Wavelet Transform Based Finger Movement Recognition
Dalgacık Dönüşümü Tabanlı Parmak Hareketi Tanıma

Muhammed Sami KARAKUL[1,*], Ahmet GÖKÇEN[1]
[1]Department of Computer Engineering, Iskenderun Technical University, Hatay, Turkey
ORCIDs: 0000-0003-2729-7572, 0000-0002-7569-5447
E-mails: msami.karakul@iste.edu.tr, ahmet.gokcen@iste.edu.tr
*Corresponding author.

***Abstract*—Electromyography has been used for Human-Computer interactions (HCI). Gesture recognition such as hand and finger movements is helpful to have a better HCI experience. This study investigates methods used on a publicly available dataset. To the best of our knowledge, this dataset has never been used with wavelets previously. This study uses Discrete Wavelet Transforms (DWT) with three different wavelets such as Symlet 4, Daubechies 4, and Haar wavelets. The time and frequency domain features have been extracted from the result of the DWT which uses three different wavelets. The features have been tested with a proposed Convolutional Neural Network (CNN) model. To the best of our knowledge, this CNN architecture hasn't been used before. The results with different metrics and confusion matrix for each trial are given in the results section. The highest and the lowest accuracy rates have been achieved with the Symlet 4 wavelet and Haar wavelet, respectively. The performance ranking of the reported wavelets is Symlet 4, Daubechies, and Haar with accuracy rates of 91.56%, 90.66%, and 90.02%, respectively.**

Keywords—finger movement recognition, surface electromyography, convolutional neural networks, discrete wavelet transforms

***Özetçe*—Elektromiyografi (EMG), İnsan-Bilgisayar Etkileşimleri (IBE) için kullanılmaktadır. El ve parmak hareketlerini içeren jest tanıma, daha iyi bir HCI deneyimi sunmak için faydalı olabilmektedir. Bu çalışma, topluluğa açık bir veri seti üzerinde dalgacıkların kullanımını araştırmaktadır. Bildiğimiz kadarıyla, bu veri seti daha önce dalgacık yöntemi uygulanarak kullanılmamıştır. Bu çalışmada, Symlet 4, Daubechies 4 ve Haar dalgacıkları olmak üzere üç farklı dalgacıkla Ayrık Dalgacık Dönüşümlerini (ADD) kullanılmıştır. Zaman ve frekans alanı öznitelikleri ADD'nin sonuçlarından çıkarılmıştır. Önerilen Evrişimli Sinir Ağı (Convolutional Neural Networks - CNN) modeli ile öznitelikler test edilmiştir. Bildiğimiz kadarıyla, bu CNN mimarisi daha önce kullanılmamıştır. Farklı metrikler ve her denemeye ait karmaşıklık matrisleri sonuçlar bölümünde sunulmuştur. En yüksek ve en düşük doğruluk oranları sırasıyla Symlet 4 dalgacığı ve Haar dalgacığı ile elde edilmiştir. Rapor edilen dalgacıkların performans sıralaması Symlet 4, Daubechies ve Haar olup, sırasıyla %91,56, %90,66 ve %90,02 doğruluk oranlarına sahiptirler.**

Anahtar Kelimeler—parmak hareketi tanınması, yüzey elektromiyografisi, evrişimsel sinir ağları, ayrık dalgacık dönüşümleri

I. Introduction

Hand gesture recognition has an important role in Human-Computer Interactions (HCIs) to be used on systems such as prostheses and device control systems [1]. To build a system that recognizes hand gestures, several biomedical signals including steady-state visual-evoked potentials (SSVEP) [2]–[8], electroencephalography (EEG) [9]–[11], and electromyography (EMG) [12], [13] have been used in the literature. information about muscle activity is required. The recording of muscle activity is called electromyography (EMG) and can be recorded by using invasive or non-invasive methods [14]. The muscle activity recorded by using non-invasive electrodes is called a surface electromyogram (sEMG) [15]. In previous studies, many different EMG datasets have been used with different methods. In some studies, researchers have built their datasets and worked on those datasets [16]–[23] and on some other researchers have used datasets which were already collected and published on different platforms [24], [25]. Researchers have worked on both time and frequency domains to successfully classify the EMG signals. EMG signals have been classified from their raw version, with the features extracted from their raw version and the preprocessed versions of the raw signals' features. Geng et al. have introduced a method to classify the sEMG signals from the sEMG signal images [26]. They have compared Hyper-Parameter (HD) configuration results and different databases with different classification algorithms including their ConvNet architecture. They have achieved an 89.3% accuracy rate. Zhou et al. compared the Random Forest classifiers' (RF) classification results of the time-domain features they extracted one at a time and as a group of features and achieved a 92.94% accuracy rate [24]. Wahid et al. have followed a strategy called the Multi Window Majority Strategy to improve the classification accuracy [25]. They have used different windows varied between 50ms and 500ms and they have set overlapping ranges between 0% and 80% rate. In the results of their comparison, the best result they achieved was from an RF classifier with an 80.70% accuracy rate.

