Hybrid Brain Computer Interface for Movement Control of Upper Limb Prostheses

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***Abstract*—Electroencephalography (EEG) and Electromyography (EMG) signals are playing significant role in controlling bio-robotics applications, such as prostheses. Brain Computer Interfaces (BCIs) for amputees allow them to use their remaining functionalities as control possibilities by turning brain signals into commands for external devices. However, BCIs that use the EEG signals alone are not yet fully acceptable in bio-robotic applications. Myoelectric control systems use EMG signals recorded on the residual muscles of amputated limbs to control prosthesis, but the residual muscles cannot often provide enough signal to control a multiple degrees of freedom prosthetics. This paper introduces a new hybrid BCI model that integrates EEG and EMG signal processing with machine learning models to efficiently improve classification accuracy and increase the control performance of different upper limb movements for above elbow amputees. Experiments have been carried out on a large dataset of 64 channel EEG signals, combined with 32 channel surface EMG (sEMG) signals, acquired simultaneously from above-elbow amputees to decode five hand and wrist motions. Classification accuracy is used for evaluating the classification performance with 5-fold cross validation. Experimental results demonstrate that the proposed model achieves a high classification accuracy, exceeding 98.8%, using 6th order Autoregressive (AR) model coefficients with three proposed combined set of features from time domain, frequency domain and entropies. This suggested model outperforms previously proposed models in the literature with up to 8.9% improvement ratio; this implies that Hybrid-BCI can be reliably used to improve the control performance of upper limb movements. Furthermore, the model may be easily applied into real-time hybrid BCI application.**

Keywords— Hybrid Brain computer interface, Amputee, machine learning, prosthetics, SVM, signal processing, upper limb movements, QDA, KNN, Motion classification, Signal Fusion

I. INTRODUCTION

Biological signals such as Electromyography (EMG) and Electroencephalography (EEG) can be used as an input signal to control prosthesis. Prosthesis is a device extension which is used to replace a missing body part [1, 2]. Amputees who lost all or part of the upper limb may use a prosthesis depending on their requirement. Externally powered prosthesis hold an importance since it is capable of imitating natural limb motions. However, the way they are controlled stand way back from the natural limb. EMG signals are the signals extracted from the muscles, which gives information related to muscle activity [1]. The surface electromyography (sEMG) signals are used by most of the electrically powered prostheses. These signals are collected from the skin surface, recorded on the residual muscles of amputated limbs and used indirectly as reference signals for the controller of the prostheses [3, 4]. Loss of muscles due to amputations makes EMG signals unavailable which in turn affect the controllability of the prostheses [1]. This makes mimicking the correct motion with an artificial limb very difficult [5]. On the other hand, with recent advancements of technology, brain computer interfaces (BCI) have attracted a lot of interest in the bio-robotics area. BCIs are devices that utilize the non-muscular channels of the brain (e.g., EEG) for communication and control. The BCI is a well-known emerging technology with which people can communicate with their environment and control prosthetic or other external devices using only their brain activity [22]. However, BCIs which use the EEG signals alone as the primary input are not yet fully acceptable in bio-robotic applications due to difficulties such as low reliability, low accuracy, low user adaptability and low data transfer rates. To overcome issues with both EEG- and EMG-based control methods, a combination of both systems, building on the advantages of each signal and diminish the limitations of each might be a promising approach [2]. Li et al. [3] introduced a hybrid model that combines sEMG and EEG signals as parallel inputs to classify five upper limb motions and used four time-domain features to extract features and then fed them into a linear discriminant analysis (LDA) classifier. The channel selection is carried out using Sequential Forward Selection algorithm. Ruhunage et al. [21] proposed a transhumeral prosthetic arm which is controlled by EMG signals with RMS as extracted feature and fuzzy-neuro network algorithm to control the elbow joint of the prosthetic arm and EEG signals with Steady State Visual Evoked Potentials (SSVEP) based method to control the prosthetic hand open/close intension. In this study, a hybrid brain–computer interface system that combines EEG with EMG signals is introduced to improve classification accuracy and increase the control performance of upper-limb prostheses. The paper is organized as follows; Section 2 introduces the proposed hybrid model and the various feature extraction techniques applied in our study and classifiers that have been used for classification of upper limb movements. Section 3 presents performance evaluation procedure and the corresponding experimental results and discussion. Finally, Section 4 provides the conclusion of the study and suggestions for future work.

