DOI: https://doi.org/10.33103/uot.ijccce.23.2.14

Recognition of Upper Limb Movements Based on Hybrid EEG and EMG Signals for Human-Robot Interaction

Huda M. Rada[1], Alia Karim Abdul Hassan[2], Ali H. Al-Timemy[3]

[1]*Computer Science Department, Science College, University of Baghdad, Baghdad, Iraq*

[2]*Computer Science Department, University of Technology, Baghdad, Iraq*

[3]*Biomedical Eng. Department, Al-Khwarizmi College of Eng., University of Baghdad, Baghdad, Iraq*

[1]*huda.rada@sc.uobaghdad.edu.iq*, [2]*110018@uotechnology.edu.iq*, [3]*ali.altimemy@kecbu.uobaghdad.edu.iq*

Abstract*— Upper limb amputation is a condition that severely limits the amputee's movement. Patients who have lost the use of one or more of their upper extremities have difficulty performing activities of daily living. To help improve the control of upper limb prosthesis with pattern recognition, non-invasive approaches (EEG and EMG signals) is proposed in this paper and are integrated with machine learning techniques to recognize the upper-limb motions of subjects. EMG and EEG signals are combined, and five features are utilized to classify seven hand movements such as (wrist flexion (WF), outward part of the wrist (WE), hand open (HO), hand close (HC), pronation (PRO), supination (SUP), and rest (RST)). Experiments demonstrate that using mean absolute value (MAV), waveform length (WL), Wilson Amplitude (WAMP), Sine Slope Changes (SSC), and Cardinality features of the proposed algorithm achieves a classification accuracy of 89.6% when classifying seven distinct types of hand and wrist movement.*

Index Terms*— Human Robot Interaction, Bio-signals Analysis, LDA classifier.*

I. INTRODUCTION

Upper limb amputation is a condition that severely limits amputees' ability to conduct daily tasks. The electro muscular prosthesis's objective is to help restore the function of these lost limbs by utilizing signals from the remaining muscles. Unfortunately, there are several challenges facing patients with missing upper limbs in terms of the difficulty of obtaining this signal, as well as the percentage of upper limb amputation, as most research is currently directed to study in this field to help amputees live as normal a life as possible [1]. The most highly rehabilitative type of artificial limb is a hand prosthesis controlled by bioelectrical methods. This is because they can combine the aesthetic component, grabbing power and speed, and several opportunities for adaptability to various degrees of handicap [2]. Upper-limb amputees commonly use multifunctional prostheses to restore lost motion functions. Electromyography (EMG) is a type of neural signal that carries motor commands and can be extracted noninvasively from the muscle surface of residual limbs. However, it's plays an important role in the control of modern motorized prostheses due to its relative simplicity of acquisition and rich neural information content [3,4]. An additional neural signal, Electroencephalography (EEG), also contains information about mental activities of the brain but is unaffected by amputation [5]. Multiple attempts have been made to use EEG as a brain-computer interface (BCI) for potential applications: Chen et al. used EEG to control robotic arms that performed hand movements for paralyzed subjects by decoding EEG signals recorded with an implanted microelectrode array [6]. Multiple-source signal fusion is one way to solve the problem of not having enough information to control a prosthesis [7]. In this method, non-EMG signals are added to EMG signals to get more accurate motor commands [8]. This study proposes an algorithm for classifying the upper limb motions of below-elbow amputees by fusing EMG

Received 24/September/2022; Accepted 10/November/2022

ISSN (Print) 1811-9212 *ISSN (Online) 2617-3352*

DOI: https://doi.org/10.33103/uot.ijccce.23.2.14

and EEG data as parallel input. The following is a summary of the main contributions of the current work:

1- Combining five-feature group, which are Mean absolute value (MAV), Waveform length (WL), Wilson Amplitude (WAMP), Sine Slope Changes (SSC), and Cardinality features, and Formants to extract 60- dimensional feature vectors for each subject from combined four channels from EEG and eight channels from EMG.

2- Exploring the influence of using EEG or EMG individually, and fusing (EEG, EMG) Signals, in order to improve classification accuracy using the LDA classifier.

II. RELATED WORKS

This work focuses mainly on recognition of upper limb movements based on fusion bio-signals analysis, there are some previous works have concerned the study of such a system. Biswas et al. propose a method to classify three upper limb movements (i.e., extension, flexion, and rotation) using accelerometer data and gyroscope data, with a 10-fold cross-validation accuracy of 88% using accelerometer data and 83% using gyroscope data for healthy participants, using a Linear Discriminant Analysis classifier and a Support Vector Machine [9]. Li in [7] proved that The two different signal types underwent separate pre-processing steps before being combined as a parallel control input. A classifier trained by the Linear Discriminant Analysis (LDA) algorithm for motion recognition was fed with four time-domain features. Additionally, the Sequential Forward Selection method was used to perform channel selections (SFS). Using 32 channels for EEG and 32 channels for EMG, they were able to achieve 87.5% accuracy. In [10] EEG and EMG are two possible combinations of the electrophysiological signal sources. In order to prepare the data for preliminary classification, signal processing and classification techniques were used. EEG and EMG were combined using a theory-based method. Any mathematically ambiguous or inaccurate data could potentially be modelled using this method. The formula for the mass functions that underlies this theory is specific. When using a classifier NN with two EMG channels and one EEG channel as inputs, the results were 78.65% according to the target application.

Despite the fact that these physiological signals have been widely exploited, they are very weak and subject to a variety of interferences. For instance, power line noise and motion distortions would surely reduce the motion intention detection accuracy of wearable systems that use EMG or EEG data as control sources [11].

The rest of this work is organized as follows. The proposed algorithm is detailed in section III, and it looks at the theoretical background of Time-domain feature extraction concepts and Dimensionality Reduction. The experimental results and analysis are shown in section IV. Finally, section V outlines the work's conclusions and plans.

III. THE PROPOSED ALGORITHM

The proposed algorithm for classifying different hand Guster motions in Time-Domain Feature Extraction includes signals Pre-Processing to fusion (EEG, EMG) data stage, Time-domain (features extraction, dimensionality reduction), and classification stages. Firstly, Pre-processing for the given signals EEG and EMG includes segmentation with overlap window size. After that, there are Time Domain Extractions with different features is presented. Following the PCA dimension reduction presentation, the LDA classifier is finally used to identify seven other shoulder girdle motions for prosthesis control such as (wrist flexion (WF), outward part of the wrist (WE), hand open (HO), hand close (HC), pronation (PRO), supination (SUP), and rest (RST)). Algorithm 1. Illustrates the main steps

Received 24/September/2022; Accepted 10/November/2022

ISSN (Print) 1811-9212 *ISSN (Online) 2617-3352*

DOI: https://doi.org/10.33103/uot.ijccce.23.2.14

of the proposed algorithm, and the subsections that follow provide more detailed descriptions of these stages.

