Research Article

EEG Based Four Class Human Limb Movement Detection by Mel Frequency Cepstral Coefficients and Quadratic Multi-Class Support Vector Machine

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Abstract: Brain Computer Interface (BCI) facilitates the user to regulate the peripheral devices with electroencephalogram (EEG) signals. These signals are recorded from the surface of the brain called the scalp. The acquired EEG signals are further processed using feature extraction approach and finally classified into movements using classification techniques. This research article mainly focuses on classification of motor movements recorded in the form of EEG signals of four limb movements. The database used in this study has already ben been utilized by the researchers earlier with different combinations of classification techniques based of feature extraction. The dataset has been recorded at Graz University of Technology, Austria and used for BCI competition 2008. Dataset comprises of EEG signals of four independent limb movements. These four movements represent feet movement, tongue movement, right hand and left-hand movements. In past researches, technique based on Cepstral analysis is applied primarily in area of speech recognition, mechanical parts analysis, seismological issues etc. Efficacy of EEG brain signal classification, using cepstral analysis-based features is discovered in this study. Mel-Frequency Cepstral Coefficients (MFCCs) is employed as a technique of extracting features from EEG signals. Features classification is performed on various classifiers and compared on the basis of their mean percentage accuracy achieved. Variants of support vector machine (SVM) have been used for classification of four movements. Significant improvement in results has been exhibited by quadratic multiclass SVM (Q-mSVM) in terms of classification accuracy. The technique shows average accuracy percentage of 78.48% and maximum accuracy of 88.19% for one of the subjects. The proposed method has shown superior experimental results as compared to the previous studies using the same dataset for calculating multi-class classification accuracy.

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Introduction

Brain Computer Interface (BCI) is an evolving technology for developing a straight communication channel leading from brain to the peripheral devices (Yang, 2013). It encodes the brain activity through electroencephalogram (EEG) signals recorded via non-invasive electrodes from the surface of the brain called scalp. This is the activity of single neuron firing inside the brain. This technology enables the users to regulate peripheral devices directly from brain and thus improves the quality of

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life for disabled patients (Hiremath *et al*., 2o15). In BCI domain, a system records the specific patterns of EEG signals coming directly from brain, followed by an artificial intelligent that translate those brain signals to drive an actuator. At first these EEG signals are filtered to eradicate the artifacts (noise). Subsequently feature extraction procedure is then employed for recognizing discriminative information present in brain signals. The pre-processed EEG signals are further classified according to the feature vectors. Control interface step is finally employed for translating the input EEG signals for the control of external devices such as upper or lower limb prosthesis, wheelchair or to control computer (Hassanaien and Azar, 2015). The initial and the most important step in BCI is to acquire suitable signal from brain with a signal acquisition device. The non-invasive signal acquisition system in BCI avoids health hazards and related health and ethical standards. A usual non-invasive BCI system demonstrate preceding stages: data acquisition, noise or artifacts removal by preprocessing, extracting features of EEG signals, classifying the signals according to the particular application, controlling the external devices and providing the appropriate feedback (Cichocki *et al*., 2008). In invasive BCIs (Krepki *et al*., 2007), such as electrocorticogram (ECoG), an electrode or a multi-unit electrode group or array is positioned under the scalp to acquire electrical potentials from inside the brain cortex. This will require a surgical procedure for recording brain activity and brain signals obtained through invasive BCIs exhibit high signal to noise ratio. With these signals, a very little prior training of the user is required and this technique is appropriate for patients with damaged parts of neurological systems. It can also be employed for restoring the lost functions in the brain. In case of non-invasive BCIs, more than one type of brain signals can be used for the applications. These non-invasive brain signals include, magnetic resonance imaging (MRI), magnetoencephalography (MEG), functional near infrared spectroscopy (fNIRS), near infrared spectroscopy (NIRS), functional magnetic resonance imaging (fMRI) and EEG. Since the systems do not measure neural activity directly but couple it with regional changes in flow of blood inside the body, they cannot be used as ambulatory BCI systems due to large bulk. EEG signals are used in popular and mainstream non-invasive BCI systems, as these warrants portability, low cost, easy to handle and fine temporal resolution of the apparatus.