Too et al. have used both time-domain and frequency-domain features and compared the results based on the Linear Discriminant Analysis (LDA) classifier [22]. Researchers have acquired their dataset which includes six different finger movements. Researchers have used Fast Fourier Transform (FFT) to convert EMG signals into frequency domains. The results they have reported show that they have achieved a 91.34% accuracy rate using frequency domain features while the time domain features' accuracy results were 87.17%. Altin et al. have published another research that compares time and frequency domains [23]. Researchers have first acquired the EMG signals from the elbow. Their dataset includes two different classes (elbow flexion and elbow extension). Researchers have extracted 11 features from the time domain and 6 different features from the frequency domain. They have compared all feature performances separately based on the results of K-Nearest Neighbor (kNN) classifiers' results and the best results they have achieved are from the AutoRegressive Coefficient feature from the time domain and Median Frequency from the frequency domain with the result of 93% and 83% accuracy rate, respectively. Duque et al. have used Discrete Wavelet Transform (DWT) and kNN to diagnose neuromuscular disorders [27]. Researchers have used Daubechies order eight wavelet as wavelet and extracted six statistical features from the results of the DWT. They have compared the classification results of the features with and without relevance analysis. The best result they have achieved is a 93.08% accuracy rate with stochastic relevance measure. Phinyomark et al. have classified EMG patterns from Wavelet Transform Coefficients [28]. They have focused on finding the optimal wavelet function and the wavelet component type. They extracted a total of 25 features based on time and frequency domains and compared the performances.

In this study, authors have used DWT with different wavelets and compared their results based on the classification performances of the CNN model. The used wavelets are Daubechies 4, Symlet 4, and Haar wavelets.

II. Methods

A. Dataset

The EMG dataset has been taken from a publicly available source [29]. The dataset includes sEMG recordings of seven different finger gestures which are thumb, index finger, middle finger, ring finger, little finger, rest, and the victory gesture. The EMG recordings have been made from the Thalmic Labs MYO Armband device. The data were acquired from 10 subjects while they were performing the gesture [17] for 20-30 trials.

B. Discrete Wavelet Transform (DWT)

DWT has been evaluated with three different wavelets which are Daubechies 4, Haar, and Symlet 4. Decomposition has been limited to six and only sixth-level coefficients have been used from all of the DWTs. Both time and frequency domain features have been extracted from the DWT results. All DWT processes have been evaluated with a Python library named PyWave [30].

C. Feature Extraction

Both time and frequency domain features have been extracted from the DWT results. Features have been extracted from the EMG signals received on each sensor. The extracted time domain features are root mean square (RMS), waveform length (WL), mean absolute value (MAV), variance (VAR), and standard deviation (STD) and the extracted frequency domains are mean power frequency (MPF), total power (TTP), mean frequency (MF), median frequency (MDF) and frequency ratio (FR). After extracting features, the total feature number becomes 80 (8 sensors x 10 features).

1) Time Domain Features:

- Root Mean Square (RMS): Root mean square is a time domain feature and calculated using Equation 1.

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} X_n^2} \tag{1}$$

where, x is the voltage value at *i*th sampling and N is the range of the window [31].