Algorithm 1: Classifying Wrist and Hand motion	
Input	**EEG, EMG signals, window size (win_size) , widow increment (win_inc).**
Output	**Classes (wrist flexion (WF), outward part of the wrist (WE), hand open (HO), hand close (HC), pronation (PRO), supination (SUP), and rest (RST).**
Step1:	*// Create a Matrix (SD) that stores twelve channels values (four channels for EEG signals, and eight channels for EMG signals) preparing for pre-processing step*
	Set feature training() ← null **Set class training() ← null** **Set feature testing() ← null** **Set class testing() ← null** **Divide** the EEG,EMG signals S into overlapped segments based on win_size,win_inc.
Step2 : Feature Extraction	**Extract** Mean absolute value, waveform length, Wilson Amplitude, Number of Slope Sign Changes, and Cardinality. for training signal file, and for testing signal file **Apply** the get class function to assign the class for each segment for the training and testing file. // Store the result of each of training and testing files **Set feature training ← Result of training file** **Set class training ← Result of class file** **Set feature testing ← Result of testing file** **Set class testing ← Result of class file**
Step 3:	// reduce the dimension of the obtained results from 60 features column to 35 features column **Apply** PCA dimension reduction algorithm
Step 4:	// Classify the obtained results from the previous step to seven type of wrist and hand motion **Apply LDA classifier to obtain the classes**

Step 1: Data Collection and Pre-processing

This step includes data collection and pre-processing. Data were collected from three healthy limb subjects in the laboratory of the Department of Biomedical Engineering. Al-Khwarizmi College of Engineering, University of Baghdad. To classify hand movements, a set of seven movements was selected: wrist flexion (WF), outward part of the wrist (WE), hand open (HO), hand close (HC), pronation (PRO), supination (SUP), and rest (RST). Eight EMG channels were recorded in the data. Furthermore, four EEG channels were provided by placing on the forehead *Fig. 1*, the overall layout of the suggested work scheme is depicted in *Fig. 2*. All subjects they received a thorough explanation of the events, and they received some brief training to get them acclimated to the process. Each participant in the experiment was instructed to do the exercise in turn for a duration of 10 seconds, after which the motions were recorded three more times. EMG and EEG were recorded simultaneously while performing the movement. EMG signals were collected. They used of a high-density EMG system where the signal frequency was 200 Hz for eight channels; Electrodes were placed on the surface of the

Received 24/September/2022; Accepted 10/November/2022
 ISSN (Print) 1811-9212 ISSN (Online) 2617-3352

DOI: https://doi.org/10.33103/uot.ijccce.23.2.14

skin to check for residues arm for each subject. On the other hand, EEG Muse were collected on 252 Fs, and with 4 channels Raw.

FIG. 1. EEG MUSE RAW 4 CHANNELS AND EMG ARMBAND PLACEMENT 8 CHANNELS.

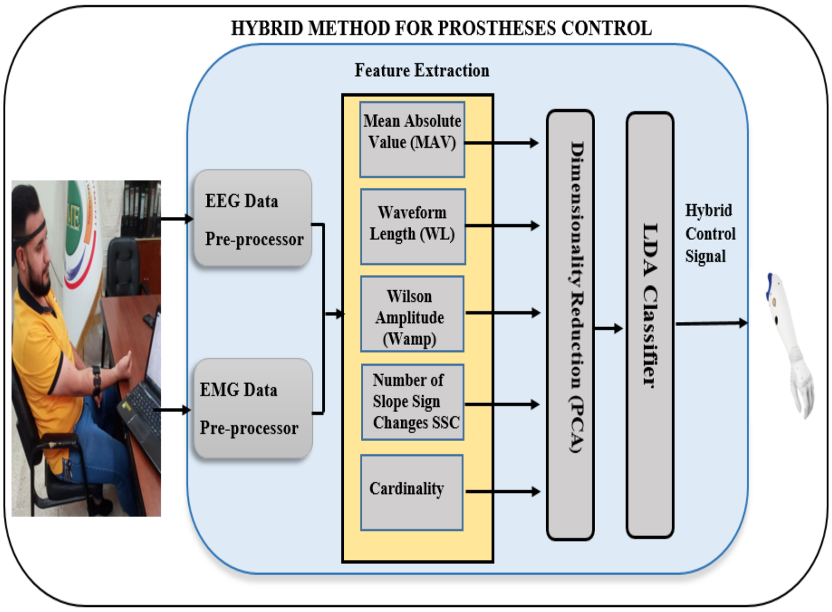
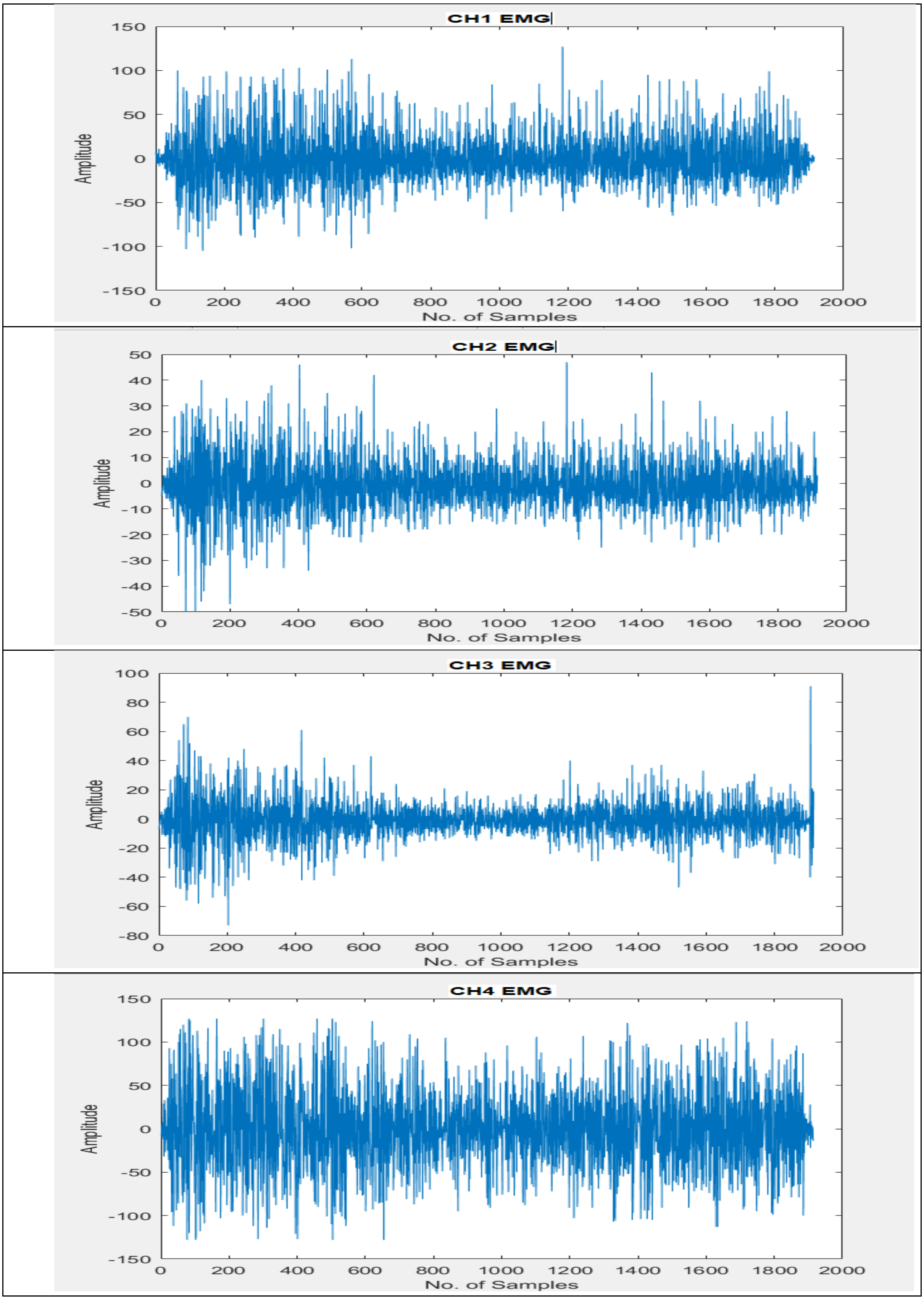