II. METHODOLOGY

The proposed hybrid model consists of four phases that includes EEG & EMG data acquisition phase, pre-processing and segmentation phase, feature extraction and selection phase and Classification phase as shown in Fig. 1.

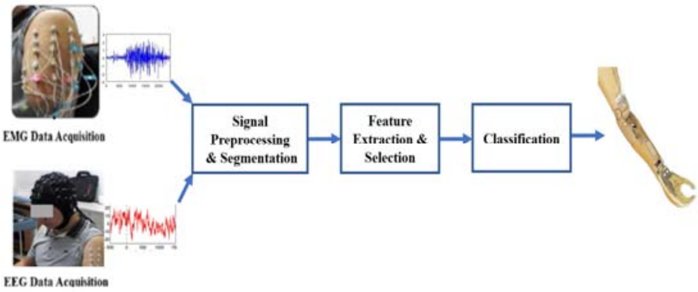

Fig. 1. Proposed Model diagram

A. Data Acquisition

The dataset used in this study were collected by Li et.al [3,4]. This dataset can be described as follows: four male transhumeral (with average age of 41.50±7.05 years and mean residual limb of 25.50±4.20 cm as measured from the shoulder blade downwards) were recruited in the experiments [4]. Five motion classes of hand open (HO), hand close (HC), wrist pronation (WP), wrist supination (WS), and no movement (NM) were tested. Each motion was hold for 5 s and a rest of 5 s (i.e. NM) was scheduled between two neighboring motions, to prevent the subjects from undergoing muscle and mental fatigue that may cause artifacts and thus affect the quality of signals. Each subject repeated the five motions (each of HO, HC, WP, and WS) ten times during data recording sessions. The sEMG and EEG were simultaneously recorded during the motion performance as shown in the EEG and sEMG data acquisition figures [3] in Fig. 1. The sEMG signals were collected with a high-density sEMG system, where 32 monopolar electrodes were placed on the skin surface of the residual arm for each subject. The EEG signals were acquired by a 64- channel EEG cap integrated with a Neuroscan system that represents state of the art systems for the acquisition and analysis of EEG data. Each subject performed a target movement that appeared on a screen and stopped doing the movement when it disappeared. The EEG recording system could automatically mark a vertical line on the EEG recordings as the onset/endpoint of the movement when a target motion picture appeared/disappeared on the screen. And the 64-channel Al-AgCl electrodes were distributed according to the 10–20 system standards, which is a well-accepted way to place scalp electrodes for EEG acquisition [3].

B. Data preprocessing and Segmentation

The sEMG signals were filtered with a band pass filter from 10 to 500 Hz and sampled at a rate of 1024 Hz; the EEG signals were filtered with a band pass from 0.05 to 100 Hz and sampled at a rate of 1000 Hz. The mean of baseline for each channel in EEG signals was removed and the EEG epochs of each motion class were extracted based on the onset-endpoint lines. For a motion class, each of its EEG epochs consisted of 5-s EEG recordings plus 120-ms EEG recordings before the onset of the movement, totally having 5120 data points [3]. To detect artifacts such as eye movements and blinks in each EEG data epoch, an adaptive threshold that was equal to the 1.2 times of the mean absolute value of an epoch data was applied. Furthermore, a 50 Hz notch filter was used to remove the power-line noise for both sEMG and EEG recordings.

