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Brain wave classification for divergent hand movements

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Brain-Computer Interface (BCI) is an emerging technology in medical diagnosis and rehabilitation. In this study, by the acquisition of Electroencephalogram (EEG) signals from 30 healthy participants who perform four different hand movements, necessary features are extracted and classified to determine their accuracies. Statistical time domain features are extracted from the mu and beta frequency band. The Event related desynchronization (ERD)/Event related synchronization (ERS) measurements are extracted, from which it was evident that both mu and beta frequency bands are more efficient in the C3 channel. By applying the Paired Samples *t*-test, the extracted features are analyzed and were determined to have a 95% significant level of difference between the mu and beta band, being statistically efficient in the beta band of the C3 channel. By employing different classifiers such as Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Naïve Bayesian classifier and Binary Decision Tree (BDT) algorithms on both channel's mu and beta frequency bands, it was observed that the performance of beta frequency band classifiers shows 90% accuracy in binary class classification. In the comparative study of all these classifiers, LDA and Naïve Bayes show above 95% accuracy for binary class classification.

Keywords: EEG, DWT, ERD/ERS, Classification, SVM, Binary decision tree, Discriminant Analysis, Naïve Bayes

1 Introduction

Brain-Computer Interface (BCI) involves the acquisition of brain signals while performing various activities and converts the acquired data, which is in the form of a biological signal into digital commands that can be used to control external devices in the field of rehabilitation[1-5]. These devices act as external support for people suffering from severe motor dysfunction which are a consequence of stroke majorly, to perform the basic motor works essentially in everyday life. Brain signals are acquired for BCI using various methods such as Electroencephalography (EEG)[6,7], Electrocorticography (ECoG)[8,9], Electromyography (EMG)[10-11], Functional Magnetic Resonance Imaging (fMRI)[12,13], Magnetoencephalography (MEG)[14], etc. Among these, the ECoG and EEG signals are two most commonly used BCI modalities since they represent the human brain's electrical response in practice. ECoG records the neurological signals from the brain with precision and its excellent spatial resolution aids in faster training and interfacing with BCI[15]. Though many studies have been performed with ECoG to extract control signals for BCI[16,17] it also possesses the disadvantage of being an invasive procedure since it requires a clinical surgery to place the electrodes on the surface of the cerebral cortex of the brain. On the contrary, EEG tracks the neuro-electrical activities right from the scalp and therefore their non-invasive property makes them useful for real implications in BCI as opposed to ECoG.

1.1 Electrode system

The 10-20 electrode system is a widely accepted standard in EEG experiments to describe the position of electrodes on the scalp. This method is predicted on the relation between the associate conductor situation and thecerebral mantle of underlying space. The numbers '10' and '20' imply the gap of 10% or 20% of the bone's full front, back, right or left gap between adjacent electrode areas. Fig 1 shows the 10-20 electrode placement system. The electrode positions selected are C3, C4, and CZ as they measure the motor evoked potential[18]. A study performed using Transcranial Electrical Stimulation (TES) at points C3 (+) and C4 (-) resulted in the activation of upper contralateral limb (right) and the upper homolateral limb (left). Since the cue performed was based only on the forearm, the choice of electrodes was C3, C4, and CZ. Impedance is the measure of an impediment to the flow of alternating current at a given frequency, expressed in ohms. A larger value

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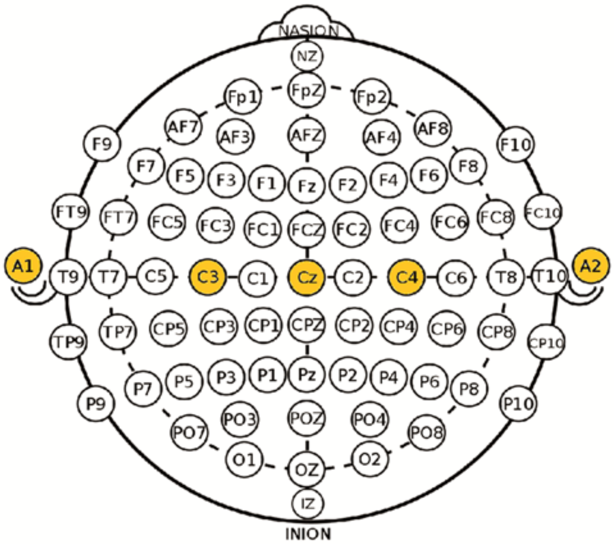