EEG signals are now investigated for personal biometric identification at IDIAP in Switzerland (Marcel *et al*., 2007). Every individual possesses a unique and distinctive brain wave-pattern which can be used for verification. It is impossible to mimic or steal the EEG based identification pattern because it is sensitive to stress, mood and person dependent.

The literature reveals that under the same recording conditions EEG signals recording exhibits high inter subject inconsistency and low intra subject inconsistency. In (Sun and Shiliang, 2008; Bao *et al*., 2009; Hu and Jian-Feng, 2009; Jiang *et al*., 2009) the subjects were shown a specific image and directed to move hand, finger, foot or tongue correspondingly for recording EEG signals. In (Brigham *et al*., 2010) the subjects had to exhibit specific motions by looking at black and white drawings of the common object.

Wolpaw *et al*. (2002) presented the brain computer interface architecture for communication and control, which is the main purpose of BCI research. Xiao *et al*. (2013) classified ten classes of movements of finger pairs utilizing Power spectral density for feature extraction of EEG signals and decomposed it using principal component analysis. Classification was done using support vector machines. Vuckovic and Sepulveda (2008) used Gabor coefficients as features to classify the flexion and extension of left and right wrists. They employed 2-stage 4-class Elman's neural network for classification purposes. Mohamed *et al*. (2011) classified the finger and wrists movements using artificial neural network, Bhattacharya distance for feature extraction and independent component analysis for filtration purposes. Wang *et al*. (2009) classified left and right finger movements using the architecture of common spatial decomposition as feature extraction approach and support vector clustering as classification algorithm. Literature survey of brain computer interface reveals that most variants of Neural Networks, Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA) and Support vector Machines (SVM) and are used as classifiers for motor movements EEG signals (Lotte *et al*., 2007). Lehtonen *et al*. (2008) presented architecture for online classification for finger movement using one trial EEG signal. A scheme for regulating electrical prosthesis using steady-state visual evoked potentials was proposed by (Muller-Putz *et al*., 2007). He controlled two degree of freedom hand prosthesis and experiments were performed on four patients having accuracy between 44% to 88%.

Long *et al*. (2011) used hybrid feature selection for controlling 2-D mouse cursor from both hands EEG signals. LaFleur *et al*. (2013) controlled three-dimensional motion of Quadcopter with a non-invasive brain computer interface. He got 90.5% accuracy with five subjects. In our previous research (Amna *et al*., 2017), we employed power spectral density for recognition of finger movements using EEG data and two stage logistics regression (Hosmer *et al*., 2013) for the classification of EEG signals. (Kalaivani *et al*., 2014) explored the EEG signals for detection of abnormalities of brain signals. Liao *et al*. (2014) performed BCI application by individual finger movements using a single hand EEG signal. Guger *et al*. (2001) used an EEG-based BCI system for fast transition of estimation and classification.

Vučković *et al*. (2012) explored the EEG signals by proposing a two class and four stage brain computer interface system for imaginary right and left wrists movements. Yom-Tov *et al*. (2002) proposed the method of classification of movements while selecting features from one particular movement-related potential. Lee *et al*. (2018) proposed an architecture for the eradication of EEG artefacts generated due to brain stimulation under effect of high voltages. Wang *et al*. (2018) worked on epileptic seizures and proposed an accurate method for its recognition using EEG signals. Jacobs *et al*. (2018) proposed a machine learning technique based on non-invasive EEG that generates an advance alarm of a clinical seizure onset.

Nguyen *et al*. (2012) explored the identification of persons based on EEG signals due to their uniqueness and distinctiveness. Support Vector Machine was used as classifier and Mel-Frequency cepstral coefficients (MFCC) as features in the research. Teh and Paulraj (2015) proposed the use of fractal dimension (FD) and MFCC with feed-forward multi-layer Perceptron trained by using Levenberg-Marquadt technique.

