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Factors influencing low intension detection rate in a non-invasive EEG-based brain computer interface system

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ABSTRACT

Motor imagery (MI) responses extracted from the brain in the form of EEG signals have been widely utilized for intention detection in brain computer interface (BCI) systems. However, due to the non-linearity and the non-stationarity of EEG signals, BCI systems suffer from low MI prediction rate with both known and unknown influncing factors. This paper investigates the impact of visual stimulus, feature dimensions and artifacts on MI task detection rate, towards improving MI prediction rate. Three EEG datasets were utilized to facilitate the investigation. Three filters (band-pass, notch and common average reference) and the independent component analysis (ICA) were applied on each datasets, to eliminate the impact of artifact. Three sets of features where extracted from artifact free ICA components, from which more relevant features were selected. Moreover, the selected feature subsets were incorporated into three classifiers, NB, Regression Tree and K-NN to predict four MI and hybrid tasks. K-NN classifier outperformed the other two classifies in each dataset. The highest classification accuracy is obtained in hybrid task EEG dataset. Moreover, accurately predicted EEG classes were applied to a robotic arm control.

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1. INTRODUCTION

Brain computer interface (BCI) systems in recent years have emerged as a breakthrough technology, capable of aiding individuals suffering from severe motor disabilities interact with the surrounding environment using only imagined movements. Brain computer interface is a process of extracting neural activities of the brain in the form of EEG signals, and transforming them into control commands utilized to control electronic equipment. However, during acquisition of EEG signals from the brain several interferences exist (such as physiological and non-physiological artifacts) which may have significant impact on the quality of recorded EEG signals. Moreover, during translation of EEG signals into control commands the dimension of extracted feature set may also have significant impact on the performance signal classifiers, mainly as a result of redundant features contained within the extracted feature set. As such low MI detection and prediction is still one of the most significant challenges in EEG based BCI systems. Recently countless techniques have been developed to address the challenge of low MI detection and prediction. [1] proposed a BCI system that utilized EEG dataset acquired from BCI competition III-a database, whereby four band-pass filters were firstly applied on EEG dataset to eliminate artifacts. Moreover, common spatial pattern technique was utilized to extract features from pre-processed EEG dataset. As such SVM was utilized to predict two MI classes from extracted features, and a highest classification accuracy of 85.5% was achieved. [2] proposed a BCI system that utilizes EEG dataset acquired from BCI competition II database from which a 0.5Hz - 30Hz elliptic band-pass filter was applied to eliminate artifacts. Furthermore, statistical features were extracted from pre-processed EEG dataset, whereby SVM and multi-perceptron classifiers were both applied on extracted features to predict two MI classes. The highest classification accuracy of 85% and 85.71% were obtained from both signal classifiers respectively. Multiple filters were reported by combining with one-to-one classification [3]. This paper investigates the impact of visual stimulus, artifacts and feature dimension on prediction rate. To evaluate the above mentioned factors a hybrid EEG based BCI system consisting of five stages is proposed. In this case a signal acquisition stage utilized to record EEG datasets, a pre-processing stage utilized to filter and decompose EEG signals to remove noise and artifactual components, whereby artifact free ICA components are utilized to extract three sets of features from each of the three datasets during feature extraction stage. Moreover, relevant signal feature subsets with high predictive power are selected, and used as inputs to signal classifiers to predict four MI task during feature selection and classification stage respectively.