Fig. 1 — 10-20 Electrode Placement System

indicates higher current flow resistance. Hence higher the impedance, the smaller the amplitude of the EEG signals. In EEG studies, impedance should be at least 100Ω but no more than 5kΩ. As the BCI records and processes the EEG signals, the acquired data should have the least component of environmental noise and artifacts for effective classification. Processing of these low amplitude and noise filled EEG signals require special care during data acquisition and filtering. After recording the EEG signals, they are processed via filtering, followed by which the essential features are extracted, and using the extracted features different tasks are classified using various classifiers. The classifier accuracies are determined to suggest a suitable classifier for BCI application.

The current study aims to contribute to the extant work in the field of EEG signal analysis by implementing an EEG-based BCI method using an extracted collection of time-frequency features (TFFs), to distinguish between forearm movements tasks in the same hand. The use of time-frequency features as time-frequency delineation of EEG signals, facilitate the extraction of principle TFFs that includes distinguishable information about different hand movement's tasks within the same hand. The hand movements used in here are primarily wrist and forearm movements such as squeezing of an object, Finger-tip bottle hold, and a closed fist. This manifold set of hand movements contributes to the need for classifying the hand positions, due to the considerable inter and intra-person to person variations of the EEG signals associated with different hand positions. This study was overall conducted to facilitate any assistive devices which are controlled by bio-signal. The research was an offline process, which could be inbuilt in the Machine-based interface to check its movement tasks based on the input time-frequency features of different hand positions. Future research can be concerned with the inbuilt of these extracted features like a control bio-signal, using the controller to drive a hand exoskeleton.

2 Materials and Methods

2.1 Experimental procedure and data collection

The study involved 30 typically developed right-handed participants (14 Males, 16 Females, Age: 18 to 22 years) and was carried out in a shielded chamber hall. The participants had no prior education about the experimental protocol. A protocol containing visual cues of four different hand gestures (Rest position, ball Squeeze action, finger-tip bottle hold action and closed fist action) was designed for the participants to perform and EEG signals were acquired from the labeled position in Fig 1 i.e., C3, C4, and CZ when the individuals are in action. The 'C' letter is used primarily for the central region which provides information electrical activity signals for various hand movements. The participants were first given a brief description of how the recording procedure will be done. The participants were requested to stay in a relaxed position for 5 minutes, and then the data recording was performed. The protocol was performed twice by everyone. The recording time for each trial was about 1 minute and 20 seconds with a sampling rate of 256 *Hz*. Fig 2 depicts the visual cues which were employed in the protocol. Fig 3 depicts the sequence in which the actions were performed along with their duration.

2.2 Signal pre-processing

After recording the brain signals from the three channels C3, C4, and CZ, the acquired data is then processed to remove the noise and other motion artifacts (unwanted signals such as Electrooculogram (EOG), Electrocardiogram (ECG) and powerline interferences) associated with the required signal. Signal pre-processing, also known as a signal enhancement, is the process of removing noise from the raw EEG signal and extracting different frequency bands with suitable filtering techniques. Various origins of artifacts evident in the brain signal, which can highly interfere and corrupt the EEG signals, are power line, EOG, and ECG. Ocular artifacts (OA) are electrical signals which are produced by eye blinks and movement of the eyeball during the recording of EEG signals [19]. The OA is always predominant, compared to other contaminating electrophysiological signals and power line sources are the external noise interference.

2.2.1 Eye blink removal technique

In general, the frequency range of EEG signals is between 0 *Hz* and 64 *Hz* and the ocular artifacts are between 0Hz to 8*Hz* [18]. The power spectrum of the visually identified eye blink signal range was found to be between 0 *Hz* to 5 *Hz*. Automatic identification and removal of various artifacts allow a clear distinction between various frequency ranges amidst the EEG signals to analyze different brain activities based on the frequency bands. This approach is achieved by automatically defining the ocular artifacts and applying the Adaptive Thresholding technique based on the wavelet transform to facilitate the removal of ocular artifacts using the MATLAB software.