- Wavelength (WL): Wavelength is the cumulative length of the EMG signal over time and is a measure of the complexity of the EMG signal [32]. It is calculated using Equation 2.

$$WL = \sum_{n=1}^{N-1} |x_{n+1} - x_n| \tag{2}$$

- Mean Absolute Value (MAV): Mean absolute value feature is an average of the absolute value of the EMG signal voltage value in a time and calculated using Equation 3 [32].

$$MAV = \frac{1}{N}\sum_{n=1}^{N-1} |x_n| \tag{3}$$

- Variance (VAR): VAR is calculated by the power of the EMG signal. Since the mean value of the EMG signal is close to zero, the mean value of the EMG signal has been kept out [33]. VAR feature calculated using Equation 4 [23].

$$VAR = \frac{1}{N-1}\sum_{n=1}^{N} x_n^2 \tag{4}$$

- Standard Deviation (SD): Standard Deviation represents interference such as noise and measures the spread of the signal values from the mean calculating with the comparison to the mean [34]. STD features calculated using Equation 5 [23]

$$STD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N} (x_n - \overline{x})} \tag{5}$$

2) Frequency Domain Features:

- Mean Power Frequency (MPF): MPF is defined as Equation 6 which is the average power of the EMG power spectrum [32]. *M* is the number of samples and *P* is the power spectral density of the sEMG signals.

$$MPF = \sum_{j=1}^{M} P_j \Big/ M \tag{6}$$

- Total Power (TTP): TTP is the sum of the EMG power spectrum [32]. *M* is the number of samples and *P* is the power spectral density of the sEMG signals.

$$TTP = \sum_{j=1}^{M} P_j \tag{7}$$

- Mean Frequency (MNF): MNF is the average frequency and is computed by dividing the product of the EMG spectrum by the total sum of spectrum intensity [32]. *M* is the number of samples and *P* is the power spectral density of the EMG signals.

$$MNF = \sum_{j=1}^{M} f_i P_j \Big/ \sum_{j=1}^{M} P_j \tag{8}$$

- Median Frequency (MDF): MDF is the half of the Total Power feature and it can be described as the frequency that divided the power density spectrum into two equal regions [35].

$$\sum_{j=1}^{MDF} P_j = \sum_{j=1}^{M} P_j = \frac{1}{2} \sum_{j=1}^{M} P_j \tag{9}$$

- Frequency Ratio (FR): FR is the feature that is used to distinguish between contraction and relaxation of the muscle with the ratio of the EMG signals low and high-frequency components [32].

$$FR = \sum_{j=LLC}^{ULC} P_j \Big/ \sum_{j=LHC}^{UHC} P_j \tag{10}$$

D. Proposed Convolutional Neural Network (CNN) Architecture

In this study, extracted features and their performances have been examined with different built CNN architectures. As far as the authors' knowledge, this CNN model has not been proposed yet. The CNN architecture has been given in Figure 1. Since the dataset is 1 dimensional (1-D), the CNN model had to be 1-D as well. The kernel sizes started from 64 and were rearranged by multiplying the kernel size after each layer. Before the third layer with the kernel size of 256, 5x1 Max Pooling has been applied (Fig. 1).

III. Results

In this study, Symlet 4, Daubechies 4 and Haar wavelets have been used on DWT to extract the features. Features have been extracted from the results of the DWT. Extracted features are both time and frequency features. This study also examines the effects of the usage of different types of features together. The wavelet feature performances have been compared in Table I. The table shows the performances of the wavelet and not the features because the features have been tested together.

Wavelet name	Accuracy	Precision	F1 Score	Recall
Daubechies 4	90.66	90.42	90.14	90.04
Haar	90.02	89.93	89.97	90.39
Symlet 4	91.56	91.30	91.44	91.69

Table I: Comparison between the results achieved with the features extracted from different wavelets.

As seen in Table I, the model gave the highest accuracy with the features from Symlet 4, the second highest accuracy with Daubechies, and the lowest accuracy rate with Haar. The results show that square-shaped wavelets such as Haar wavelets are not as effective as orthogonal wavelets on finger movement classification problems with this dataset. Because the Symlet 4 wavelet gave the best accuracy resulting features it could be said that the least symmetric wavelets are a better fit in this problem base. The confusion matrix for the features extracted from DWTs using Symlet 4, Daubechies 4, and Haar are given in Figure 2, Figure 3, and Figure 4, respectively.

