hz [10]. The output was $\omega = W_f(a,b)$.

F. Feature extraction

At each trimmed time window, it was proposed to perform the extraction of 14 features, of which 11 were provided by Standard Algorithms and 3 by Fractal Algorithms.

1) Standard algorithms: These algorithms are based on common statistical tools. The equation for each of them is shown below, where ω_i represents the partitioning of the EMG signal.

1) *Standard deviation (SD)*: Let L be the length of ω and μ be the mean of the signal; then one obtains

$$\sigma = \sqrt{\frac{1}{L} \sum_{i=1}^{L} (\omega_i - \mu)^2} \tag{2}$$

for sample ω_i at sampling time i.

2) *Root Mean Square (RMS)*: Let L be the length of ω, then

$$RMS = \sqrt{\frac{1}{L} \sum_{i=1}^{L} (\omega_i)^2} \tag{3}$$

3) *Coefficient of Variation (COV)*: This dimensionless quantity defines the ratio of standard deviation to mean of the signal, then

$$COV = \frac{\sigma}{\mu} \tag{4}$$

4) *Variance (VAR)*: Let L be the length of ω and μ the mean of the signal, then

$$VAR = \frac{1}{L} \sum_{i=1}^{L} (\omega_i - \mu)^2 \tag{5}$$

5) *Mean Absolute Value (MAV)*: This quantifies the average of the norm induced by $\mathcal{L}_1$, then

$$MAV = \frac{1}{L} \sum_{i=1}^{L} |\omega_i| \tag{6}$$

6) *Modified Mean Absolute Value (MMAV)*: A w-weighted extension of the MAV function:

$$MMAV = \frac{1}{L} \sum_{i=1}^{L} w_i \, |\omega_i| \tag{7}$$

where $w_i = 1$ if $i = [0.25L, 0.75L]$ else $w_i = 0.5$.

7) *Modified Mean Absolute Value 2 (MMAV2)*: A useful extension of MAV, given by:

$$MMAV2 = \frac{1}{L} \sum_{i=1}^{L} w_i |\omega_i| \tag{8}$$

where $w_i = 1$ if $i = [0.25L, 0.75L]$ else $w_i = 0.5$ else $i < 0.25L$ then $w_i = 4i/L$ else if $w_i > 0.75L$ then $w_i = 4(i-L)/L$.

8) *Variance of EMG (VAREMG)*: It measures the averaged EMG spectral power, quantified by:

$$VAREMG = \frac{1}{L} \sum_{i=1}^{L} (\omega_i)^2 \tag{9}$$

9) *Simple Square Integral (SSI)*: The EMG spectral power

$$SSI = \sum_{i=1}^{L} (\omega_i)^2 \tag{10}$$

10) *Integrated EMG (IEMG)*: is the sum of absolute values of the amplitude of the EMG signal; its equation is as follows:

$$IEMG = \sum_{i=1}^{N} |\omega_i| \tag{11}$$

11) *Enhanced Wavelength (EWL)*: A modification of wavelength given by:

$$EWL = \sum_{i=2}^{L} |(\omega_i - \omega_{i-1})|^p \tag{12}$$

where $p = 0.75L$ if $i = [0.2L, 0.8L]$ else $p = 0.5$.

2) Fractal Algorithms: To complement the information with features that indicate the dynamics and variability of the data, fractal geometry analysis of the signals was employed using the following techniques.

1) *Hurst exponent (Hrs)*: Using the Reescaled Range (RS) method, the mean M_i of subgroups Sg_i of the total signal w_i was calculated first, then the difference $D_i = L_i - M_i, \quad i = 1, 2, \cdots, m$ is calculated and the deviations $V_i = \sum_{j=1}^{i} G_j, \quad i = 1, 2, \cdots, m$, for range R_i:

$$R_n = \max_{i=1:m}(V_i) - \min_{i=1:m}(V_i) \tag{13}$$

Finally, the range R_n was normalized by S_n (standard deviation of L_i) and calculated for each length subgroup m,

$$\left\langle \frac{R}{S} \right\rangle_m = \frac{1}{d} \sum_{n=1}^{d} \frac{R_n}{S_n} \approx cm^H \tag{14}$$

where c is a positive constant and H stands for the Hurst exponent, which can also be interpreted as the persistence of the signal between 0 and 1, the closer to 1 the more persistent the signal is in this length of the data m, [11].