This research presents a method of classification of EEG motor imagery using quadratic multiclass SVM and MFCC features. BCI competition 2008, Graz dataset 2a has been used during the research and significant improvement in the average classification accuracy (78.48%) as compared to recent researches in percentage accuracy has been discovered during research. Since the technique used in this research has shown significant improvement in classification accuracy, so it will result in improvement of online real time application of BCI which is the biggest limitation in BCI research.

Materials and Methods

Data acquisition

BCI Competition 2008-Graz dataset 2A (Brunner *et al*., 2008) has been used for this research. The EEG signals are recorded on 9 healthy subjects. The acquired BCI data comprises of EEG signals of four imagination of movements of left hand (class 1), right hand (class 2), both feet (class 3) and tongue (class 4). Figure 1 demonstrates the timing diagram of the EEG data acquisition protocol.

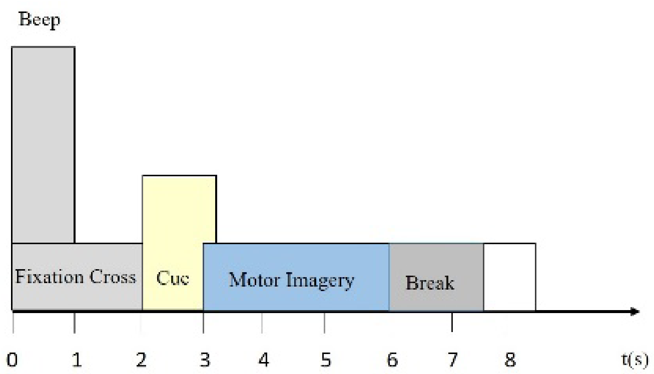

Figure 1: *Data acquisition protocol according to timing (Brunner et al., 2008).*

Data recording is performed on headset having twenty-five Ag/AgCl electrodes. Electrodes were placed at 3.5cm from each other in a pattern as shown in Figure 2. Three electrodes were used for recording EOG signals while twenty-two channels were providing EEG signals. Data was recorded at a sampling rate of 250 Hz. In our research, we have only used twenty-two EEG channels for classification of four motor movements and three EOG channels were left unused since EOG channels deal with the eye movement.

Proposed scheme

Our proposed classification scheme is a blend of MFCC as features and Q-mSVM as classification technique. The architecture scheme is shown in Figure 3.

For each subject, data for all 4-classes is used. In this study three second data (3 to 6 second time interval as shown in Figure 1) for each movement in every trail (288 trials) is used. Data is arranged according to classes 1 to 4 for further processing and classification. While extracting the features 70% data of each class is utilized for training of classifier using 5-fold cross validation and subsequently 30% unseen data of each class is used for test. The classifier training was carried out using extracted features and was tested on data by calculating the percentage classification accuracy for 4-classes.

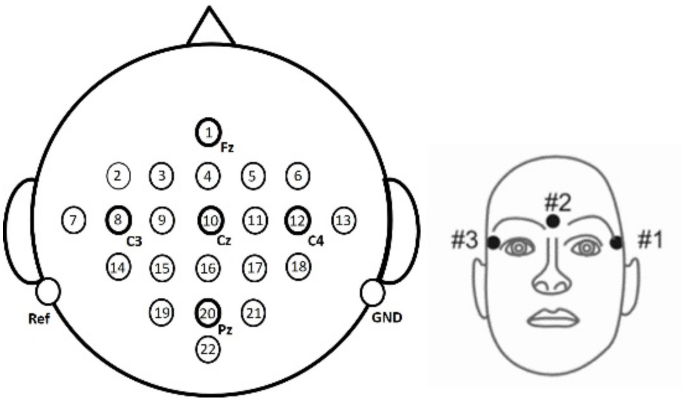

Figure 2: *Left: Electrode montage based on international 10-20 system. Right: Placement of three monopolar EOG electrodes (Brunner et al., 2008).*