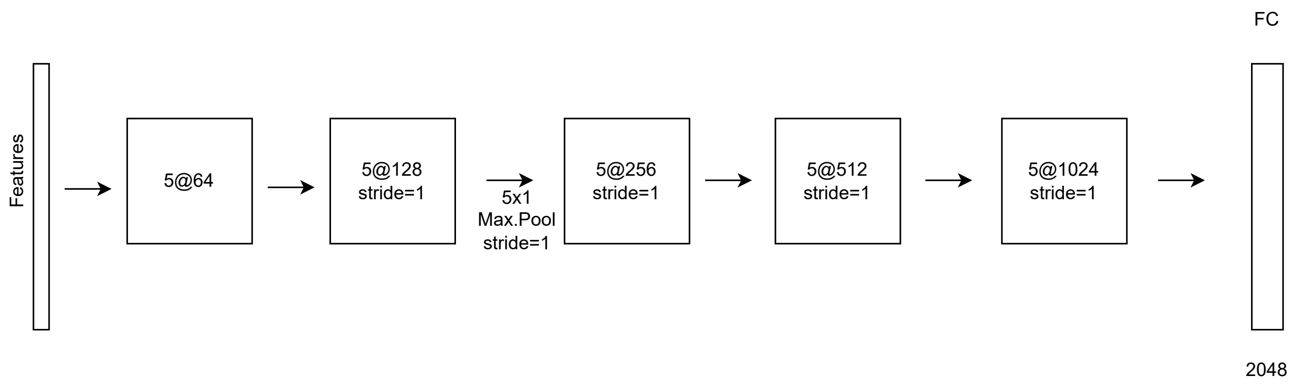

Figure 1: Proposed CNN Architecture.

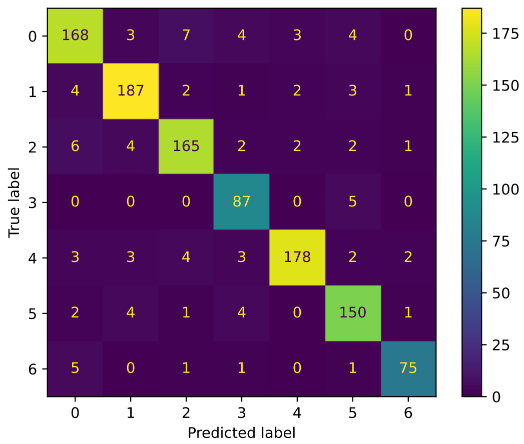

Figure 2: Confusion Matrix of the features extracted from DWT using Symlet 4 wavelet.

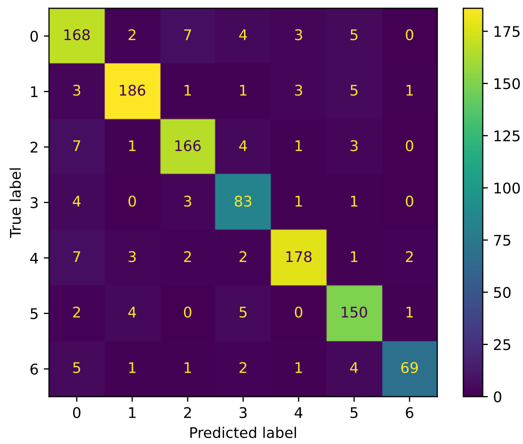

Figure 3: Confusion Matrix of the features extracted from DWT using Daubechies 4 wavelet.

The difference between the two highest-performing wavelets is the victory gesture motion. The victory gesture motion has been successfully classified from the features extracted from the DWT results of the Symlet 4 wavelet compared to the Daubechies 4 wavelet.

The highest differences between the results of orthogonal and square-shaped wavelets are from "1" and "2" labels in the confusion matrix which are the labels of the little finger motion and middle finger motion, respectively. This means that the little finger motion and middle finger motion are hard to recognize from the features extracted from DWT results using the Haar wavelet.

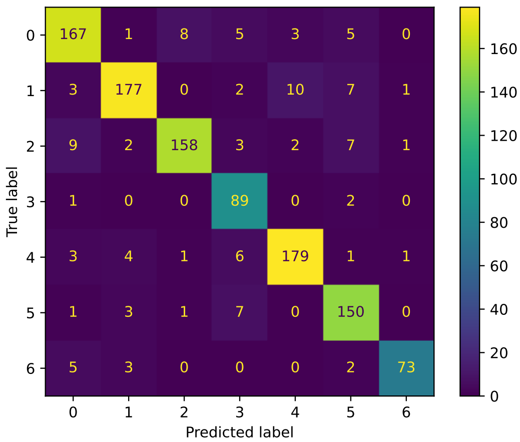

Figure 4: Confusion Matrix of the features extracted from DWT using Haar wavelet.