2. RESEARCH METHOD

2.1. EEG signal acquisition

A publicly available database (BCI competition IV-a) and two online recorded EEG datasets using a gtec EEG recording system were utilized [4]. BCI competition IV-a dataset was acquired from nine healthy subjects using twenty-two Ag/AgCl channels position on the scalp according to a 10-20 electrode positioning system as illustrated in Figure 1(b), whereby EEG signals were recorded at a sampling rate of 250Hz [5]. At the beginning of the experiment a fixed cross and a two second beeping sound were utilized to notify the subjects to begin imagining, and each subject was required to performed four motor imagery task (left hand, right hand, tongue and both feet) [6]. Furthermore, two EEG datasets were non-invasively recorded from one subject at a sampling rate of 250Hz using 16 electrodes. In this case imagine only EEG dataset recorded while the subject performed four motor imagery tasks as illustrated in Figure 1(a). Secondly a hybrid tasks EEG dataset recorded while the subject performed a combination of SSVEP and MI tasks. As such visual stimulus in the form of four flashing balls were displayed on an LCD monitor, while the subject performed four MI tasks [7]. For both online recorded EEG datasets at the beginning of a trial the subject was requested to imagine the required MI task for 300 seconds [8]. Moreover, a beeping sound was utilized to notify the subject to begin imagining any of the four MI tasks (left hand, right hand, tongue and both feet) [9]. As such the same process was repeated for the other three MI classes and as a result a trial lasted for twenty minutes. For hybrid EEG dataset the same experimentation paradigm as MI tasks was repeated, in this case the visual stimulus were tagged with four different frequencies (29 Hz, 13.3 Hz, 17 Hz, 21 Hz) corresponding to each MI task [10].

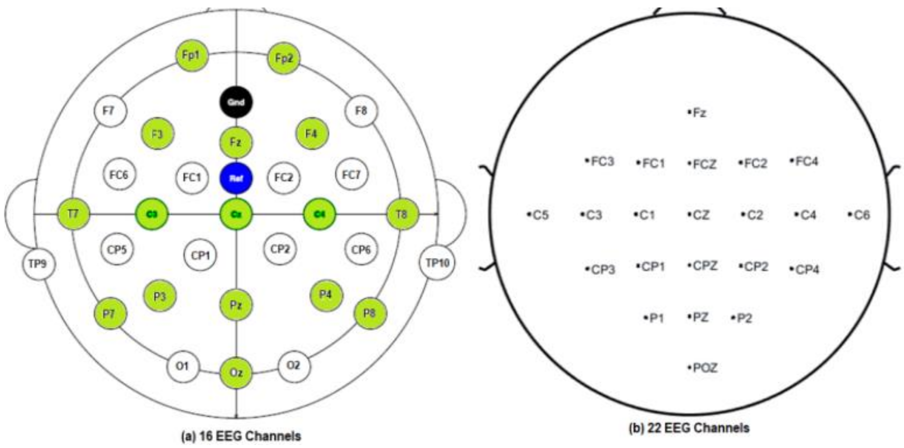

Figure 1. 10-20 electrode positioning system for online recorded EEG datasets (b) 10-20 electrode positioning system for BCI competition IV-a dataset [6]

2.2. EEG signal preprocessing

In this section a 0.5-60 Hz band-pass, 48-52 Hz notch and a CAR filter were firstly applied on both sets of recorded EEG data to eliminate the impact of non-physiological artifacts [11]. Subsequently, a 0.5-100 Hz band-pass and a 50Hz notch filter was also applied on BCI competition IV-a dataset. EEGLAB was utilized to implement runICA algorithm, consequently sixteen and twenty-two ICA components were generated from both filtered online recorded and BCI competition EEG dataset respectively, from which artifactual components can be rejected [12]. Furthermore, sixteen ICA components acquired from imagined only dataset were manually evaluated to eliminate artifactual windows using a sliding window technique. Moreover, each component was divided into twenty blocks containing twenty windows each, then a sliding window represented by two red vertical lines was applied on each block to remove artifactual windows as illustrated in Figure. 2.