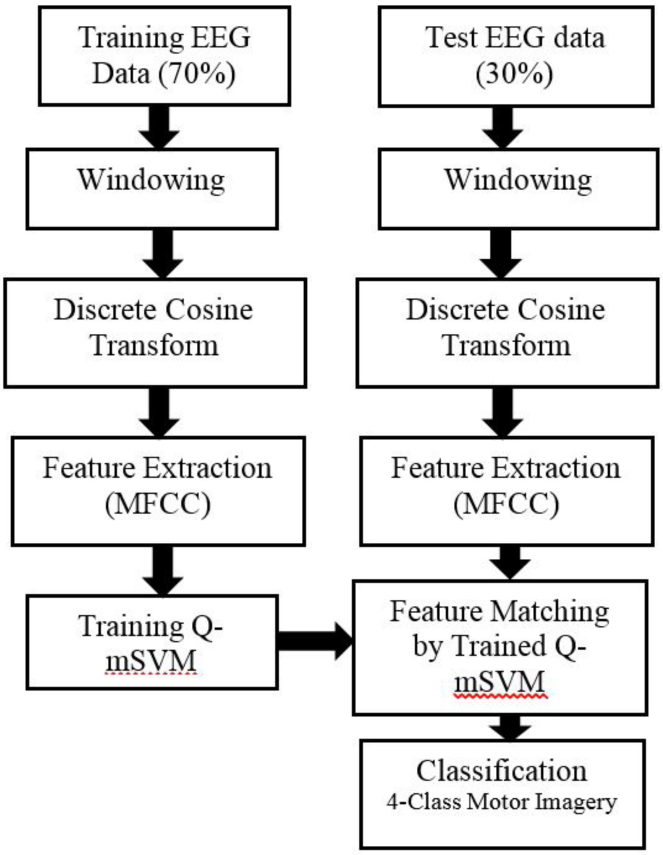

Figure 3: *Architecture of proposed scheme of classication.*

Classification and feature extraction techniques are discussed in detail in preceding sections.

Feature extraction

MFCCs are extensively utilized in sound signal processing for identification of different sounds due to its robustness, non-linear frequency scale and de-correlated nature (Dharanipragada *et al.*, 2006). In this research, we considered the similarity of sound signals with EEG signal and MFCCs as features. The rate of change of different spectral band of EEG signals due to different imagined motor movement marks the similarity with sound signals. At the first stage, the spectrum is transformed using mel scale to get mel frequency cepstrum. Subsequently the power of spectrum as feature is calculated using Equation 1.

$$P_{x[n]} = |F(\log(|F(x[n])|^2)|^2 \quad \text{... (1)}$$

Where F is the Fourier Transform, x[n] is the signal and P is the power of signal.

A complex cepstrum of a signal x[n] is defined by using its Z-transform and is given by Equation 2.

$$C_{x[n]} = Z^{-1}\log(Z[x[n]]) \quad \text{.... (2)}$$

Before the MFCCs are extracted the signal is processed using following steps to obtain the signal spectrum:

- Framing and windowing the signal.
- Taking the Fourier transform for power of the signal.
- The resultant spectrum magnitude is wrapped by mel scale and discrete cosine transform (DCT) is calculated. Since the EEG signals are changing at a very rapid pace due to firing of neurons inside the brain with thinking process, the computational efficiency can be increased by taking log of this spectrum (Kinnunen, 2003) and (Pullella, 2011). The name mel comes from the word melody to indicate that the scale is based on pitch comparisons. In other words, mel scale is defined as a perceptual scale of pitches, Equations 3 and 4 are used to convert signal frequency from hertz (Hz) to mel (m).