FIG. 2. THE GENERAL DESIGN OF THE PROPOSED WORK SCHEME.

At a sampling rate of 1 kHz, raw data are gathered from which useful features can be extracted. The eight-channel EMG signals are shown in *Fig. 3*; the data was segmented using an overlapped segmentation approach with a window size of 150 ms and an increment of 50 ms. *Fig. 4* depicts the four channels used to record EEG data.

Received 24/September/2022; Accepted 10/November/2022

DOI: https://doi.org/10.33103/uot.ijccce.23.2.14



Received 24/September/2022; Accepted 10/November/2022

ISSN (Print) 1811-9212 ISSN (Online) 2617-3352

DOI: https://doi.org/10.33103/uot.ijccce.23.2.14

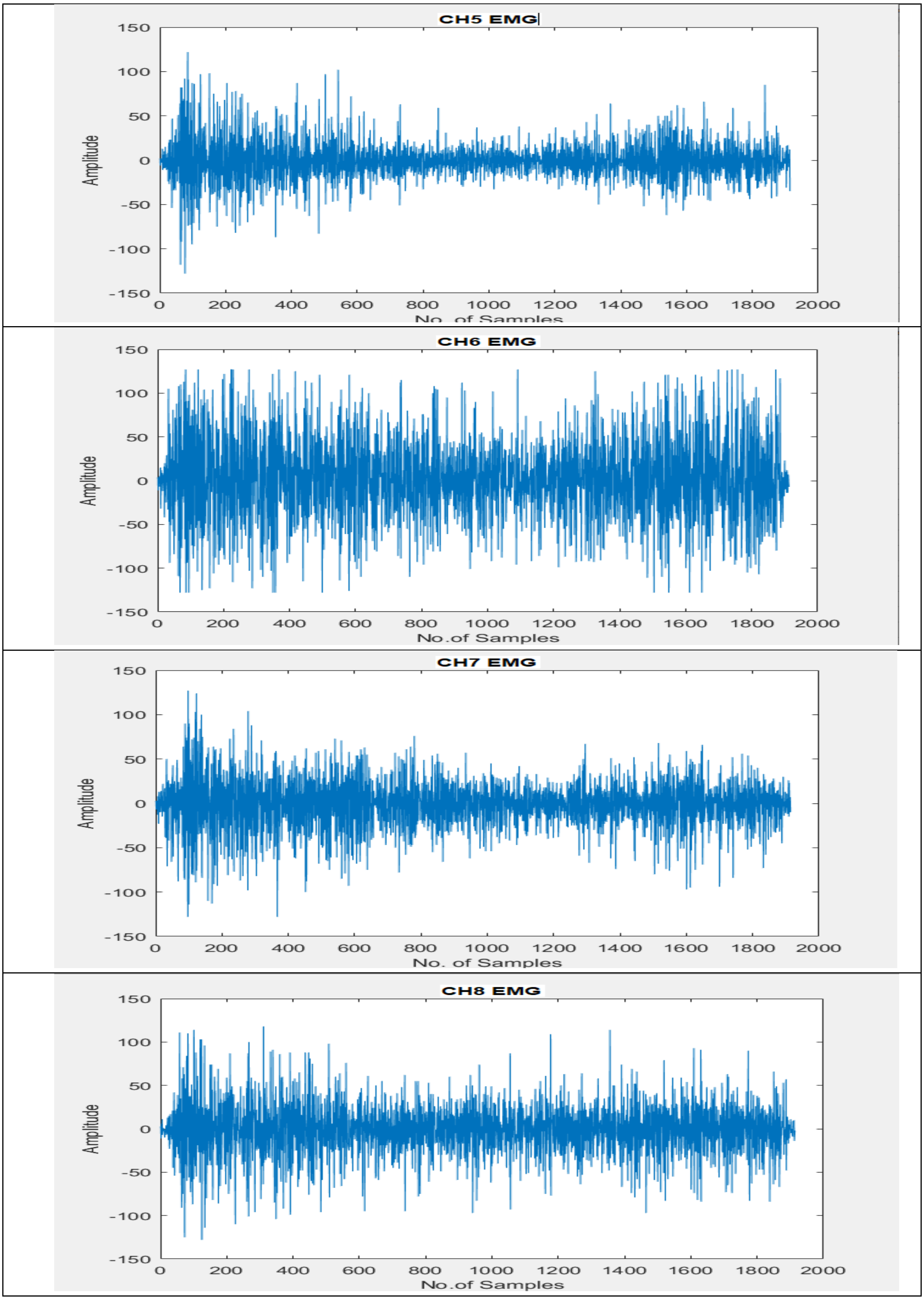


FIG. 3. EXAMPLES OF EMG DATA (8 CHANNELS) IN THE PRE-PROCESSING CONDITION.

Received 24/September/2022; Accepted 10/November/2022
 ISSN (Print) 1811-9212 ISSN (Online) 2617-3352