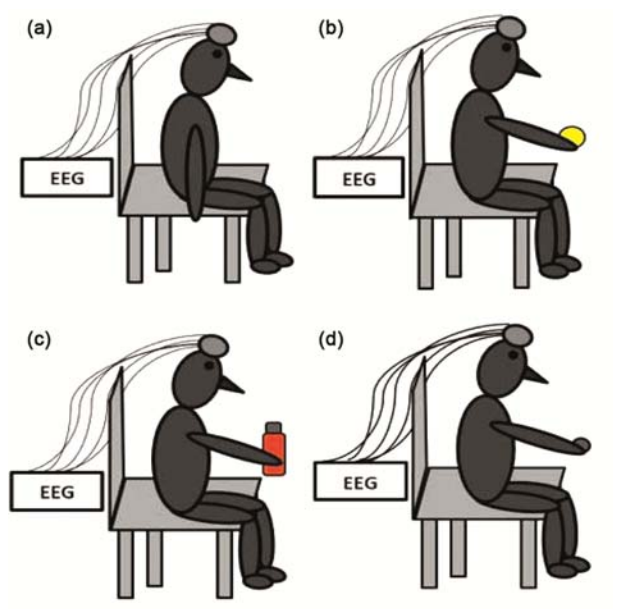

Fig. 2 — Protocol followed, and the Visual cues employed

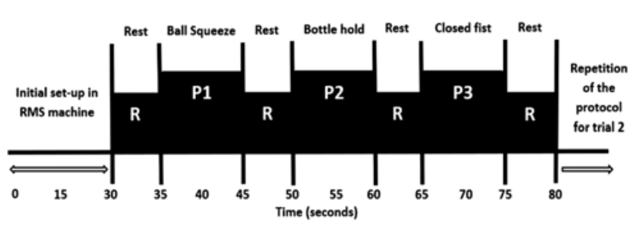

Fig. 3 — Sequence of actions performed and their duration

2.2.2 Wavelet transform

Wavelet Transform is a non-stationary signal analysis method in the time-frequency domain, suitable for EEG signals. It is a useful tool to separate and sort the signal into various frequency elements in different time scales. Four different wavelet function types are available: “db4”, “db8”, “sym4” and “coif5”. Of these, sym4 which is the modified version of Daubechies wavelets with improved symmetry was used to decompose the contaminated EEG signals into five frequency bands; Delta, Theta, Alpha, Beta, and Gamma. The bandwidth and frequencies corresponding to different rates of decomposition of EEG signal A5, D5, D4, D3, D2, and D1 with a sampling frequency Fs = 256 *Hz* are shown in Table 1.

As the obtained power spectrum of EOG was in the range of 0 to 5 *Hz*, level 5 contained the noise frequency and was detected as the signal contaminated with most EOG. The Stationary wavelet transforms (SWT)[20] algorithm was designed to nullify the invariance in the transition of the Discrete wavelet transform (DWT). Level 5, detected using DWT was applied to SWT with sym4 as a wavelet function to the contaminated EEG signal with OA for removing the artifact. The detailed coefficient was considered, and their maximum value was taken for all 30 subjects. From the values determined, the threshold limit with a minimum probability value was selected and applied to soft-like thresholding[21] to minimize noise. Fig 4(a & b) represent the raw EEG signal acquired and the EOG artifact removed EEG signal respectively.

2.2.3 Signal filtering

Different frequency bands of EEG correspond to specific neurological activities of the brain. The five major frequency bands in EEG are the alpha waves that correspond to awake and resting condition and is of the frequency range 8 *Hz* - 13 *Hz*, also the alpha waves acquired in the motor cortex region (C3, C4, CZ) during hand movements is called as mu waves,

Table 1 — Decomposition in corresponding frequency bands

Frequency Range (*Hz*)	Level of Decomposition	Frequency Band	Frequency Bandwidth
0 – 4	A5	Delta	4
4 – 8	D5	Theta	4
8 – 16	D4	Alpha	16
16 – 32	D3	Beta	18
32 – 64	D2	Gamma	32
64 – 128	D1	Noise	64