$$m = 2595 log_{10}\left(\frac{f}{100} + 1\right) \quad \text{... (3)}$$

$$m = 1127 log_e\left(\frac{f}{100} + 1\right) \quad \text{... (4)}$$

The signal is pre-emphasized to reduce the blurring

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effects which is caused during computation of MFCC vector. First order finite impulse response (FIR) filter of the form (Kinnunen, 2003) is given in Equation 5 to reduce the blurring effect.

$$H(z) = 1 - az^{-1} \quad (5)$$

Where; $0.9 \leq a \leq 0.99$

Signal framing is done keeping in view the quasi-stationary nature of signals. Signal framing is defined as the division of signal into small sections. EEG signals are non-stationary in nature due to very rapid changes in neuronal activity depending upon thought process inside the brain. However, framing allows us to consider and observe these signals discrete sections over short duration of time. During these short durations these signals are considered to be exhibiting stable characteristics and can be considered stationary (Kinnunen, 2003), (Pullella, 2011). To increase continuity between adjacent frames, windowing function is applied for each frame. While dealing with time domain cases, windowing operation can be achieved by multiplying the frame and window function on point to point basis. The windowing operation corresponds to the convolution between the short term spectrum and the windowing function frequency response. Most commonly used function is the Hamming Window, given in Equation 6 which is defined as by (Kinnunen, 2003; Pullella, 2011).

$$w_H(n) = 0.54 - 0.46\cos\left(\frac{2n\pi}{N-1}\right) \quad \dots(6)$$

Where n= 0,1, ……., N-1 and N is the number of frames in which the signal has been divided.

Firstly, Discrete Fourier Transform (DFT) is computed using a windowed frame of signal and subsequently magnitude spectrum is obtained. Mathematically DFT is defined as Equation 7.

$$S(k) = \sum_{n=0}^{N-1} s(n)e^{\frac{-j2\pi}{N}kn} \quad \dots(7)$$

where $s(n)$ is the time sample of windowed frame.

Mel filter bank is used for Mel-frequency wrapping which contains bandpass filter set with constant spacing and bandwidths. Wrapping of the filter bank (having a triangular filter bandpass frequency response) comprises of one filter for each desired Mel-frequency component. The triangular filter is spread over a frequency range from zero to Nyquist frequency. The recognition accuracy of the system is effected by the number of filters which are to be set according to mel frequency components. DCT is performed on Mel-spectrum logarithm (log) as the last stage and resulting amplitudes are called the MFCCs. If the energy of the *mth* Mel-filter output is given as $\tilde{S}(m)$, the MFCCs will be given by Equation 8.

$$c_j = \sqrt{\frac{2}{N_f}} \sum_{m=1}^{N_f} \log(\tilde{S}(m)) \cos\left[\frac{j\pi}{N_f}(m-0.5)\right] \quad \dots(8)$$

Where j= 0,1, ……., j-1, with j being the number of MFCCs, N_f is the number of Mel-filters and c_j are the MFCCs. The signal information is spread over the MFCCs in a way that the first few will carry the maximum information. Keeping in view (Fathi, 2011), number of resulting coefficients is selected between 12 and 20. For our study we have chosen 12 MFCCs as referred to static parameters of the frame (Rainer *et al*., 2008) while casting-off the zeroth coefficient which represents the mean log energy of the frame. The extraction of static parameters in terms of features reduces the inherent inconsistency of EEG signals. 12 MFCCs for each frame is used as features for further classification of four imagined motor movements.

Classification method

SVM is a binary classification technique which discriminates between groups (classes) of data by defining a separating hyperplane. In other words, if the classifier is given a labeled training data (supervised learning), the algorithm marks an optimal hyperplane. This hyperplane is used to classify the new examples (test data) by assigning it the requisite class label. Support vector machines were initially proposed by (Vapnik, 1999) based on statistical learning architecture. SVM can solve non-linear relationships problems, perform multiple classifications associated with small sample sizes. SVM classification mechanism construct an optimal hyperplane as decision surface to classify the different classes. In order to do so the space between the two classes is maximized.