DOI: https://doi.org/10.33103/uot.ijccce.23.2.14

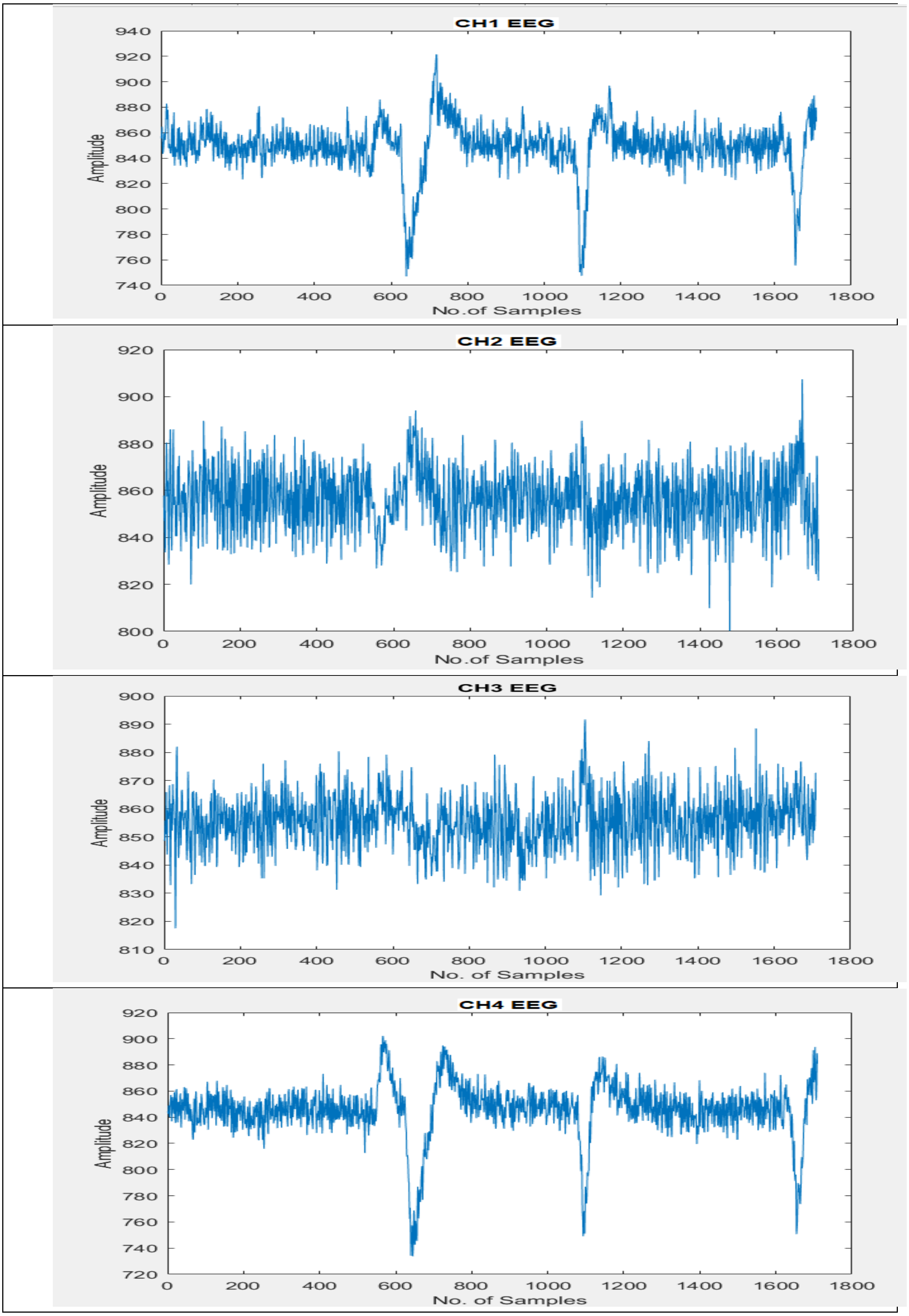


FIG. 4. EXAMPLS OF EEG (4 CHANNELS) IN THE PRE-PROCESSING CONDITION.

Received 24/September/2022; Accepted 10/November/2022
 ISSN (Print) 1811-9212 *ISSN (Online) 2617-3352*

DOI: https://doi.org/10.33103/uot.ijccce.23.2.14

Step 2: Feature Extraction Methods

The most useful features in classification research are those that use time-domain (TD) data. The key benefit is the straightforward extraction process, which, when compared to other methods like frequency domain (FD) and time-frequency domain (TFD), delivers great results. Several studies showed the usefulness of TD, especially in terms of its quickness, simplicity, and lack of any necessary transformation.[12]. The main disadvantage of the TD is that the features are produced by the signal's stationary nature. Therefore, when dealing with non-stationary signals like the EMG collected mostly in dynamic movements, the characteristics are likely to exhibit very significant fluctuations [13]. The TD characteristics are highly vulnerable to noise picked up during data collection because they are entirely based on EMG amplitudes. To distinguish between class movements, the temporal and spectral information is crucial. Additionally, this will serve as the primary criterion for separating TD from FD performance in the categorization [14].

Many studies have made use of those characteristics. However, it's worth noting that not every combination of characteristics was utilized. It has been decided which features would be used in the classification research. The following sections detail the extensive testing performed on five TD features.

1. Mean absolute value (MAV)

Researchers studying EMG and EEG signals frequently and extensively use the MAV feature. The integrated EMG (IEMG) value is computed using the rectified EMG's moving average. Other names for this trait include ARV (i.e., average rectified value) [15]. MAV is mathematically given as:

$$\mathrm{MAV}=\frac{1}{N}\sum_{i=1}^{N}|xi| \tag{1}$$

Where xi represents the signal of the EMG and EEG, whereas N represents the signal’s sample number.

2. Waveform length (WL)

One definition of WL is as a measure of the complexity of an EMG ,and EEG signal that accounts for the sum of all fluctuations across the entire signal. In the context of absolute derivative signals, this property is also known as the full value, and its name is "wavelength" (WAVE). An equation has been derived for determining WL, and it looks like this [16]:

$$\mathrm{WL}=\log\left(\frac{\sum_{i=0}^{n-1}|\Delta \mathrm{x}\ |}{\sum_{i=0}^{n-1}|\ \Delta 2x\ |}\right) \tag{2}$$

3. Wilson Amplitude (WAMP)

This is the quantity of instances where the difference between two successive amplitudes is greater than a predetermined threshold. It can be stated as follows[17] :

$$\mathrm{WAMP}=\sum_{i=1}^{N}u(|x_{i+1}-x_i|-T \tag{3}$$

In this study, a threshold V of 0.05 is taken into account. This characteristic reflects the firing of motor unit action potentials (MUAP), which in turn reflects the intensity of muscle contraction [18].

Received 24/September/2022; Accepted 10/November/2022

ISSN (Print) 1811-9212 ISSN (Online) 2617-3352

DOI: https://doi.org/10.33103/uot.ijccce.23.2.14

4. Slope sign change (SSC)

The SSC can be thought of as a recognizable kind of ZC behavior. It measures changes in the sign of the slope to encode signal frequency information [19]. Within their threshold function, the negative and positive slope changes have been counted three times sequentially. As a result, background EMG noise will not be present. This feature's mathematical expression is:

$$\text{SSC} = \sum_{i=2}^{n-1} [\, f[(x_i - x_{i-1}) \times (x_i - x_{i+1})]] \tag{4}$$
$$f(x) = \begin{cases} 1, if\ x \geq threshod \\ 0,\ otherwise \end{cases}$$

The threshold parameter for this feature should be set to a value between 50 and 100 mV [15, 19]. But if the background noise and gain values of the instrument are not set to the same level, it can be different [20].

5. Cardinality feature

A recently proposed and promising property is called "cardinality," which is represented by counting the number of components in a set of things while omitting all comparable objects among the elements in that collection [21]. When compared to other widely-used individual features in the literature, cardinality was found to be one that maintains a high level of accuracy regardless of changes in the sample frequency, the size of the window, the number of movement classes, or any of the other variables [22].

Those characteristics have also been shown to yield very high classification accuracy in hand movement detection algorithms, outperforming both Frequency Domain (FD) and Time-Frequency Domain (TFD) methods[23]. This was the driving force behind this research's decision to use the TD features indicated previously in the EMG signal gathered for this study.