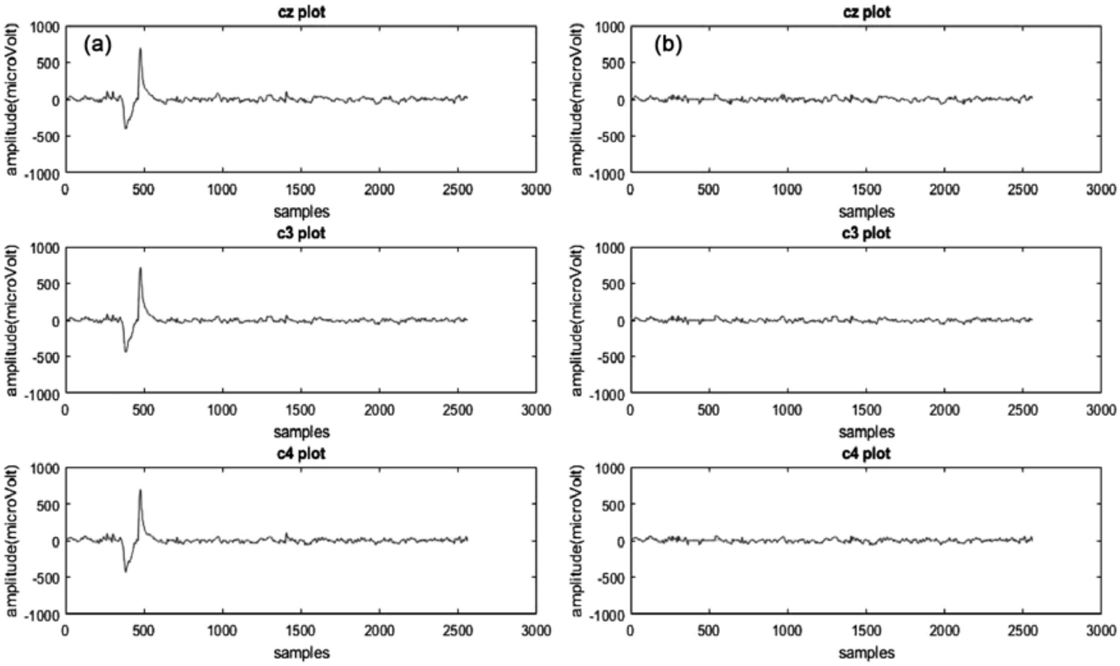

Fig. 4 — (a) Raw EEG contaminated with EOG (b) EOG artifact removed EEG

beta waves that correspond to awake condition with mental activity and is of frequency range from 13 *Hz* to 30 *Hz*, gamma waves that correspond to a frequency range from 30 *Hz* to 44 *Hz*, delta waves that correspond to deep sleep and the frequency range is from 0.5 *Hz* to 4 *Hz* and Theta waves that correspond to sleeping condition and the frequency range is from 4 *Hz* to 8 *Hz*. These are correlated with brain states of fatigue, sleep, REM, and other kinds. These frequency waves were separated using a fourth-order Butterworth bandpass filter. The filter was applied to the denoised signal of C3, C4, and CZ channels individually with a sampling rate of 256 *Hz* in MATLAB Signal Processing Toolbox to obtain different bands of brain signals separately. The designed filter removes the DC offset of each electrode, drifts due to electrode impedance over time placement, powerline 50 *Hz* noise, and other instrument noise manually.

2.3 Feature extraction

Feature Extraction[22] is a technique for reducing large input data matrix to a collection of appropriate matrices from which the detailed information about the actions performed can be interpreted and can be further employed for classification after statistically analyzing them. For extracting features from the denoised EEG signal data, methods usually employed is the time-domain, frequency-domain, and time-frequency domain. As EEG signals are generally a non-stationary signal, it was more fitting to use the extraction method for the time domain function. Time-domain features such as Mean, Band power[23], Activity, Skewness, Kurtosis, Mobility, Complexity, Shannon's Entropy[23], Higuchi's Fractal Dimension, ERD/ERS were extracted from the mu and beta frequency band of the pre-processed EEG data to characterize the hand movements of the 30 participants. Higuchi's Algorithm was employed in the case of Fractal Dimension. The extracted feature information reflects the physiology and anatomy of the activity going on within the brain while performing the action tasks. The extracted features were statistically analyzed to determine their significant level of difference among the mu and beta band within both the channels C3 and C4 individually.