SVM as binary classifier can also take into account

Multi-class problems by using it in one of the two configurations; one-vs-one and one-vs-all. In our study we used one-against-one or pairwise classification architecture to solve multivariate classification case. In one-vs-one classification scheme, two pairs of classes are selected at one time and a binary classifier is trained. There are $n(n-1)/2$ possible class-pair formed where n corresponds to the total number of classes. In testing phase, voting strategy is followed, where all the binary classifiers are tested and vote for class for all input data points. The final class is decided on maximum number of votes out of all binary pairs.

This research article employs Multi-class Support Vector Machine (mSVM) to classify 4-class motor imagery EEG signals corresponding to four distinct movements. In the field of machine learning, pattern analysis algorithms are used with different kernel methods to identify a distinct pattern. On the basis of kernel, three types of mSVM namely, Linear mSVM (L-mSVM), Quadratic mSVM (Q-mSVM) and Cubic mSVM (C-mSVM) were used for classification of 4-class motor imagery EEG signals. Q-mSVM showed the best average classification results (discussed in detail in results and discussion section).

The nonlinear classification paradigm of support vector machine employs kernel function instead of computing the inner dot product. The nonlinear problems of support vector machine are converted into linear classification scheme by raising their dimensions. To solve the two-class feature classification, the sample set is expressed as (x_i, y_i), i = 1,2,3 ….. l, $x \in R^N$, where $y_i \in \{+1, -1\}$. The discriminant function could be expressed as Equation 9.

$$y_i[(w.x_i) + b] - 1 \geq 0, i = 1,2,3 \ldots\ldots\ldots l \quad \ldots(9)$$

Lagrange multiplier could transform this into a dual problem and the conversion objective function can be optimized using Equation 10 as under:

$$\min Q(a) = \frac{1}{2}\sum_{i,j=1}^{l} a_i a_j y_i y_j . K(x_i, x_j) - \sum_{i=1}^{l} a_i \quad \ldots(10)$$

Equation 13 satisfies the conditions $\Sigma^l_{i=1} a_i y_i = 0$. $0 \leq a_i \leq C$, 0 where a_i corresponds to lagrange multipliers of M for each constraint. To solve the above problem, a kernel $K(x, x_i)$ is selected and we have employed quadratic based kernel in this research article. The quadratic kernel can be mathematically computed as given in Equation 11.

$$K(x, x_i) = (1 + x^T x_i)^2 \quad \ldots(11)$$

The optimal classification function of support vector machine can be obtained as given in Equation 12.

$$f(x) = sgn\left(\sum_{i=1}^{l} a_i^* y_i K(x, x_i) + b^*\right) \quad \ldots(12)$$

Where a^* and b^* are the optimal parameters utilized for determining the optimal classification surface, which can be optimally computed by a support vector.

Results and Discussions

In this study, EEG data for each of the nine healthy subjects of all four classes have been used for classification of movement. Three variants of SVM are used for classification of movements for each subject as discussed in section II B. MFCC have been used as features for classification as discussed in section II A. The proposed classification scheme has been applied on each subject data for twenty times and average of classification accuracy is taken. Classification accuracy is calculated on the basis of confusion matrix generated after the trained classifier predicts the movement by analyzing the test sample. Confusion matrix of one iteration for subject 9 used for calculating the average classification accuracy (81.9%) is shown in Table 1. Correctly classified test samples (true positive) are mentioned on the diagonal of table.

Table 1: *Confusion matrix of classification accuracy-subject 9.*

	Class	Predicted Class by Q-mSVM			
		Left hand	**Right hand**	**Both feet**	**Tongue**
True Class	Left hand	19	5	-	-
	Right hand	5	16	3	-
	Both feet	-	-	23	1
	Tongue	5	-	-	19

The true positive rate measures the percentage of classes of movements which are correctly identified as the same class. For example, for left hand movements (Table 1) percentage of true positive rate is calculated as under;

$$True\ Positive\ Rate = 19/24 = 79\%$$

Complementarily, the false negative rate is the percentage of classes of movements wrongly identified as some movement. For example, for left hand movements (Table 1) percentage of false negative rate is calculated as under;

$$False\ Negative\ Rate = 5/24 = 21\%$$

Table 2 shows the true positive and false negative rates of Q-mSVM for same iteration of subject 9. Classification accuracies for all the 9 subjects on average of twenty iterations using three variants of SVM are shown in Figure 4. Performance of Q-mSVM as classifier in all subjects is the best less subject 2 and subject 4.