2) *Hurst Exponent with Variogram:*

$$\gamma(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} (X_{t+h} - x_t)^2 \tag{15}$$

The variogram Y(h) is a spatial adjustment or modeling considered as an estimator of population variance and structural analysis, where the population must have a trend of stationarity and is used to describe the relationship of paired observations separated by a distance h and, in other cases, with a direction, [12].

3) *Higuchi (HFD):* This algorithm it used to calculate the Higuchi Fractal Dimension (HFD) of a time series and is used to analyze the complexity and irregularity of data [13]. Where the length of Lm(k) is defined by:

$$L_m(k) = \frac{\sum_{i=1}^{\left\langle \frac{N-m}{k} \right\rangle} \left| X_N(m+ik) - X_N(m+(i-1)k) \right|}{\frac{\left\langle \frac{N-m}{k} \right\rangle k^2}{N-1}} \tag{16}$$

G. Classification

To develop an efficient Machine Learning model, it is essential to have data diversity. This implies that the data of the same class should be balanced and as different as possible from another class [14].

In order to maximize the classification of exercises, the results were regrouped by the type of algorithm applied, as shown in Figure 5. Within each group, the windows with the most different results between exercises were searched. To calculate the separation of the data, the Manhattan Distance was used, which is the sum of the absolute differences in the coordinates between all the points.

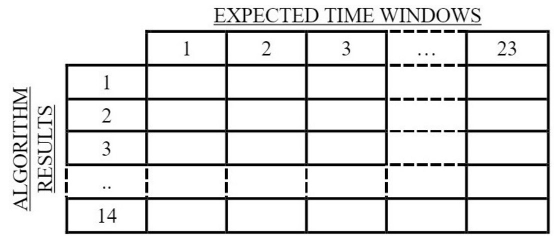

Fig. 5. Feature table in different time windows.

Due to the large number of possible combinations that require a great amount of time and computational resources, the implementation of the Genetic Algorithm was proposed. This programming technique is oriented to the optimization of the search for the best solution. The algorithm starts with an initial random population of combinations, the population evolves and improves according to the most suitable combination until it converges to an optimal solution or close to the global optimum [15].

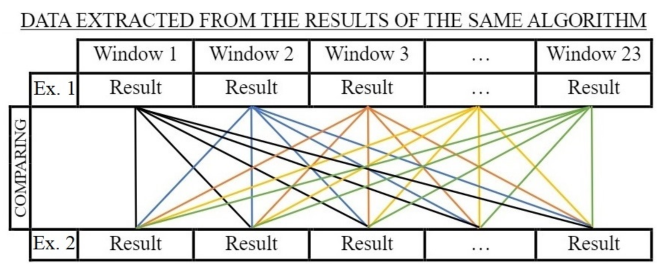

Fig. 6. The results of multiple exercises are compared to find the greatest possible separation.

With the most separate results found for each exercise and algorithm, the most appropriate time windows for processing each exercise performed by the subjects were obtained. A complete reprocessing was performed using the individual time windows obtained using the genetic algorithm.

Finally, a table was constructed with the results of the 14 algorithms, for all subjects, electrodes and repetitions. Each column represented a type of algorithm and each row was labeled with the corresponding exercise. This feature table was used as input for the WEKA software during the classification process.

H. Metrics

The objective is to evaluate the exercise classification performance based on the features extracted from the EMG signals. For this, it is necessary to identify the most appropriate classifier by using measures that indicate the performance of each one, thus allowing their comparison. Within the WEKA software, 10 classifiers were selected covering a variety of approaches and properties: NaiveBayes, Multilayer Perceptron, SMO, IBk, Hoeffding Tree, J48, LMT, Random Forest, Random Tree and REP Tree.

1) *Correct Instances (CI)*: This metric represents the classifier's accuracy by the percentage of correctly classified instances. It is calculated by dividing the number of correct predictions by the total number of predictions and multiplying by 100. The higher this value, the higher the classification accuracy.
2) *Confusion Matrix*: It is a table that shows the classification performance in terms of prediction results for each class. The number of classes determines the number of rows and columns of the matrix, where correctly and incorrectly classified instances are broken down for each class. This allows for the identification of false positives, false negatives, true positives, and true negatives.

III. Results

The results obtained from the analysis performed with WEKA software using ten different classifiers are presented below. These results are grouped in different categories that allowed us to evaluate the performance of each classifier in different scenarios. The tables contain the classification accuracy in percentage, as well as the average and standard deviation.