Step 3: Dimensionality Reduction Method

To extract a few useful features, One typical method for overcoming this issue is to use dimensionality reduction techniques[24]. Principle Component Analysis (PCA) algorithm were used dimensional reduction.

- Principal component analysis (PCA)

PCA is a mathematical technique that decreases the dimensionality of data while preserving the majority of variation1. In contrast, Principal Component Analysis is an example of an orthogonal transformation that produces samples with linearly uncorrelated characteristics from data derived from correlated variables. There are fewer or the same amount of variables as in the beginning, and the new features are the primary components. As an unsupervised technique, PCA discards tagged data. PCA can be quite useful, but it does have some limitations [25].

1- It assumes that there is a linear connection between the variables.
2- All variables must be quantitatively scaled in order to make sense of it.
3- It is missing a probabilistic model framework that has been deemed essential in a number of contexts, including Bayesian decision making and mixture modeling.

Step 4: Classifier

In the classification problem, the learner must learn a function that converts a vector into one of the various classes by examining several instances of input-output feature vectors. There are many methodologies in pattern classification, such as the LDA method [26].

Received 24/September/2022; Accepted 10/November/2022

DOI: https://doi.org/10.33103/uot.ijccce.23.2.14

- Linear Discriminant Analysis (LDA)

The main job of LDA is to search such vector(s) in the vector space that provide better separation of the classes of the data. The class separability can be evaluated by projecting the original data points on to these vector(s). Hence, if the classes are overlapped for a given data points, LDA tries to better separate them by applying some transformation mechanism. LDA has two advantages [27]:

1) It improves the strength of the predictive model by transforming or projecting the original feature vectors into reduced vector space where the class separability is maximized.
2) Second, it reduces the time complexity of the predictive model enormously. After the dimensionality reduction by LDA, the transformed data is applied to neural network for classification.

The proposed algorithm was experimented and evaluated with following step.

Step 5: Experimental Setup

The data was initially segmented using the overlapping segmentation approach with a 150 ms window size and a 50 ms window increment. EMG signal duration was 10 seconds, with a 200 Hz frequency. Channel placements by employing an armband that has eight channels are as follows: 1-4 Ant, 1 Lateral Ant Side, Ch4 Medium Ant Side, 5-8 Post Side. See *Fig. 5*, and the EEG Muse with 252 Fs, Raw 4 channels EEG.

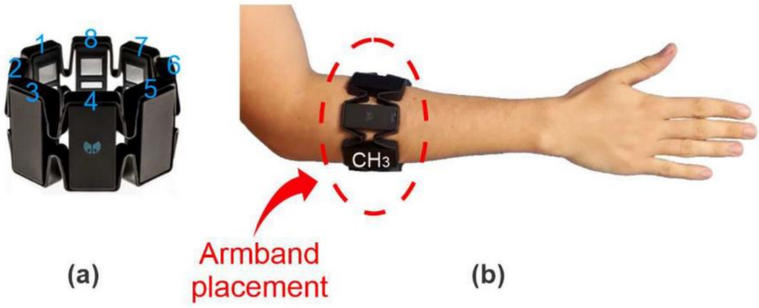


FIG. 5. (A): ARMBAND DEVICE (B): A PHOTO SHOWING AN EXAMPLE OF THE DETAILED ELECTRODE LOCATION FOR WEARABLE ARMBAND FOR INTACT_LIMBED SUBJECT.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

The proposed algorithm was experimented and evaluated with following step. Testing Error and Classification Accuracy Based on EEG, EMG, and fusion EEG, and EMG.

The average Testing errors for the single-signal approaches of 8-ch only EMG, 4-ch only EEG, and Fusion of 12-ch EMG and EEG to all subjects are shown in *Fig. 6* at 12.93%, 38.66%, and 10.43%, respectively. The time domain is a collection of features used in the first experiment, including (MAV, WL, SSC, MAV, Wamp. and Cardinality). According to *Fig. 7*, the subject one value-based PCA (Dimensionality Reduction) achieved classification accuracy is computed using the LDA classifier. The classification performance confusion matrix for intact-limb subject 1 utilizing the (8-ch EMG) is 88.8%, (4-ch EEG) is 57.8%, and dual signal (8-ch EMG + 4-ch EEG) is 89.8%, respectively.

The second experiment is conducted with the Time Domain characteristics, which include (MAV, WL, SSC, MAV, Wamp. and Cardinality). As illustrated in *Fig. 8,* the acquired classification accuracy is computed for subject two value-based PCA (Dimensionality Reduction) with the LDA classifier. This figure depicts the confusion matrix for classification performances for intact-limb subject 2 utilizing

Received 24/September/2022; Accepted 10/November/2022

ISSN (Print) 1811-9212 ISSN (Online) 2617-3352

DOI: https://doi.org/10.33103/uot.ijccce.23.2.14

the single signal approaches (8-ch EMG) at 87.4%, (4-ch EEG) at 54.4%, and (8-ch EMG + 4-ch EMG) at 92.9%.

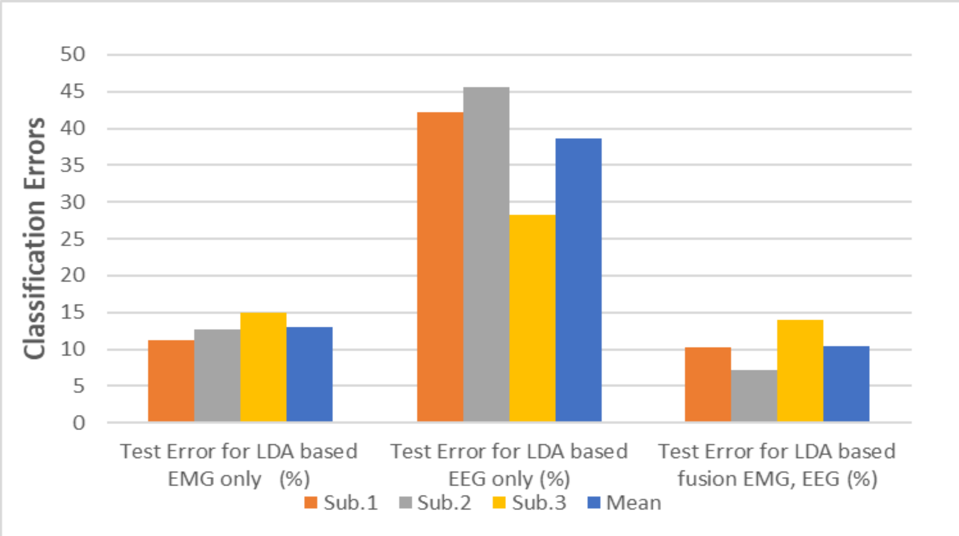
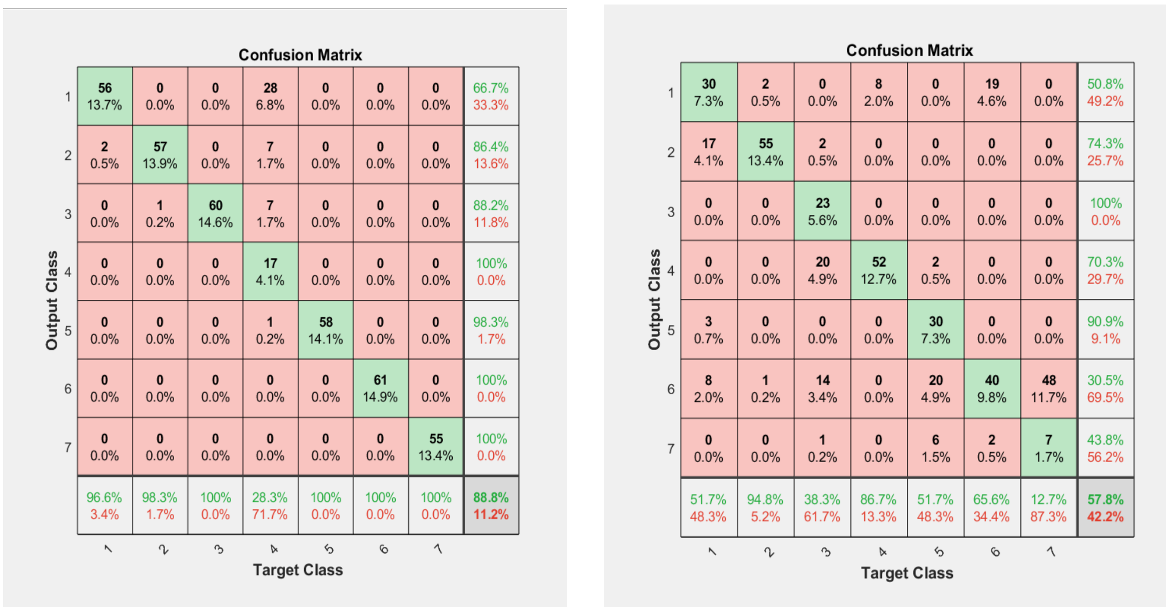