2.4 Statistical analysis of features

The ability of extracted features and their level of significance among the mu and beta band within the C3 and C4 channels were studied more closely by performing statistical tests. In this study, a Paired Samples *t*-test was performed using the IBM SPSS statistics software to determine whether the difference in values of the extracted features between the mu and beta band is significant in either of the two channels [24,25]. This kind of statistical test has been employed to compare the values of all the nine extracted features (Mean, Band Power, Activity, Skewness, Kurtosis, Mobility, Complexity, Shannon's Entropy, and Higuchi's Fractal Dimension) in the mu and beta band within each channel separately for all the four movements. P values of the t-tests performed show that the difference in the feature values extracted from the mu and beta band is more significant in the C3 channel due to all the actions being performed by the right hand.

2.5 Feature classification

The classifier accuracy was calculated by feeding the extracted features to different classification algorithms, such as Support Vector Machine (SVM)[26] with different kernel functions, e.g. radial basis function (RBF) with Kernel scale as Auto and Box Constraint. As a linear discriminant classifier, Linear Discriminant Analysis (LDA) was employed, and for the non-linear classification Support Vector Machine (SVM) and Naïve Bayes with normal distribution were used. The extracted feature values from the participants were divided into training and testing phase where 70% i.e., 21 participants were considered as training datasets and the remaining 30%, i.e., 9 participants were testing dataset. The training data was used to generate a model, and this is used to predict the target values of the test data.

3 Results and Discussion

One of the major key plays of EEG research is to either filter out or to reduce the artifacts contaminated with the actual signal of interest. Existing studies demonstrate different arithmetic methods for eliminating ocular and other artifacts that can often contribute to the loss of meaningful data. Acquisition of the EEG signal and its study is consummated by feature extraction and through different classifiers to rate the accuracies of the classification of different movements. Prevailing methods for blink removal involve the automatic identification of artifact components initially. Following this, the parameters are simplified and eventually reduced with limited loss of desired information from segments that were originally artifact-free. These methods are based on Independent Component Analysis (ICA), which is spatially limited. Finally, these artifacts are subtracted from the EEG data to obtain the required signal. However, with this technique, there will be significant removal of the blink signal, but a huge loss of desired data. To overcome this, the method of Adaptive Thresholding was chosen. This method operates on the OA zone to prevent the loss of components of low frequency in the non-OA zones and thus retains the form of the EEG signal in non-artifact zones. This is of great significance in clinical diagnosis.

3.1 Event related desynchronization/synchronization

Sensory and cognitive perception and motor activities result not only in event-related potential (ERP) but also in ERD or ERS shift throughout the ongoing EEG. The former represents a decrease in rhythmic activity by brief and circumscribed amplitude; the latter is an increase in amplitude. Unilateral voluntary movement of the upper limbs is followed by an ERD in mu and beta bands located above the motor contralateral sensor area. After the motion-offset, this ERD can be followed by a maximum beta return or beta-ERS. The basic ERD / ERS measurements are that the energy associated with a seeded frequency band is displayed parallel (as a percentage) to the power of the equivalent EEG derivations reported at some point in the reference or baseline era, just a few seconds before the operation. By using the equation (1) the ERD/ERS% is calculated,

$$\frac{\text{ERD}}{\text{ERS}}\ \% = \left[\frac{\text{Act}-\text{Ref}}{\text{Ref}}\right] * 100\% \qquad \ldots (1)$$

The intensity within the length of the frequency band of interest after the action is given by Act, while that of the reference duration is given by Ref. In the current study, the Rest period was considered as the reference period and the other action performed was considered as Act. The raw EEG signal was filtered into a range of 8–30 *Hz*. The defined frequency band was preferred as it embraced the mu and beta frequency bands, which proved to be the most appropriate for the classification of movement in the specific channel. Fig 5(a) and 5(b) represents the contralateral ERD/ERS in channel C3 and C4 mu and beta band dominancy for Ball Squeezing action performed using the right hand. It confines the result that both mu and beta frequency bands are more devoted to the C3 channel, compared to C4 and CZ channels. The analysis shows the distinguishable characteristics of the EEG signal for different hand positions and the features extracted from these frequencies are more helpful in classification.