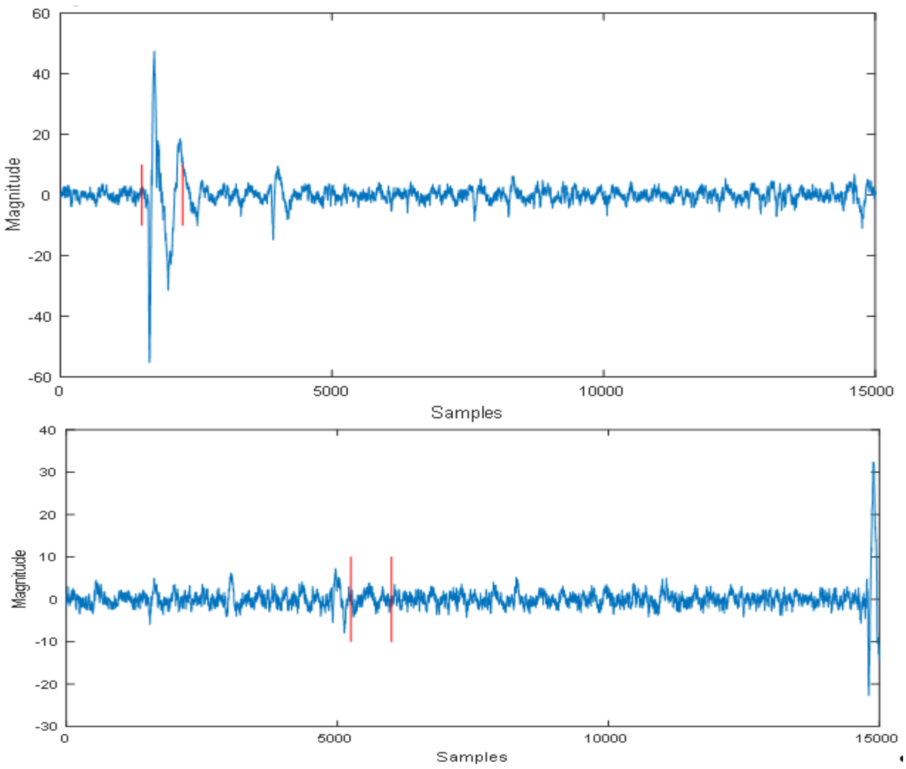

Figure 2. Sliding window approach applied on imagine only ICA components

2.3. Feature extraction

Three sets of features were extracted from each ICA component and component eight online recorded and BCI competition IV-a datasets respectively. Fast fourier transform (FFT) denoted by (1) was utilized to extract band-power features in the form of five frequency bands (namely delta (δ): 0.5 – 3 Hz, theta (θ): 4 – 8 Hz, alpha (α): 8 – 12 Hz, beta (β):12 – 30 Hz and gemma (γ): 30 – 60 Hz) from ICA components [13-15].

$$X(f) = F\{x(t)\} = \int x(t)e^{-2\pi f t dt} \quad (1)$$

FFT is denoted by $X(f)$ and EEG signals in time domain denoted by $x(t)$[16]. MATLAB statistical toolbox was utilized to extract ten signal features from each of the three EEG datasets (namely mean, median, standard deviation, mean absolute deviation, skewness, kurtosis, spectral entropy and dominant frequency features (maximum frequency, maximum value, maximum ratio)) [17].

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^2} \quad (2)$$

In this case standard deviation (σ) is denoted by (2), and signals within a specific window denoted by x_i. Moreover, the arithmetic mean of signals within a specific window is denoted by $\overline{x}$, with N representing the data points in total within a specific window [18].

$$M = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (3)$$

Mean of a signal (M) denoted by (3), whereby signals within a specific window are denoted by x_i and with n signifying the overall samples within a window [18].

$$Med_{even} = \frac{\frac{n}{2}+(\frac{n}{2}+1)}{2} \tag{4}$$

$$Med_{odd} = \frac{(n+1)}{2} \tag{5}$$

Median of a signal is computed using either (4) or (5) depending on whether n is even or odd, whereby the overall sample points within a certain window is denoted by n [18].

$$P(\omega_i) = \frac{1}{N}|X(\omega_i)|^2 \tag{6}$$

$$P_i = \frac{P(\omega_i)}{\sum P(\omega_i)} \tag{7}$$

$$PSE = -\sum_{i=1}^{n} P_i \ln P_i \tag{8}$$

Power spectral entropy (PSE) in (8) is dependent on power spectral density $P(\omega_i)$, and the normalized power spectral density P_i defined both (6) and (7) respectively. Whereby $X(\omega_i)$ and N in (6) signifies the value of signals within a certain window, and the overall samples with a certain window respectively. Moreover, the combination of all signal values acquired through the PSD is denoted by $\sum P(\omega_i)$ in (7) [18].