TABLE I
RESULTS SEPARATED BY ELECTRODES (FIRST FIVE CLASSIFIERS, %)

Electrodes	NB	MP	SMO	IBk	HT
E1	42.85	83.57	53.92	68.21	41.07
E2	42.5	86.07	60.35	70.35	44.64
E3	56.78	92.5	67.85	67.5	52.85
E4	46.78	90.35	50.71	63.92	33.92
SD	6.66	4.04	7.58	2.67	7.87
Average	47.23	88.12	58.21	67.50	43.12

TABLE II
RESULTS SEPARATED BY ELECTRODES (LAST 5 CLASSIFIERS, %)

Electrodes	J48	LMT	RF	RT	REP
E1	68.57	92.14	80.35	64.28	71.42
E2	67.85	85	79.28	62.85	63.57
E3	70	91.78	80.35	64.28	65.71
E4	70.71	90.35	79.28	58.92	60
SD	1.31	3.30	0.62	2.53	4.78
Average	69.28	89.82	79.82	62.58	65.18

TABLE III
RESULTS SEPARATED BY SUBJECTS (FIRST 5 CLASSIFIERS, %)

Subjects	NB	MP	SMO	IBk	HT
S1	60	97.85	59.25	77.14	57.14
S2	57.14	94.28	68.57	72.85	53.57
S3	69.28	94.28	79.28	87.85	55
S4	46.42	88.57	67.14	80.71	45
S5	61.42	93.57	67.14	64.28	55
S6	71.42	95.71	76.42	75.71	50
S7	61.42	91.42	67.85	72.14	50
S8	67.14	97.85	74.28	76.42	64.14
SD	7.92	3.13	6.37	6.83	5.70
Average	61.78	94.19	69.99	75.89	53.73

TABLE IV
RESULTS SEPARATED BY SUBJECTS (LAST 5 CLASSIFIERS, %)

Subjects	J48	LMT	RF	RT	REP
S1	77.14	94.28	86.42	77.85	73.57
S2	72.14	94.28	79.28	58.57	59.28
S3	83.57	95	86.42	75.71	77.14
S4	73.57	88.57	77.85	70.71	74.28
S5	64.28	97.14	77.14	70	59.28
S6	73.57	97.14	86.42	68.57	71.42
S7	68.57	91.42	74.28	64.28	65
S8	77.85	95.71	82.14	72.14	75
SD	5.90	2.92	4.81	6.14	7.18
Average	73.84	94.19	81.24	69.73	69.37

TABLE V
CLASSIFICATION RESULTS FOR ALL ELECTRODES, SUBJECTS, AND ALGORITHMS (FIRST 5 CLASSIFIERS, %)

NB	MP	SMO	IBk	HT
43.57	90.89	67.58	72.14	40.98

TABLE VI
CLASSIFICATION RESULTS FOR ALL ELECTRODES, SUBJECTS, AND ALGORITHMS (LAST FIVE CLASSIFIERS, %)

J48	LMT	RF	RT	REP
71.96	92.41	85.89	67.94	69.37

IV. Discussion

This work aims to demonstrate a high classification level for seven forearm and wrist exercises. To achieve this, MATLAB was used during the processing of the EMG signals, which consisted of filtering, cropping, normalization, and wavelets. Fourteen features based on basic statistics and fractal information were extracted to perform the exercise classification with the WEKA software. The hypothesis is that the sampling frequency of the data acquisition device at 2000Hz provides a level of detail in the signals that is precise enough for classification, as the optimal range for EMG is 150-350 Hz. Finally, the results indicated that the classification remains favorable in cases where data from a single individual or electrode is used.

V. Conclusion

This study provides a highly reliable and robust exercise classification method. The use of four channels while the subject performs seven exercises for eight subjects was proposed, along with pre-processing (windowing, filtering, normalization, and wavelet application), followed by the use of 14 different algorithms to extract features (SD, RMS, COV, VAR, MAV, MMAV, MMAV2, VAREMG, SSI, IEMG, EWL, Hurst, HurstVar, Higuchi), and then finding the most suitable time instant of EMG signals to finally calculate the classification in WEKA.

It is reported that the most suitable classifier is Multilayer Perceptron, achieving an accuracy of 92.41% when combining the 14 features using the four electrodes. Future work will focus on the implementation of EEG to investigate the subjects' ability to think about movement without actually performing it, and to understand the signals obtained when some of the 7 exercises are performed with the EMG processing already done.