3.2 Paired samples t-test

The results of the Paired Samples *t*-test showed that most of the extracted features were statistically significant and different between the mu and beta frequency band within the C3 channel for all the actions. The *t* and *P* values obtained for features extracted from Rest condition and the other three conditions are shown in Table 2. Table 3 illustrates the Mean and Standard Deviation values for the features in mu and beta band within the C3 channel. *P* values of features marked by * are above 0.05 and hence these features did not create a

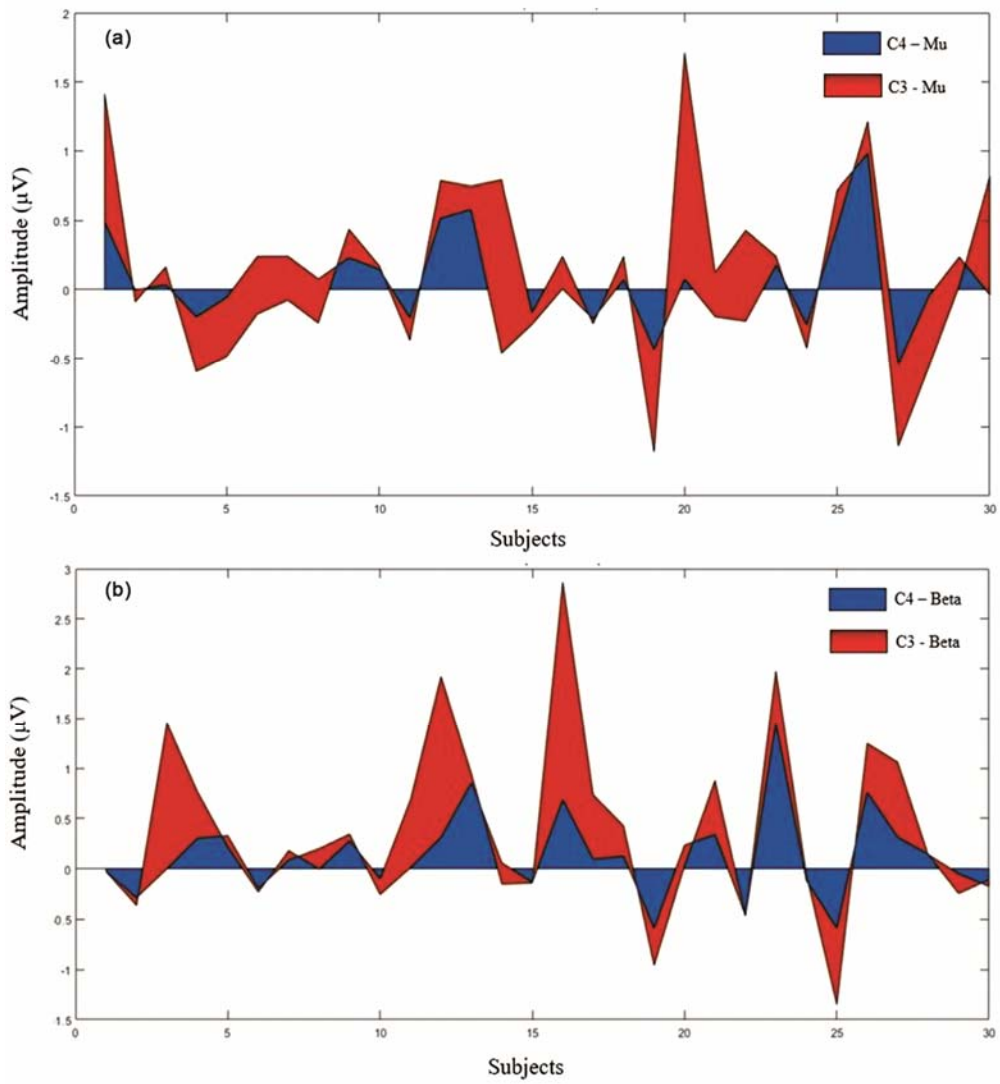

Fig. 5 — ERD/ERS obtained for (a) Mu band (b) beta band

Table 2 — P values of Paired Samples t-test for features extracted within the beta band of C3 channel for Rest, Position 1, Position 2, and Position 3