$$MAD = \frac{1}{N}\sum_{i=1}^{N}|x_n - \overline{x}| \tag{9}$$

As shown in (9) defines the mean absolute deviation (MAD) of a signal, whereby x_n represents signals within a specific window. $\overline{x}$ represents the arithmetic mean of signals within a specific window and N representing the data points in total within a specific window [19]. Skewness and kurtosis is defined using both (10) and (11), whereby M represents the overall samples within a signal and y representing sub-bands[20]. Wavelet packet transform (WPT) was utilized to extract 255 wavalet features from pre-processed EEG signals [21, 22].

$$\emptyset = \sqrt{\frac{1}{M}\sum_{j=1}^{M}\frac{(y_j-\mu)^3}{\sigma^3}} \tag{10}$$

$$\emptyset = \sqrt{\frac{1}{M}\sum_{j=1}^{M}\frac{(y_j-\mu)^4}{\sigma^4}} \tag{11}$$

$$A_i(t) = \sum_{k=-\infty}^{\infty} A_{i-1}(k)\emptyset_i(t-k) \tag{12}$$

$$D_i(t) = \sum_{k=-\infty}^{\infty} A_{i-1}(k)\,\psi_i(t-k) \tag{13}$$

Two filters denoted by $x(t)$ were utilized to decompose signals into multiple separate coeffients through a wavelet transform, whereby n represents the number of samples. A lowpass and highpas filter in the form of a wavelet and a scaling function decomposed signals into detail (13) and approximation coeffients (12) respectively [23, 24]. As such decomposed approximation coefficients in each level resulted in WPT tree comprising of both detail and approximation coefficients as illustrated in Figure 3 [25, 26].

$$x(t) = \sum_{k=-\infty}^{\infty} A_{i-1}(k)\emptyset_i(t-k) + \sum_{i=1}^{L}\sum_{k=-\infty}^{\infty} A_{i-1}(k)\,\psi_i(t-k) \tag{14}$$

As shown in (14) was utilized to reconstruct decomposed wavelet coefficients from which wavelet features are extracted using overlapping window approach and separated into several windows with each window size set to 750, and each window incremented by 750 or 750 spaces apart [27, 28].