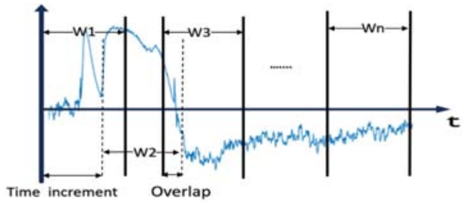

Fig. 2. Overlapped Segmentation scheme

An overlapped segmentation scheme is deployed with 150ms, 200ms, 250ms window lengths and an increment of 100ms. Fig. 2 shows an example how the overlapped segmentation scheme is done.

C. Feature Extraction

In this phase, auto-regressive (AR) model coefficients combined with three proposed sets of time domain, frequency domain and entropy-based features were calculated for each segment. The time domain features include root mean square (RMS), waveform length (WL) and william amplitude (WAMP) while the frequency domain features include autoregressive (AR) coefficients, frequency ratio (FR), the modified mean and modified median of signal frequencies (MMNF, MMDF). Sample entropy and log energy entropy were the entropy-based features calculated for each segment. The features of each channel were extracted from segments with various lengths, and then, concatenated to construct the feature vectors as illustrated in Fig. 3.

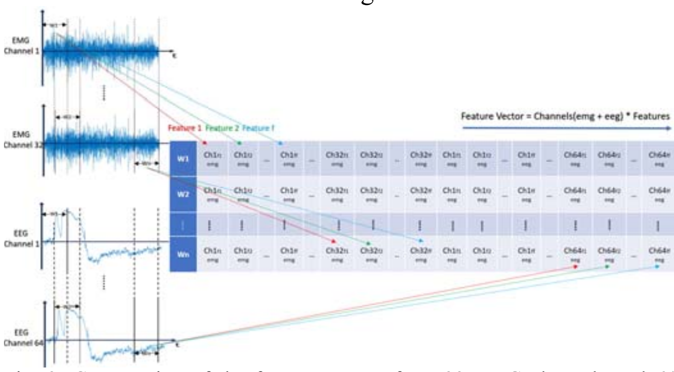

Fig. 3. Construction of the feature vectors from 32 EMG channels and 64 EEG channels, where "f" features extracted from each channel and "n" time windows ("W").

1) Autoregressive Coefficients

Autoregressive (AR) model described each sample of signal as a linear combination of previous samples plus a white noise error term. The AR model is expressed as:

$$x_k = \sum_{i=1}^{p} a_i x_{k-i} + e_k \tag{1}$$

where a_i represents the AR coefficients, p is the AR model order, and e_k is the residual white noise which is independent from the previous points, and parameter p is the order of the AR model [21]. In this study, we used both 4^{th} order based on the suggestions in [9, 14] and 6^{th} order based on the suggestions in [19, 21] in the AR model.

2) Entropy-Based Features

Entropy is a measure of complexity and randomness of dynamic systems, describing the rate of information creation [17]. The nonlinear parameters can be useful to describe the dynamics of the EEG and EMG signals considering the nonlinear and non-stationary nature of the signals [15]. Sample entropy and Log energy entropy were computed for each segment.

a) Sample Entropy

Sample entropy is defined as the negative natural logarithm of the conditional probability that two sequences similar for m points remain similar at the next point within a tolerance width r, where self matches are not included in the calculating the probability [16]. In order to compute the sample entropy, the scalar time series $\{x_1, x_2, \ldots, x_i, \ldots, x_n\}$ is first embedded in a delayed m-dimensional space, where vectors are constructed as:

$$x(p) = [x(p+K)]_{K=0}^{m-1}, p = 1,2,\ldots,n-m+1 \tag{2}$$

The probability $B^m(r)$ that two sequences match for m points is computed by counting the average number of vector pairs, for which the distance is lower than the tolerance r. Similarly, $A^m(r)$ is defined for an embedding dimension of $m + 1$ [17]. The sample entropy is then calculated as:

$$Sample\ Entropy(x, m, r) = -\ln(A^m(r)/B^m(r)) \tag{3}$$

The tolerance r can be chosen as (0.15 – 0.25) * SD, the standard deviation of the original time series. In this study, we set $m = 2$ and $r = 0.25 * SD$.