Features	Rest		P1: Ball Squeeze		P2: Bottle hold		P3: Closed fist	
	P value	*t* value	*P* value	*t* value	*P* value	*t* value	*P* value	*t* value
Mean	0.284*	1.091	0.793*	0.265	0.514*	0.660	0.022	2.422
Band Power	0.037	2.188	0.000	4.630	0.018	2.500	0.031	2.269
Activity	0.037	2.188	0.000	4.630	0.018	2.501	0.031	2.269
Skewness	0.566*	0.581	0.467*	0.737	0.627*	0.490	0.257*	1.156
Kurtosis	0.000	4.802	0.000	5.926	0.013	2.632	0.001	3.861
Mobility	0.326*	1.000	0.000	70.953	0.000	75.212	0.000	85.340
Complexity	0.000	32.992	0.000	24.335	0.000	38.002	0.000	30.790
Shannon’s Entropy	0.000	7.086	0.000	12.053	0.000	12.381	0.000	9.645
Higuchi’s Fractal Dimension	0.000	39.252	0.000	56.318	0.000	67.666	0.000	76.385

Table 3 — Mean and Standard Deviation of Features in Mu and Beta band of C3 channel

Feature	Band	Rest		P1: Ball Squeeze		P2: Bottle hold		P3: Closed Fist	
		Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
Mean	Mu	-0.043	1.254	0.093	0.615	-0.137	1.653	-0.360	2.462
	Beta	-0.098	1.332	0.092	0.612	-0.139	1.647	-0.366	2.465
Band Power	Mu	71.664	33.672	59.925	22.553	68.039	24.147	68.389	30.168
	Beta	87.873	34.222	81.913	25.258	80.251	24.660	83.541	30.859
Activity	Mu	71.720	33.698	59.953	22.564	68.070	24.155	69.421	30.183
	Beta	87.940	34.249	81.953	25.275	80.289	24.674	83.579	30.871
Skewness	Mu	0.000	0.050	-0.001	0.005	0.000	0.003	-0.004	0.026
	Beta	0.009	0.045	0.004	0.004	0.004	0.038	0.001	0.011
Kurtosis	Mu	3.432	0.955	3.495	0.718	3.574	0.818	3.521	0.524
	Beta	4.187	0.783	4.591	0.744	4.204	0.838	4.240	0.899
Mobility	Mu	3.432	0.955	3.495	0.718	3.574	0.818	3.521	0.524
	Beta	4.187	0.783	4.591	0.744	4.204	0.838	4.240	0.899
Complexity	Mu	0.083	0.847	0.254	0.005	0.254	0.006	0.250	0.005
	Beta	0.488	0.013	0.489	0.015	0.489	0.015	0.492	0.013
Shannon's	Mu	522975	157354	1233592	450948	1345112	514050	1326782	531467
Entropy	Beta	1015517	421700	2386317	833041	2367591	811334	2453784	948351
Higuchi's Fractal	Mu	1.040	0.002	1.040	0.001	1.040	0.001	1.039	0.001
Dimension	Beta	1.168	0.017	1.171	0.012	1.168	0.010	1.170	0.009

significant difference between the two frequency bands. In the case of the Rest position, the analysis performed on the "Mean", "Skewness" and "Mobility" feature values between mu and beta band resulted that there was no meaningful difference. The analysis performed on the remaining features namely, "Band Power", “Activity”, “Kurtosis”, Complexity”, “Shannon’s Entropy” and “Higuchi’s Fractal Dimension” feature displayed that there was a pointed difference between their values in mu and beta band with its significance as $p < 0.05$. In the case of Position 1 (Ball Squeeze), the analysis performed on the "Mean" and "Skewness" feature values between mu and beta band resulted in no pointed difference. However, the analysis performed on the "Band Power", “Activity”, “Kurtosis”, “Mobility”, “Complexity”, “Shannon’s Entropy” and “Higuchi’s Fractal dimension” feature resulted in a meaningful difference between their value in mu and beta band of C3 channel with its significance as $p < 0.05$. In the case of the Position 2 (Finger-tip Bottle Hold), the analysis performed on the "Mean" and "Skewness" feature values between mu and beta band showed that there was no pointed difference. However, the analysis performed on the "Band Power", “Activity”, “Kurtosis”, “Mobility”, “Complexity”, “Shannon’s Entropy” and “Higuchi’s Fractal dimension” feature resulted in a meaningful difference between their value in mu and beta band of C3 channel with its significance as $p < 0.05$. In the case of Position 3 (Closed Fist), the analysis performed on the "Skewness" feature values between mu and beta band resulted in no pointed difference. However, the analysis performed on the “Mean”, "Band Power", “Activity”, “Kurtosis”, “Mobility”, “Complexity”, “Shannon’s Entropy” and “Higuchi’s Fractal dimension” feature resulted in a meaningful difference between their value in mu and beta band of C3 channel with its significance as $p < 0.05$.