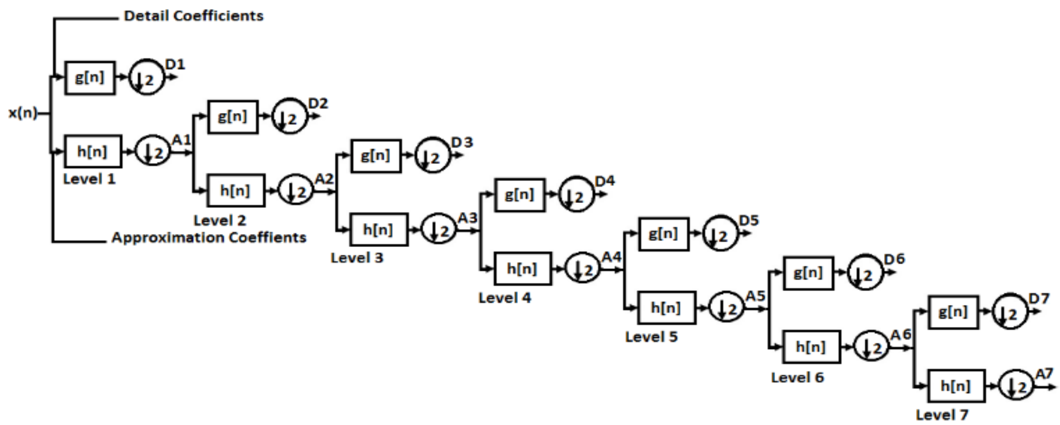

Figure 3. Seven decomposition levels using 4th order daebuchies wavelet

2.4. Feature selection and classification

In this section differential evolution based channel and feature selection (DEFS) algorithm was applied on extracted features, to eliminate redundant features and the challenge dimensionality [26]. In this case DEFS algorithm was utilized to train three signal classifiers and then select the best feature subsets using six input parameters. Features were divided into training and testing set, with the last column of the features matrices being the class labels. As such the speed with which features converge between the 1st and 500th generation was evaluated and utilized as a criterion to determine the DNF (in this case 30, 50, 80) and PSIZE (150) parameter in which the DEFS algorithm performs at its optimal best using the error rate. The desired number of features (DNF) was set to 80 and 130 for online recorded and BCI competition IV-a dataset respectively, while the population size (PSIZE) was set to 150. Consequently, the number of iterations was set to start at zero while the number of generations (GEN) was set to 1000 as our terminating condition. Three signal classifiers (K-nearest neighbor, Naïve bayes and Regression tree) were applied on extracted features to predict both MI and hybrid tasks [29, 30]. As such the performance of each of the three signal classifiers was firstly evaluated to determine the best performing classifier, whereby the best performing classifier was then utilized during robotic arm control. Extracted feature sets were divided into test and training set incorporated into each of the three classifiers. Moreover, the best 80 and 130 feature subsets were also incorporated into each of the three signal classifiers utilized to predict both MI and hybrid tasks.

3. RESULTS AND ANALYSIS

3.1. EEG data source and pre-processing

Three sets of EEG data are utilized in the proposed BCI system. Firstly a publicly available database (BCI completion IV-a) consisting of EEG signals acquired from 22 EEG channels, subject two dataset was utilized for this experiment and the dataset consisted of a signal length of 677169 frames per epoch [8]. Secondly two online recorded datasets acquired from 16 EEG channels attached to gGEMMA sensor cap. Both datasets were recorded for 20 minutes and resulted in a signal length of 300000 frames per epoch [9]. Twenty-two ICA components acquired from BCI competition IV-a were visually inspected, whereby EEG spectrum or power spectrum of each component was evaluated [9]. As such spectral peaks at certain frequencies and dipole-like scalp maps were evaluated mainly to reject artifactual components as shown in Figure 4 and Figure 5 respectively. In this case ICA component eight was selected for further signal processing.

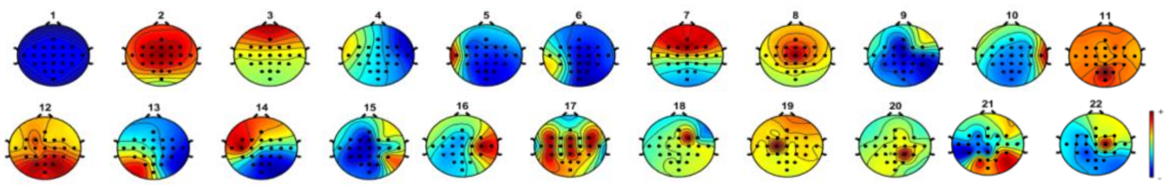

Figure 4. Twenty-two ICA components generated from BCI competition IV-a dataset

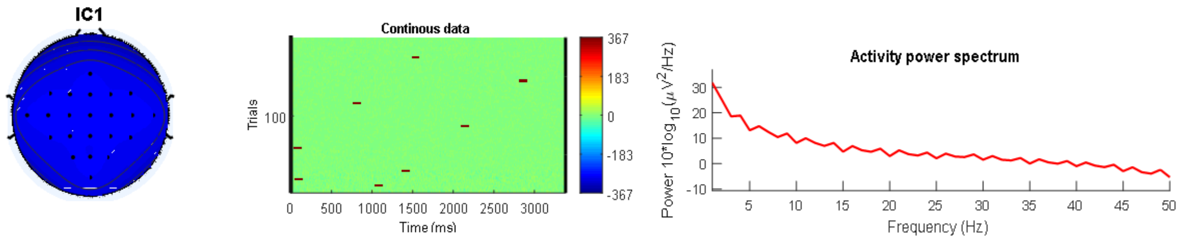

Figure 5. Component spectra and maps

A sliding window approach utilized to remove artifactual windows from all sixteen ICA components acquired from imagine only EEG dataset, whereby 2295 artifactual windows were removed from all components. As such a minimum of 53 and a maximum of 243 windows were removed per component.

3.2. Extracted and DEFS selected feature sets

Three sets of features were extracted from each of the three datasets namely wavelet, band-power and statistical features as illustrated in Table 1. Consequently, BCI competition IV-a and both online recorded datasets resulted in a 4590x271 and 480x271 feature matrix respectively [6]. Both 4590 and 480 represented the number of samples while 271 represented the total number of feature with the last column signifying the class labels.