FIG. 6. THE ERROR RATES FOR LDA CLASSIFIER WITH EMG ONLY, LDA CLASSIFIER WITH EEG ONLY, AND LDA CLASSIFIER FOR FUSION EMG, EEG FOR OF INTACT-LIMBED SUBJECTS.

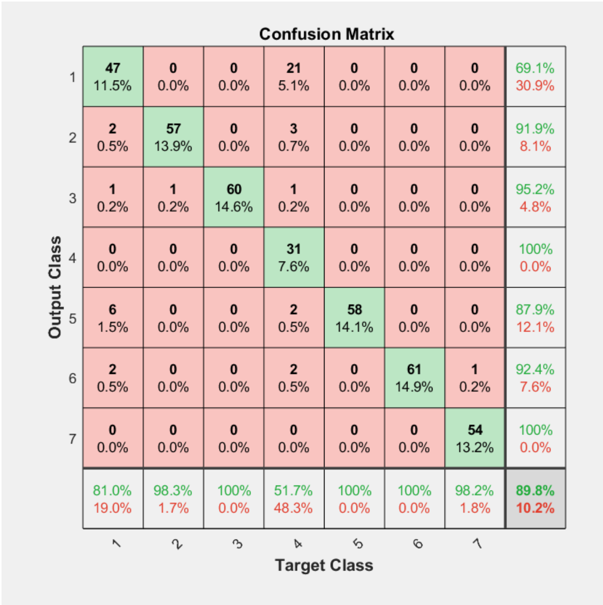
Once more, the last experiment is conducted using the collection of features known as Time Domain, including (MAV, WL, SSC, MAV, Wamp. and Cardinality). For subject three value-based PCA (Dimensionality Reduction), the acquired classification accuracy is calculated using the LDA classifier, as shown in *Fig. 9*. The classification performance confusion matrix for intact-limb subject three is shown in this figure for the single signal approaches of (8-ch EMG) which is 85.0%, (4-ch EEG) which is 71.8%, and (8-ch EMG + 4-ch EEG) which is 86.1%, respectively.



(A) (B)

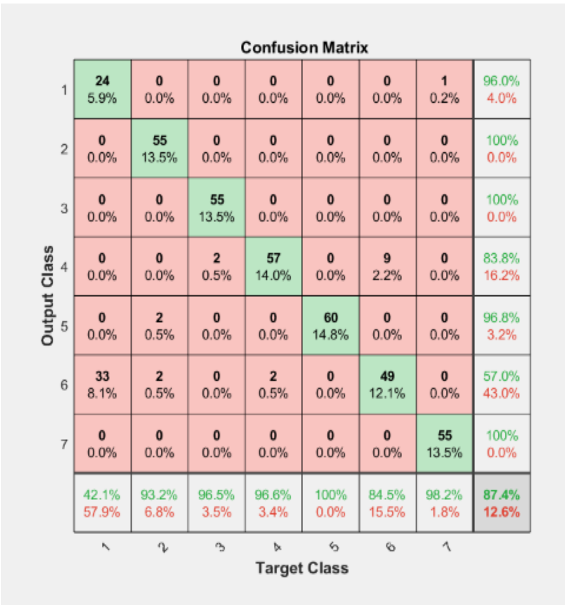
Received 24/September/2022; Accepted 10/November/2022

DOI: https://doi.org/10.33103/uot.ijccce.23.2.14

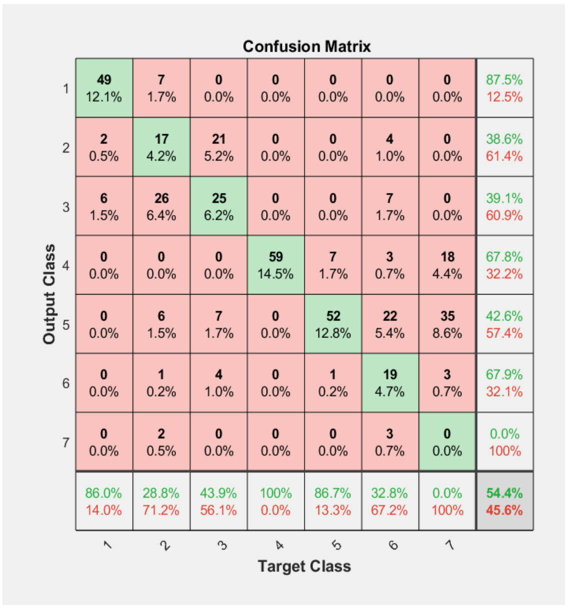


(C)

FIG. 7. (A) CONFUSION MATRICES OF ACCURACY FOR SUBJECT 1(EMG ONLY).
(B) CONFUSION MATRICES OF ACCURACY FOR SUBJECT 1(EEG ONLY).
(C) CONFUSION MATRICES OF ACCURACY FOR SUBJECT 1(EMG +EEG).