3.3 Classifier accuracies

In this study, the features which were extracted for the classification of EEG signals are statistical and most predominant whereas the existing studies are focused only on limited numbers. This study consolidates in detail about the accuracies determined by four different classifiers for binary and multiclass and was prioritized based on their performance. For classification of binary class, the combinations taken into consideration are R vs. P1, R vs. P2, R vs. P3, P1 vs. P2, P2 vs. P3 and P1 vs. P3, where ‘R’ refers to REST and P1, P2, P3 refers to three different hand gestures. In the case of classification of multiclass, all the four classes were considered. By applying four different classifiers on the binary class and multiclass of the mu band, it was interpreted that the accuracy is best for the binary classes. The accuracies obtained were efficient for the combinations of R vs. P1, R vs. P2, R vs. P3, and P1 vs. P2. The highest accuracy of all the three channels was found to be 94.45% in the Diag-quadratic type of Discriminant Analysis classifier, 93% in Naïve Bayes classifier, 88.89% in

SVM of Box constraint function and 78.89% in Binary decision tree. In the case of the beta frequency band, the four classifiers gave a good percentile for all the combinations of binary class. By arranging the classifier in the order of percentage in ascending order, the highest accuracy was found in the Naïve Bayes and discriminant analysis which was of 92.32%, SVM of kernel scale function of 88.2% accuracy and Binary Decision Tree of 79.98% for all the three channels C3, C4 and CZ. When the performances of both the frequency bands were compared, it was interpreted that the beta frequency band shows efficient accuracy in binary class than the mu frequency band. Of all these classifiers, LDA and Naïve Bayes show 90% above accuracy for binary class compared to other classifiers[1]. By changing the training and testing percentage or by adding extra feature vectors, the accuracy performance can be improved compared to this performance.

In this study, the removal of eye blink is achieved by automatically defining the Ocular Artifacts (OA) and applying the wavelet-based Adaptive Thresholding algorithm to the defined intervals to maintain the EEG signal form. A simple fourth-order Butterworth bandpass filter is employed for mu and beta frequency band separation, from which the statistical time domain features are extracted. The functional activity of the brain for different hand movements is analyzed by computing the ERD/ERS feature. The efficiency of features extracted and their significance level of difference between the mu and beta band are analyzed by performing the Paired Samples *t*-test. The extracted features are used for classification different hand movements using classifiers like Support Vector Machine (SVM), Discriminant Analysis, Binary decision tree, and Naïve Bayes classifier for binary class. The current study illustrates successful channel analysis which provides maximum classifier accuracy for different hand movements.

4 Conclusions

The study unfolded an EEG data classification algorithm, which centered on abundant features extraction followed by wavelet transformation and signal processing thereby making an unbiased resolution on the form of EEG data collected and therefore on the subject's brain state. The algorithm's principal additional benefits are the ability to run repeated EEG robustly; feature extractions with highly relevant wavelet transform as concealed EEG information is exposed and the noise effects are reduced as certain data was excluded under certain scales; Simplicity and low deliberation cost ensuring real applications; quite high ranking classification accuracy of 95%. The assumption is, therefore, that the presented algorithm can be used to distinguish EEG signals for various hand movements. In addition to the achieved high gross classification accuracy, the presented algorithm still has two directions for further study. The first factor includes applying additional features to the function matrix, e.g. by evaluating EEG data in a nonlinear series (i.e., disorder analysis). The other relates to the option of more advanced classifier methods which will inevitably lead to additional complications as well as to a great degree accurate classification algorithm. The findings of this study are expected to be useful in bio-rehabilitation applications for artificial hand movements through brain-machine interfacing.

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