Features convergence and DEFS algorithm performance is at its optimal best when the DNF is set to 80 and PSIZE to 150 as illustrated in Figure 6 [26]. As such 80 and 130 feature subsets were selected from bothonline recorded datasets and BCI competition IV-a dataset respectively as illustrated in Table 2 and Table 3 [3].

Table 1. Extracted feature sets

Features	Types of features	Feature extraction algorithm	Number of features
Band power	delta: 0.5 – 3 Hz, theta: 4 – 8 Hz, alpha: 8 – 12 Hz, beta:12 – 30 Hz, gemma:30 – 60 Hz	FFT	5
Statistical Features	Mean, Median, standard deviation, mean absolute deviation, skewness, kurtosis, spectral entropy, dominant frequency features (maximum frequency, maximum value and maximum ratio))	Statistical Computation (MATLAB statistical toolbox)	10
Wavelet features	Wavelet coefficients	WPT	255

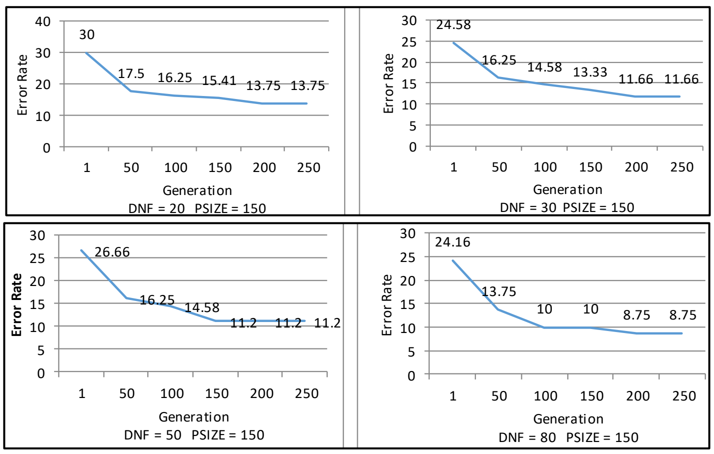

Figure 6. Feature convergence during feature selection

Table 2. 130 selected feature subsets

Desired number of features	Length of features	Category of features(number)
130	4590	Wavelet features (123), Band-power (Gamma) (1), Statistical (6), (Mean, Median, skewness, kurtosis, dominant frequency standard deviation, Maxratio)

Table 3. 80 selected feature subsets

Desired number of features	Length of features	Category of features(number)
80	4590	Wavelet features (76), Band-power (Gamma) (2), Statistical (2), (Mean, Median, skewness, kurtosis, dominant frequency standard deviation, Maxratio)

3.3. Feature classification

In this section the training set, test set and the best selected feature subsets were incorporated into each of the three signal classifiers for performance evaluation (K-NN, NB and Regression tree) [25]. Consequently, K-NN classifier outperformed all classifiers obtaining a highest accuracy of 88.2%, 69.7% and 100% BCI competition IV-a, imagine only and hybrid tasks datasets respectively as illustrated in Figure 7, Figure 8, and Figure 9.