b) Log Energy Entropy

In general, the entropy of a finite length discrete random variable, $x = [x(0), x(1),\ldots\ldots, x(N\text{-}1)]$ with probability distribution function denoted by $p(x)$ [18]. It is defined by:

$$H(x) = -\sum_{i=0}^{N-1} p_i(x) log_2(p_i(x)) \tag{4}$$

the Log Entropy entropy of x is given by:

$$H_{LogEn}(x) = -\sum_{i=0}^{N-1} (log_2(p_i(x)))^2 \tag{5}$$

3) Root mean square (RMS)

Root Mean Square relates to standard deviation, which can be expressed as:

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \tag{6}$$

4) Willison Amplitude

Willison amplitude (WAMP) is the number of times that the difference between EEG or sEMG signal amplitude among two adjacent segments that exceeds a predefined threshold to reduce noise effects [8]. It can be formulated as:

$$WAMP = \sum_{i=1}^{N} f(|x_i - x_{i+1}|) \tag{7}$$

$$f(x) = \begin{cases} 1, & if\ x > threshold \\ 0, & otherwise. \end{cases}$$

In this study, we used (WAMP) with threshold value 0.025.

5) Waveform Length

Waveform length (WL) is the cumulative length of the waveform over the time segment. WL is related to the waveform amplitude, frequency and time [7]. It is given by:

$$WL = \sum_{n=1}^{N-1} |x_{n+1} - x_n| \tag{8}$$

6) Modified Median Frequency

Modified Median Frequency (MMDF) is the frequency at which the spectrum is divided into two regions with equal amplitude. It can be expressed as:

$$\sum_{j=1}^{MMDF} A_j = \sum_{j=MMDF}^{M} A_j = \frac{1}{2}\sum_{j=1}^{M} A_j \tag{9}$$

where Aj is the EEG or sEMG amplitude spectrum at frequency bin j [7].

7) Modified Mean Frequency

Modified Mean Frequency (MMNF) is the average frequency. MMNF is calculated as the sum of the product of the amplitude spectrum and the frequency, divided by the total sum of spectrum intensity. It can be expressed as:

$$MMNF = \sum_{j=1}^{M} f_j A_j / \sum_{j=1}^{M} A_j \tag{10}$$

where f_j is the frequency of spectrum at frequency bin j [7].

8) Frequency Ratio

Frequency ratio (FR) is the ratio between the low frequency components and the high frequency components of the signal. The equation is defined as:

$$FR = \sum_{j=LLC}^{ULC} P_j / \sum_{j=LHC}^{UHC} P_j \tag{11}$$

where ULC and LLC are the upper- and lower-cutoff frequency of the low frequency band and UHC and LHC are the upper- and lower-cutoff frequency of the high frequency band, respectively. The threshold for dividing between low frequencies and high frequencies can be decided through the experiments [14].

D. FEATURE SELECTION

Features should be capable of presenting the characteristics or properties of a signal for different limb motions. Computational load should also be considered in the real-time applications [19]. Feature selection aims to choose a small subset of the relevant features from the original ones according to certain relevance evaluation criterion, which usually leads to better learning performance (e.g., higher learning accuracy for classification), lower computational cost, and better model interpretability. Feature selection is done in such a way that extracted set of features that do not contribute substantially to the classification accuracy are removed [24].

E. CLASSIFICATION

The performance of the proposed model has been tested using three classifiers: Quadratic Discriminant Analysis (QDA), K-Nearest Neighbor (KNN) and Quadratic Support Vector Machine (Quadratic SVM) to classify five upper limb movements.