The focus of future research based on this article will be on the integration of EMG signals in motor rehabilitation therapy, with the aim of strengthening treatments and improving patient recovery.

Additionally, the proposed signal processing steps may support the search for new findings that contribute to the clinical field during the combination of EMG and EEG signals.

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REFERENCES

[1] L. Moggio, A. de Sire, N. Marotta, A. Demeco, and A. Ammendolia, "Exoskeleton versus end-effector robot-assisted therapy for finger-hand motor recovery in stroke survivors: systematic review and meta-analysis," *Topics in Stroke Rehabilitation*, vol. 29, no. 8, pp. 539–550, 2022. PMID: 34420498.

[2] A. Hokazono, S. Etoh, Y. Jonoshita, K. Kawahira, and M. Shimodozono, "Combination therapy with repetitive facilitative exercise program and botulinum toxin type a to improve motor function for the upper-limb spastic paresis in chronic stroke: A randomized controlled trial," *Journal of Hand Therapy*, vol. 35, no. 4, pp. 507–515, 2022.

[3] S. Katai, M. Maeda, S. Katsuyama, Y. Maruyama, M. Midorikawa, T. Okushima, and K. Yoshida, "Cortical reorganization correlates with motor recovery after low-frequency repetitive transcranial magnetic stimulation combined with occupational therapy in chronic subcortical stroke patients," *Neuroimage: Reports*, vol. 3, no. 1, p. 100156, 2023.

[4] R. E. Singh, K. Iqbal, and J. Son, "Editorial: From depth (needle) to surface: electromyography as a diagnostic tool in identifying neuromuscular changes associated with neurological disorders," *Frontiers in Human Neuroscience*, vol. 17, 2023.

[5] M. Ghassemi, K. Triandafilou, A. Barry, M. Stoykov, E. Roth, F. Mussa-Ivaldi, D. Kamper, and R. Ranganathan, "Development of an emg-controlled serious game for rehabilitation," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. PP, pp. 1–1, 01 2019.

[6] R. Merletti and G. Cerone, "Tutorial. surface emg detection, conditioning and pre-processing: Best practices," *Journal of Electromyography and Kinesiology*, vol. 54, p. 102440, 2020.

[7] Y. Fang, J. Yang, D. Zhou, and Z. Ju, "Modelling emg driven wrist movements using a bio-inspired neural network," *Neurocomputing*, vol. 470, pp. 89–98, 2022.

[8] F. Leone, C. Gentile, A. L. Ciancio, E. Gruppioni, A. Davalli, R. Sacchetti, E. Guglielmelli, and L. Zollo, "Simultaneous semg classification of hand/wrist gestures and forces," *Frontiers in Neurorobotics*, vol. 13, 2019.

[9] World Medical Association, "World Medical Association Declaration of Helsinki: ethical principles for medical research involving human subjects," *JAMA*, vol. 310, pp. 2191–2194, Nov. 2013.

[10] K. Wang, X. Zhang, J. Ota, and Y. Huang, "Estimation of handgrip force from SEMG based on wavelet scale selection," *Sensors*, vol. 18, no. 2, p. 663, 2018.

[11] L. Ding, Y. Luo, Y. Lin, and Y. Huang, "Revisiting the relations between hurst exponent and fractional differencing parameter for long memory," *Physica A: Statistical Mechanics and its Applications*, vol. 566, p. 125603, 2021.

[12] A. Mosqueda-Herrera, D. Martinez-Peon, L. Gomez-Sanchez, M. I. Ramirez-Sosa, S. Delfin-Prieto, and F. G. Benavides-Bravo, "Characterization of kinesthetic motor imagery paradigm for wrist and forearm using an algorithm based on the hurst exponent and variogram," in *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pp. 3683–3688, 2020.

[13] C.-T. Shi, "Signal pattern recognition based on fractal features and machine learning," *Applied Sciences*, vol. 8, no. 8, 2018.

[14] Z. Gong, P. Zhong, and W. Hu, "Diversity in machine learning," *Ieee Access*, vol. 7, pp. 64323–64350, 2019.

[15] S. Mirjalili and S. Mirjalili, "Genetic algorithm," *Evolutionary Algorithms and Neural Networks: Theory and Applications*, pp. 43–55, 2019.