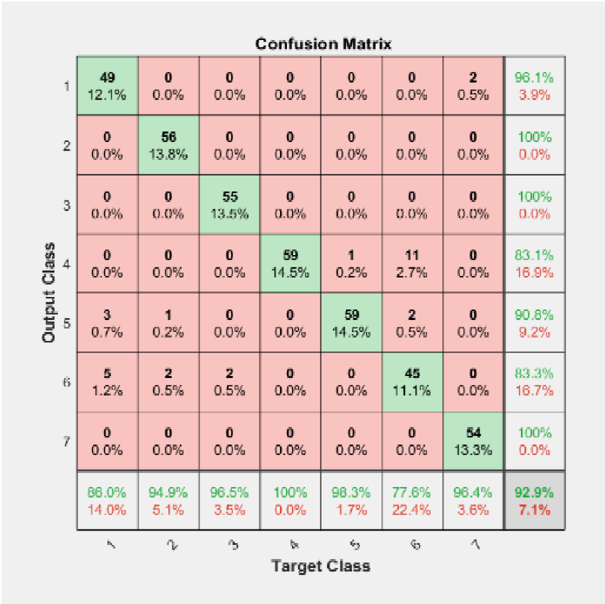
(A)



(B)

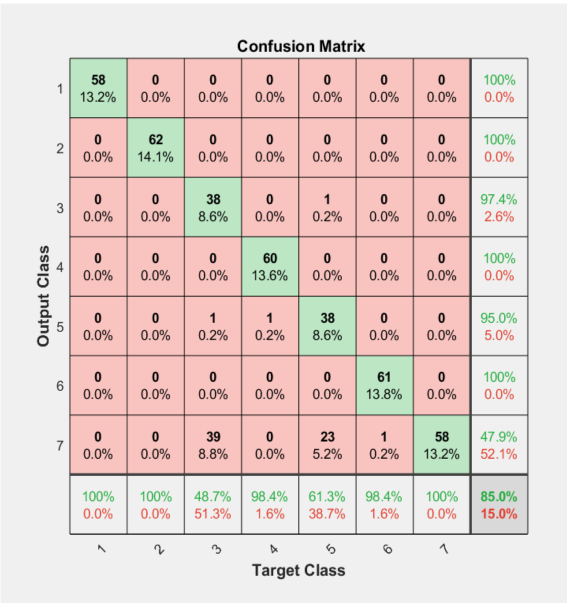
Received 24/September/2022; Accepted 10/November/2022

DOI: https://doi.org/10.33103/uot.ijccce.23.2.14

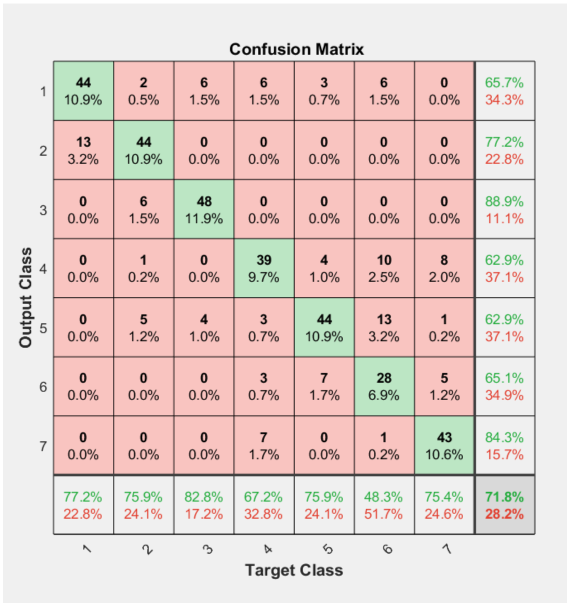


(C)

FIG. 8. (A) CONFUSION MATRICES OF ACCURACY FOR SUBJECT 2 (EMG ONLY).
(B) CONFUSION MATRICES OF ACCURACY FOR SUBJECT 2 (EEG ONLY).
(C) CONFUSION MATRICES OF ACCURACY FOR SUBJECT 2 (EMG +EEG).



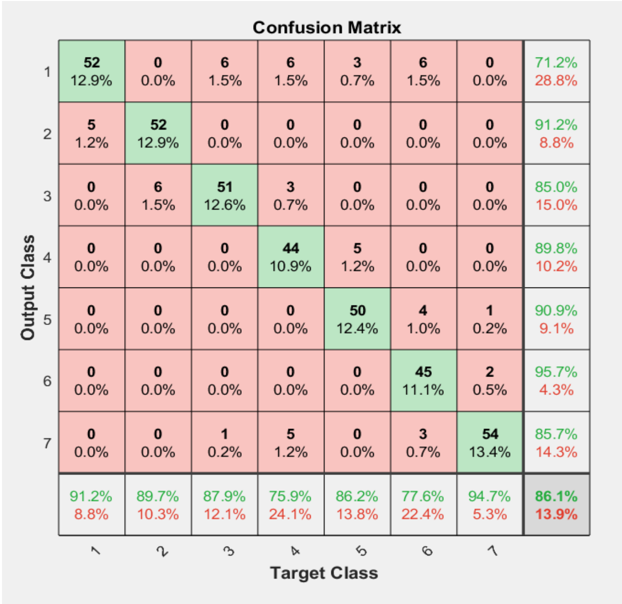
(A)



(B)

Received 24/September/2022; Accepted 10/November/2022
 ISSN (Print) 1811-9212 *ISSN (Online) 2617-3352*

DOI: https://doi.org/10.33103/uot.ijccce.23.2.14



(C)

FIG. 9. (A) CONFUSION MATRICES OF ACCURACY FOR SUBJECT 3 (EMG ONLY).
(B) CONFUSION MATRICES OF ACCURACY FOR SUBJECT 3 (EEG ONLY).
(C) CONFUSION MATRICES OF ACCURACY FOR SUBJECT 3 (EMG +EEG).

Classification results for each subject's confusion matrices are shown in *Fig. 7, 8, and 9*. These figures reveal significant inter-subject variability in both EEG and EMG. That is because bio potentials, the electrical output of human activity, can be measured by techniques like electroencephalography (EEG) and electromyography (EMG). However, the data for each of these range in amplitude and bandwidth.

To compare our study with the previous related literature, Table I demonstrates a summary of the related works mentioned above with the used methodology, No. of channels and achieved results.

TABLE I. THE SUMMARY OF THE RELATED WORKS, THEIR METHODOLOGY, USED NO. OF CHANNELS AND ACHIEVED RESULTS

Work	Method	Channels	Classifier	Accuracy
[9]	Time-domain with features (RMS,STD, information entropy,2ndRMS, Peak no., maximum peak amplitude, dispersion, kurtosis, skewsness)	3–ch. Accelerometer (Acc) or gyroscope	LDA,SVM	88% ,83%
[7]	Time-domain with features(MAV,WL,ZC,SSC)	32-ch EMG + 32-ch EEG	LDA	87.5%
[10]	Time-Frequency domain (WPT) wavelet packets transform	2-ch EMG + 1-ch EEG	ANN	78.65%
The Proposed	Time-Domain with features(MAV,WL,SSC,Wamp., Cardinality)	8-ch EMG + 4-ch EEG	LDA	89.6 %

Received 24/September/2022; Accepted 10/November/2022

DOI: https://doi.org/10.33103/uot.ijccce.23.2.14

V. CONCLUSIONS AND FUTURE WORKS

This paper aims to use EMG and EEG signals to classify seven distinct types of hand and wrist movements by amputees who have lost their limbs bellow the elbow. With regions of interest defined, the fusion of EMG and EEG data can be more accurate, allowing upper-limb amputees to use hand movements as non-invasive and intuitive control cues for prosthetic replacement. The experiment showed that PCA dimensionality reduction using an LDA classifier was facilitated by extracting regular patterns of vital signs. With an average classification accuracy of 89.6% in three intact limb subjects, the proposed PR system succeeded in recognizing seven hand-grinding movements. The results of the study can be used to improve the functionality of myoelectric prostheses for those who have lost their limbs below the elbow. For future work, it is possible to use a different type of dimensionality reduction technique, such as an auto encoder neural network, and to record vital signs from amputees in order to expand the database we have compiled.