1) Quadratic Discriminant Analysis

The discriminant function generated in QDA is given by [13]:

$$\delta_k(x) = -\frac{1}{2}\log|\Sigma k| - \frac{1}{2}(x-\mu_k)^T \Sigma k^{-1}(x-\mu_k) + \log\pi_k \tag{12}$$

Σk is the covariance matrix, it should not be the identity matrix, x is the data set and μ_k is the estimation of mean for data and the discriminant rule is given by:

$$\delta_K(x) = \min_{1 \le k \le K} d_k(X) \leftrightarrow \max_{1 \le k \le K} p(k/x) \quad (13)$$

2) K-Nearest Neighbor

The k-nearest neighbor (KNN) algorithm is a widely used simple classification technique that finds the k-many nearest neighbors in a training data set and then map them the same during the estimation process. The idea underlying the KNN method is to assign new unclassified examples to the class to which the majority of its K nearest neighbors belongs [23].

3) Support Vector Machine

An SVM constructs an optimal separating hyperplane in a high-dimension feature space of training data that are mapped using a nonlinear kernel function. Therefore, although it uses a linear learning machine method with respect to the nonlinear kernel function, it is in effect a nonlinear classifier [12]. The use of a nonlinear kernel function greatly increases the power of learning and generalization. The support vector machine can be mathematically expressed as:

$$c = \sum_i a_i k(s_i x) + b \quad (14)$$

Where S_i is support vector, a_i is weight and b is the bias that is use to classify the feature vector x. Here k is the kernel function. Quadratic Support Vector Machine is tested in this study. Mathematical representations of Quadratic Support Vector Machine is given by:

$$k(s_i.x) = e^{-\|s_i - x\|^2} \quad (15)$$

III. RESULTS AND DISCUSSION

A. PERFORMANCE METRICS

The performances of classifiers are usually evaluated by means of accuracy defined as the number of correct classifications over the total classifications [12, 13]. In this study, classification accuracy has been mathematically defined as:

$$Classification\ Accuracy = \frac{No.of\ correctly\ pridected\ data}{No.of\ total\ testing\ data}\ X\ 100 \quad (16)$$

Different methods can be used to evaluate accuracy such as Train-Test evaluation and N-fold cross validation (CV) that partition the whole dataset in N not-intersecting subsets, approximately of the same size, and use the *ith* subset as a testing set and the remaining $N-1$ subsets as training set; the process iterates until each subset is used once as a testing set, and the accuracy comes from the average of the N-tests accuracies [12]. In this study, the classification accuracy was tested with a 5-fold cross validation method.

B. EXPERIMENTAL RESULTS AND DISCUSSION

Experiments have been carried out to validate the efficiency of the proposed hybrid BCI system and study the effect of the three proposed combined feature sets, the segment length and the autoregressive coefficients order on the performance of the proposed model. All experiments were implemented using MATLAB and performed on a 2.8-GHz Intel Core i7 CPU based laptop with 16 GB of Random Access Memory (RAM). The dataset contains 96 channels (64 channels EEG + 32 channels EMG) for each motion of the five upper limb movements recorded from each subject of the four amputees and repeated 10 times.

1) Experiment 1: Study the effect of the proposed groups of combined features and classifiers

An overlapped segmentation scheme was deployed for each channel. AR coefficients were calculated for each segment. There are 96 groups of AR coefficients for 96 channels (64 channels EEG + 32 channels EMG) in the same segment. Therefore, (96 ∗ p) features were generated, where p is the order of AR model. Then, three combinations of features are added to AR coefficients. Fig. 3 shows the dimensional feature vectors calculated as (96 channels ∗ features) for each segment that were fed to three classifiers; QDA, KNN and Quadratic SVM classifiers for motion classification, tested with a 5-fold cross validation method and evaluated by classification accuracy metric.

TABLE 1. Comparison of classification accuracy between three different feature extraction groups using QDA classifier.