IV. Conclusion and Future Works

This study aims to investigate the feature performances extracted from DWTs with the usage of different wavelets. To test the results, three different wavelets have been used. The used wavelets are Daubechies 4, Haar, and Symlet 4. DWT has been executed with a Python library called PyWave [30]. This library helps users to work on the signals. The results showed that features extracted from orthogonal wavelets gave better results while the features extracted from square-shaped Haar wavelets gave the lowest accuracy. The features extracted after the DWT using Symlet 4, Daubechies 4 and Haar wavelets gave 91.56%, 90.66%, and 90.02% accuracy rates, respectively. These results showed that orthogonal wavelets are better tools for this type of problem. Different families and different wavelets could be involved in future studies. Best of our knowledge, the sEMG signal dataset has never been used with wavelet transforms and this study investigates the usage and the performance results of the wavelet transform for this dataset.

Author Contributions

Ahmet Gokcen gave the idea and decided on the used methods. Muhammed Sami Karakul did the experiments, interpreted the results, and wrote the paper.

References

[1] Jaramillo-Yanez A, Benalcazar ME, Mena-Maldonado E. Real-time hand gesture recognition using surface electromyography and machine learning: A systematic literature review. Sensors 2020; 20(9): 2467.

[2] Sayilgan E, Yuce YK, Isler Y. Evaluation of mother wavelets on steady-state visually-evoked potentials for triple-command brain-computer interfaces. Turkish Journal of Electrical Engineering & Computer Sciences 2021; 29(5): 2263-2279.

[3] Sayilgan E, Yuce YK, Isler Y. Evaluation of wavelet features selected via statistical evidence from steady-state visually-evoked potentials to predict the stimulating frequency. Journal of the Faculty of Engineering and Architecture of Gazi University 2021; 36(2): 593-605.

[4] Sayilgan E, Yuce YK, Isler Y. Investigating the effect of flickering frequency pair and mother wavelet selection in steady-state visually-evoked potentials on two-command brain-computer interfaces. Innovation and Research in BioMedical Engineering 2022; 43(6): 594-603.

[5] Yesilkaya B, Sayilgan E, Yuce YK, Perc M, Isler Y. Principal component analysis and manifold learning techniques for the design of brain-computer interfaces based on steady-state visually evoked potentials. Journal of Computational Science 2023; 68: 102000.

[6] Sayilgan E, Yuce YK, Isler Y. Frequency recognition from temporal and frequency depth of the brain-computer interface based on steady-state visual evoked potentials. Journal of Intelligent Systems with Applications 2021; 4(1): 68-73

[7] Degirmenci M, Sayilgan E, Isler Y. Evaluation of Wigner-Ville distribution features to estimate steady-state visual evoked potentials' stimulation frequency. Journal of Intelligent Systems with Applications 2021; 4(2): 133-136.

[8] Avci MB, Hamurcu R, Bozbas OA, Gurman E, Cetin AE, Sayilgan E. Design of steady-state visually-evoked potential based brain-computer interface system. Journal of Intelligent Systems with Applications 2022; 5(2): 86-89.

[9] Degirmenci M, Yuce YK, Perc M, Isler Y. Statistically significant features improve binary and multiple motor imagery tasks predictions from EEGs. Frontiers in Human Neuroscience 2023; 17: 1223307.

[10] Degirmenci M, Yuce YK, Isler Y. Classification of finger movements from statistically-significant time-domain EEG features. Journal of the Faculty of Engineering and Architecture of Gazi University, vol. 39(3), 1597-1609, 2024.

[11] Degirmenci M, Yuce YK, Perc M, Isler Y. EEG-based finger movement classification with intrinsic time-scale decomposition. Frontiers in Human Neuroscience 2024; 18: 1362135.

[12] Isler Y, Isler O. Design of expert systems using surface EMG signal for movements of multi-function prosthetic hand. Karaelmas Science and Engineering Journal 2019; 9(2): 237-243.

[13] Isler Y, Isler O. EMG controlled 3D printed bionic hand. Natural and Engineering Sciences 2019; 4(3): 59-64.

[14] Kumar DK, Pah ND, Bradley A. Wavelet analysis of surface electromyography. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2003; 11(4): 400-406.

[15] Hu Y, Wong Y, Wei W, Du Y, Kankanhalli M, Geng W. A novel attention-based hybrid CNN-RNN architecture for sEMG-based gesture recognition. PloS One 2018; 13(10): e0206049.