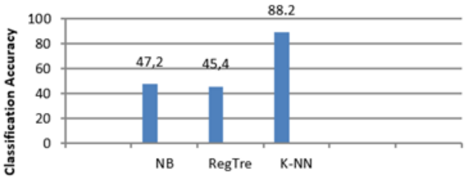

Figure 7. Classification results for BCI competition IV-a

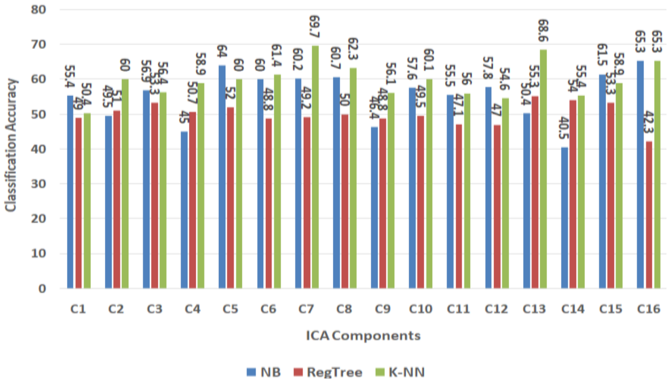

Figure 8. Classification results for imagine only EEG dataset

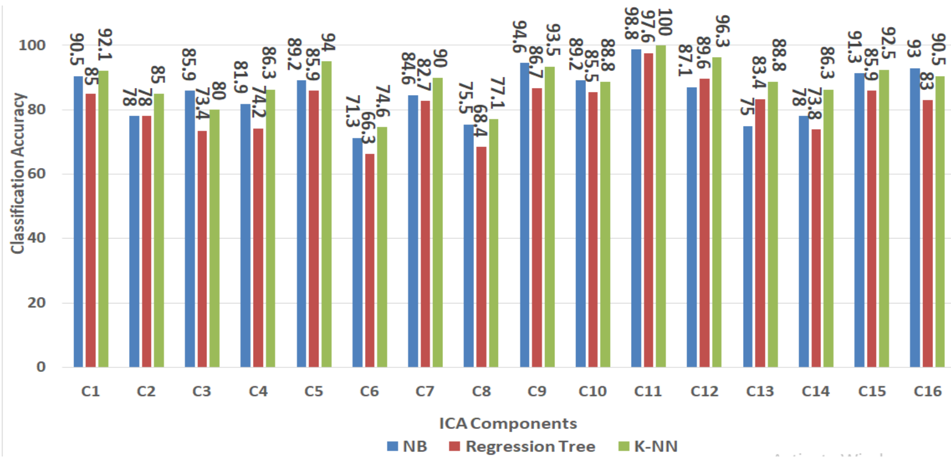

Figure 9. Classification results for hybrid tasks EEG dataset

3.4. Robotic ARM control

In this section, the success rate of each of both MI tasks and hybrid tasks was evaluated. Consequently, hybrid task obtained the highest success rate for each class as illustrated in Table 4. As such hybrid tasks were utilized to validate predicted classes through dobot magician robotic arm control. MATLAB was interfaced with arduino board via a serial communication port, whereby pins (Tx, Rx, GND and 5V) on the arduino board were connected to pins (Rx, Tx, GND and 5V) on the communication interface of the robotic arm respectively. MATLAB script was utilized to send any of the predicted classes to Arduino board. The PTP mode was set to MOVL on arduino script. Whenever arduino script received a character value (class label) from MATLAB script, four robotic movement (left, right, up and down) corresponding to each predicted class were executed.

Table 4. Success rate for each MI and hybrid task

Class	Left	Right	Up	Down	Average
MI Tasks (Competition)	80.92%	87.03%	94.66%	90.3%	88.2%
MI Tasks (Online recorded)	57.45%	55.85%	72.5%	63.58%	62.3%
Hybrid Tasks (Online recorded)	97.22%	88.95%	94.74%	95.79%	94.17%

4. CONCLUSION

A hybrid task EEG-based BCI system was presented in this study with an objective of improving MI task detection rate by investigating the impact of artifacts, extracted feature dimension and visual stimulus on MI task detection rate. Three EEG datasets consisting of MI and hybrid tasks respectively, were utilized to facilitate the investigation. A runICA algorithm was then utilized to eliminate the impact of artifacts on all filtered EEG datasets. FFT and WPT algorithms were then applied on artifact free components to extract three sets of features, from which the DEFS algorithm eliminated the impact of dimensionality by selecting relevant feature subsets. Moreover, the selected feature subsets were utilized as input parameters to three classifiers (K-NN, NB and RegTree). Consequently, K-NN classifier obtained a highest intention detection rate of 100% for hybrid tasks. Moreover, accurately predicted hybrid tasks were validated through a robotic arm control. As such this study has conclusively proven that visual stimulus, artifacts free ICA components and DEFS selected high predictive feature subsets can significantly enhence MI task prediction rate in BCI system.

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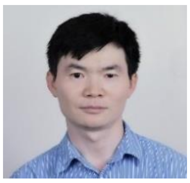

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