Combined Feature groups		Accuracy (%)
Grp1	WAMP+RMS+WL+AR	98.9118 %
Grp2	MFMD+MFMN+FR+AR	98.902 %
Grp3	AR+Log energy entropy+ Sample entropy	94.8235 %

As shown in TABLE 1, the most promising results were obtained by training a QDA classifier with 6th order AR model coefficients and three time domain features including RMS, WL and WAMP features extracted from each segment of length 250ms. Furthermore, the time-domain features (WL, RMS, and AR coefficients) are not computationally intensive, making them easy to implement in a real-time hybrid BCI application [11]. TABLE 2 shows a comparison of classification accuracy between QDA, KNN and Q-SVM classifiers for the proposed feature extraction groups. QDA has been shown to exhibit the highest level of accuracy for decoding forearm and wrist movements. The higher classification accuracy of the classifier can be attributed to the fact that QDA creates a second order decision boundary in the kernel space to cater for unstable and low variance features of EEG and EMG signals [13]. Furthermore, QDA are recognized to be highly robust against the curse of dimensionality and overfitting owing to their enhanced regularization capabilities [13, 19, 23]. The second-best classification accuracy was achieved by The KNN classifier that had higher accuracy than Q-SVM.

TABLE 2. Comparison of classification accuracy (%) between QDA classifier with KNN and Q-SVM classifiers for different feature extraction groups, for the proposed model.

Combined Feature groups		QDA	Q-SVM	KNN
Grp1	WAMP+RMS+WL+AR	98.9118	87.8824	95.5098
Grp2	MFMD+MFMN+FR+AR	98.902	89.9314	95.3529
Grp3	AR+Log energy entropy+ Sample entropy	94.8235	83.8529	93.6373

2) Experiment 2: Study the effect of segment Length

The purpose of this experiment was to study the dependence of the proposed combined groups of features on segment length in hybrid BCI classification. Fig. 4 that illustrates the performance of classification in different segment lengths, shows that segment length of value 250ms has the best performance accuracy using the three proposed groups of features and QDA classifier. The third group of features that consists of AR model and entropies experienced a significant degradation in performance by decreasing the segment length to 150ms. The results indicate that despite the difference in groups of features, the ratio of improvement in the performance using segment length 250ms has exceeded 0.7%, 1% and 2% comparing with the other smaller length using first, second and third groups of features, respectively.

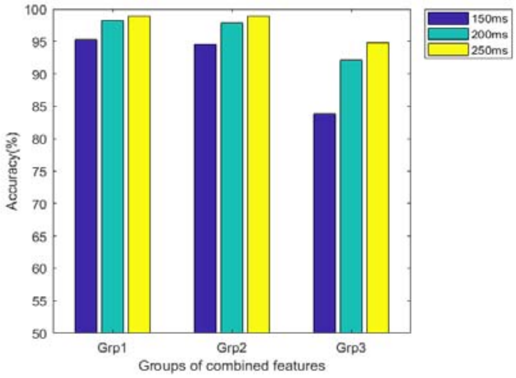

Fig. 4. The accuracy of each set of combined features with overlapped segmentation scheme of different segment length, 150ms, 200ms and 250ms and an increment of 100ms using QDA classifier.

3) Experiment 3: Study the impact of autoregressive coefficients order

In this experiment, the impact of 4th and 6th autoregressive coefficients orders on the classification accuracy was examined using the proposed groups of features and QDA classifier. TABLE 3 shows that the classification accuracies of the first and second proposed groups of features that includes time and frequency domain features were relatively higher with 6th order AR coefficients than those of 4th order AR coefficients. The third group of features that includes sample and log energy entropies achieved a higher accuracy with 4th order AR model comparing with 6th order AR model.

4) Comparisons with previously proposed methods

To further examine the efficiency of the proposed model, this section provides a performance comparison between the proposed approach and recently developed methods by Li et al. [3] and Ruhunage et al. [21]. As shown in TABLE 4, the proposed method yields the most excellent performance of 99.45% and 99.57 for subjects, TH2 and TH4, respectively. TABLE 5 illustrates the classification accuracy and time taken, for feature extraction and movement classification of the five hand and wrist movements, which are acceptable for prosthesis control. As shown in TABLE 6, there is significant improvement in classification accuracy of the proposed model reaches up to 8% and 8.986% of improvement ratio in comparison with Li et al. [3] and Ruhunage et al. [21], respectively. Furthermore, the standard deviation shows that there is no significant variation of the accuracies among the different subjects which indicates the stability of the proposed method.