[16] Haris M, Chakraborty P, Rao BV. EMG signal based finger movement recognition for prosthetic hand control. In 2015 Communication, Control and Intelligent Systems (CCIS) November, 2015, Mathura, India, pp. 194-198

[17] Naseer N, Ali F, Ahmed S, Iftikhar S, Khan RA, Nazeer H. EMG based control of individual fingers of robotic hand. In 2018 International Conference on Sustainable Information Engineering and Technology (SIET) November, 2018, pp. 6-9.

[18] Chen X, Zhang X, Zhao ZY, Yang JH, Lantz V, Wang KQ. Multiple hand gesture recognition based on surface EMG signal. In 2007 1st International conference on Bioinformatics and Biomedical Engineering, July, 2007, pp. 506-509.

[19] Arteaga MV, Castiblanco JC, Mondragon IF, Colorado JD, Alvarado-Rojas C. EMG-driven hand model based on the classification of individual finger movements. Biomedical Signal Processing and Control 2020; 58: 101834.

[20] Peleg D, Braiman E, Yom-Tov E, Inbar GF. Classification of finger activation for use in a robotic prosthesis arm. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2002; 10(4): 290-293.

[21] Zhang Z, Yu X, Qian J. Classification of Finger Movements for Prosthesis Control with Surface Electromyography. Sensors and Materials 20202; 32.

[22] Too J, Abdullah AR, Zawawi TT, Saad NM, Musa H. Classification of EMG signal based on time domain and frequency domain features.

International Journal of Human and Technology Interaction (IJHaTI) 2017; 1(1): 25-30.

[23] Altin C, Er O. Comparison of different time and frequency domain feature extraction methods on elbow gesture's EMG. European Journal of Interdisciplinary Studies 2016; 2(3): 25-34.

[24] Zhou T, Omisore OM, Du W, Wang L, Zhang Y. Adapting random forest classifier based on single and multiple features for surface electromyography signal recognition. In 2019 12th International Congress on Image and Signal Processing, Biomedical Engineering and Informatics (CISP-BMEI), October, 2019, pp. 1-6.

[25] Wahid MF, Tafreshi R, Langari R. A multi-window majority voting strategy to improve hand gesture recognition accuracies using electromyography signal. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2019; 28(2): 427-436.

[26] Geng W, Du Y, Jin W, Wei W, Hu Y, Li J. Gesture recognition by instantaneous surface EMG images. Scientific Reports 2016; 6(1): 36571.

[27] Duque CJG, Munoz LD, Mejia JG, Trejos ED. Discrete wavelet transform and k-nn classification in EMG signals for diagnosis of neuromuscular disorders. In 2014 XIX Symposium on Image, Signal Processing and Artificial Vision, November, 2014, pp. 1-5.

[28] Phinyomark A, Nuidod A, Phukpattaranont P, Limsakul C. Feature extraction and reduction of wavelet transform coefficients for EMG pattern classification. Elektronika ir Elektrotechnika 2012; 122(6): 27-32.

[29] Electro-Myography-EMG-Dataset. 13 May 2024. [Online] Retrieved from https://www.kaggle.com/datasets/nccvector/electromyography-emg-dataset.

[30] PyWave Python Library. 15 May 2024. [Online]. Retrieved from https://pypi.org/project/PyWave/.

[31] Lalitharatne TD, Hayashi Y, Teramoto K, Kiguchi K. A study on effects of muscle fatigue on EMG-based control for human upper-limb power-assist. In 2012 IEEE 6th International Conference on Information and Automation for Sustainability, November, 2012, pp. 124-128.

[32] Phinyomark A, Phukpattaranont P, Limsakul C. Feature reduction and selection for EMG signal classification. Expert Systems with Applications 2012; 39(8): 7420-7431.

[33] Phinyomark A, Hirunviriya S, Limsakul C, Phukpattaranont P. Evaluation of EMG Feature Extraction for Hand Movement Recognition Based on Euclidean Distance and Standard Deviation. ECTI-CON2010: The 2010 ECTI International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, Chiang Mai, Thailand, 2010, pp. 856-860.

[34] Daud WMBD, Yahya AB, Horng CS, Sulaima MF, Sudirman R. Features extraction of electromyography signals in time domain on biceps brachii muscle. International Journal of Modeling and Optimization 2013; 3(6): 515.

[35] Abdelouahad A, Belkhou A, Jbari A, Bellarbi L. Time and frequency parameters of sEMG signal—force relationship. In 2018 4th International Conference on Optimization and Applications (ICOA), April, 2018, pp. 1-5.