REFERENCES

[1] C. R. Louer Jr, P. Scott-Wyard, R. Hernandez, and A. D. Vergun, "Principles of Amputation Surgery, Prosthetics, and Rehabilitation in Children," JAAOS-Journal of the American Academy of Orthopaedic Surgeons, p. 10.5435, 2021.

[2] R. E. Russo, Fernández, Juana G., Rivera, Raúl R., Kuzman, Melisa G., Lopez, Juan M., Gemini, Walter A., Revuelta, Miguel A., "Algorithm of myoelectric signals processing for the control of prosthetic robotic hands," Journal of Computer Science and Technology, vol. 18, no. 1, pp. 28-34, 2018.

[3] J. Lobo-Prat, P. N. Kooren, A. H. Stienen, J. L. Herder, B. F. Koopman, and P. H. Veltink, "Non-invasive control interfaces for intention detection in active movement-assistive devices," Journal of neuroengineering and rehabilitation, vol. 11, no. 1, pp. 1-22, 2014.

[4] X. Li, S Chen, H Zhang, OW Samuel, and H Wang, "Towards reducing the impacts of unwanted movements on identification of motion intentions," Journal of Electromyography and Kinesiology, vol. 28, pp. 90-98, 2016.

[5] A. E. Hassanien and A. Azar, "Brain-computer interfaces," Switzerland: Springer, vol. 74, 2015.

[6] C. Chen, Y. Yu, S. Ma, X. Sheng, C. Lin, and D. Farina., "Hand gesture recognition based on motor unit spike trains decoded from high-density electromyography," Biomedical signal processing and control, vol. 55, p. 101637, 2020.

[7] X. Li, O. W. Samuel, X. Zhang, H. Wang, P. Fang, and G. Li, "A motion-classification strategy based on sEMG-EEG signal combination for upper-limb amputees," Journal of neuroengineering and rehabilitation, vol. 14, no. 1, pp. 1-13, 2017.

[8] W. Zihao, "Upper Limb Movement Recognition utilising EEG and EMG Signals for Rehabilitative Robotics," arXiv preprint arXiv:2207.08650, 2022.

[9] D. Biswas et al., "Recognizing upper limb movements with wrist worn inertial sensors using k-means clustering classification," Human movement science, vol. 40, pp. 59-76, 2015.

[10] F. Sbargoud, M. Djeha, M. Guiatni, and N. Ababou, "WPT-ANN and Belief Theory Based EEG/EMG Data Fusion for Movement Identification," Traitement du Signal, vol. 36, no. 5, 2019.

[11] P. Huang et al., "Identification of upper-limb movements based on muscle shape change signals for human-robot interaction," Computational and Mathematical Methods in Medicine, vol. 2020, 2020.

[12] J. Too, A. Abdullah, T. T. Zawawi, N. M. Saad, and H. Musa, "Classification of EMG signal based on time domain and frequency domain features," International Journal of Human and Technology Interaction (IJHaTI), vol. 1, no. 1, pp. 25-30, 2017.

[13] W. M. B. Bin Wan Daud, "Upper extremity electromyography signal feature extraction and classification," University of Sheffield, 2019.

[14] S. Abbaspour, M. Lindén, H. Gholamhosseini, A. Naber, and M. Ortiz-Catalan, "Evaluation of surface EMG-based recognition algorithms for decoding hand movements," Medical & biological engineering & computing, vol. 58, no. 1, pp. 83-100, 2020.

[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] M. Lohani, B. R. Payne, and D. L. Strayer, "A review of psychophysiological measures to assess cognitive states in real-world driving," Frontiers in human neuroscience, vol. 13, p. 57, 2019.

[17] X. Xi, M. Tang, S. M. Miran, and Z. Luo, "Evaluation of feature extraction and recognition for activity monitoring and fall detection based on wearable sEMG sensors," Sensors, vol. 17, no. 6, p. 1229, 2017.

[18] S. Hui and I. Park, "EMG pattern recognition based on artificial intelligent techniques," IEEE Trans. Rehabil. Eng, vol. 6, pp. 400-5, 1998.

[19] R. Boostani and M. H. Moradi, "Evaluation of the forearm EMG signal features for the control of a prosthetic hand," Physiological measurement, vol. 24, no. 2, p. 309, 2003.

[20] A. A. Badr and A. K. Abdul-Hassan, "CatBoost Machine Learning Based Feature Selection for Age and Gender Recognition in Short Speech Utterances," International Journal of Intelligent Engineering and Systems, vol. 14, no. 3, pp. 150-159, 2021.

Received 24/September/2022; Accepted 10/November/2022
 ISSN (Print) 1811-9212 ISSN (Online) 2617-3352

DOI: https://doi.org/10.33103/uot.ijccce.23.2.14

[21] S. Jimenez, F. Gonzalez, and A. Gelbukh, "Text comparison using soft cardinality," in International symposium on string processing and information retrieval, 2010: Springer, pp. 297-302.
[22] M. Ortiz-Catalan, "Cardinality as a highly descriptive feature in myoelectric pattern recognition for decoding motor volition," Frontiers in neuroscience, vol. 9, p. 416, 2015.
[23] L. J. Hargrove, K. Englehart, and B. Hudgins, "A comparison of surface and intramuscular myoelectric signal classification," IEEE transactions on biomedical engineering, vol. 54, no. 5, pp. 847-853, 2007.
[24] W. Jia, M. Sun, J. Lian, and S. Hou, "Feature dimensionality reduction: a review," Complex & Intelligent Systems, pp. 1-31, 2022.
[25] S. Khalid, T. Khalil, and S. Nasreen, "A survey of feature selection and feature extraction techniques in machine learning," in 2014 science and information conference, 2014: IEEE, pp. 372-378.
[26] D. Cai, X. He, and J. Han, "Training linear discriminant analysis in linear time," in 2008 IEEE 24th international conference on data engineering, 2008: IEEE, pp. 209-217.
[27] L. Ali, C. Zhu, Z. Zhang, and Y. Liu, "Automated detection of Parkinson’s disease based on multiple types of sustained phonations using linear discriminant analysis and genetically optimized neural network," IEEE journal of translational engineering in health and medicine, vol. 7, pp. 1-10, 2019.

Received 24/September/2022; Accepted 10/November/2022

ISSN (Print) 1811-9212 *ISSN (Online) 2617-3352*