TABLE 3. The impact of the AR coefficients order on the performance of the proposed model, for segment length 250ms using QDA classifier.

Combined Feature groups		**4th order AR coefficients**	**6th order AR coefficients**
Grp1	WAMP+RMS+WL+AR	98.7451 %	98.9118 %
Grp2	MFMD+MFMN+FR+AR	98.7843 %	98.902 %
Grp3	AR+Log energy entropy+Sample entropy	96.6765 %	94.8235 %

TABLE 4 Classification accuracies (%) of the five hand and wrist movements of the four transhumeral amputees, for segment length 250ms using 1st group combined features and QDA classifier.

Transhu-meral Amputee	**Hand and Wrist movements**					**Mean ± Std**
	HO	**HC**	**WP**	**WS**	**NM**	
TH1	97.64	100	99.22	98.82	99.02	98.94 ±0.76
TH2	99.22	99.8	99.22	99.41	99.61	99.45 ±0.23
TH3	99.8	98.82	97.65	98.82	97.26	98.47 ±0.91
TH4	99.02	99.62	100	99.41	99.8	99.57 ±0.34
Mean ± Std	98.92 ±0.79	99.56 ±0.45	99.02 ±0.85	99.12 ±0.29	98.92 ±1	99.1 ±0.24

TABLE 5 Classification accuracy and time taken for feature extraction and movement classification of the five hand and wrist movements for segment length 250ms using the 1st group of features and QDA classifier.

Wrist and Hand Movements	**Accuracy (%)**	**Average Time (s)**
Hand Open (HO)	98.92 ± 0.79	0.035088 ±0.00069
Hand Close (HC)	99.56 ± 0.45	0.034832±0.000628
Wrist Pronation (WP)	99.02 ± 0.85	0.03448375±0.000658
Wrist Supination (WS)	99.12 ± 0.295	0.03490075±0.00058
No Movement (NM)	98.92 ± 1	0.034735±0.00045

TABLE 6. Comparison between the proposed method and other methods in literature.

Paper	**Methods**		**Mean ± Std**
	Features	***Classification***	
Li et al. 2017 [3]	MAV, ZC, SSC and WL	LDA	91.7 ± 3.5

Ruhunage et al. 2017 [21]	RMS of the EMG and EEG signals with SSVEP based method	A real time fuzzy-neuro network	90.9 ± 6.4
Proposed Model	WAMP, RMS, WL, 6^{th} AR coeff.	QDA	99.1 ± 0.24

IV. CONCLUSION AND FUTURE DIRECTIONS

In this paper, a new hybrid BCI system is proposed to classify different upper limb movements for above elbow amputees whose residual muscles don't provide enough signal for motion control. A new efficient combination of feature extraction and classifier model has been proposed to decode upper limb movements. Three classifiers with enhanced feature extraction and selection phase were used to classify wrist and hand motions from the signal fusion of EEG and EMG signals. An overlapped segmentation scheme is used with different window lengths. AR model coefficients with proposed combined set of features from time domain, frequency domain and entropy-based features were studied for feature selection and extraction. QDA, KNN and Quadratic SVM classifiers are used for motion classification, tested with a 5-fold cross validation method and evaluated by classification accuracy. The effect of segment length and AR model coefficients order has been studied. The proposed method that combines 6th order AR model coefficients with three time domain features including RMS, WL and WAMP showed enhanced classification accuracy using QDA classifier with 8% improvement ratio. The proposed method can be accurately used to decode the hand and wrist motions which are some of the fundamental limb movements behind activities of daily life. In the future work, channel reduction techniques and channel selection algorithms would be applied to achieve a reduced number of EEG and EMG channels with optimal classification performance.

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