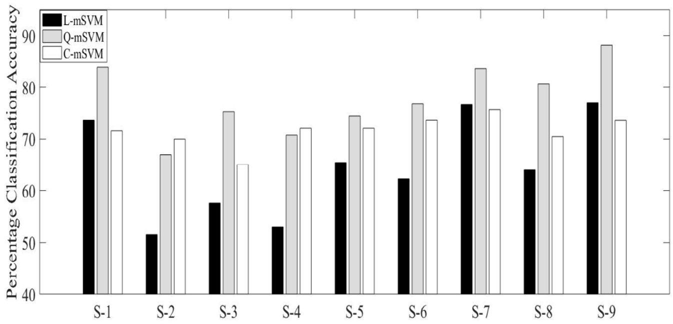

Figure 4: *Percentage classification accuracies for three variants of SVM for 9 Subjects (S-1 to S-9).*

This low performance is due to non-consistent nature of data which has resulted in low performance of classifier. This is also evident of results of other researches shown in Table 3.

Figure 5 shows that L-mSVM has a larger variation in percentage classification accuracy and its highest accuracy is comparable with C-mSVM. Q-mSVM has less variation in accuracy as compared to L-mSVM but has the highest accuracy in all three variants. C-mSVM has the least variation in accuracy, however, its highest value is below the median accuracy value of Q-mSVM. Since we are interested in highest value and comparatively less variation in percentage classification accuracy so Q-mSVM is the classifier that suits our model.

Performance of three variants of SVM on data of all 9 subjects in terms of minimum and maximum percentage classification accuracies is shown in Figure 5.

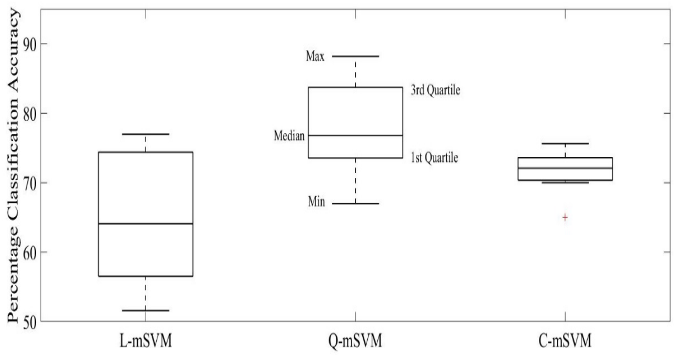

Figure 5: *Performance of three variants of SVM on data of all 9 subjects.*

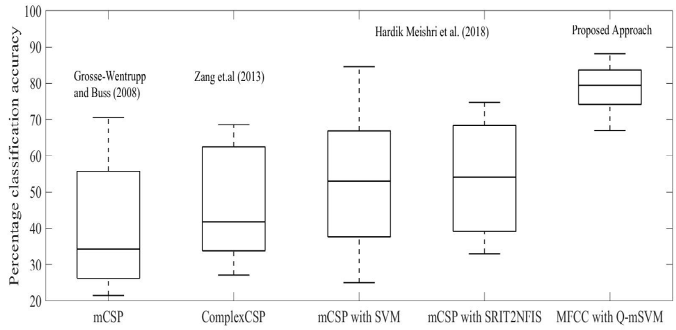

Figure 6: *Comparison of proposed approach with other research approaches on data of all 9 subjects.*

A number of research work has been carried out on the same data set (Brunner *et al.*, 2008). Grosse-Wentrup *et al.* (2008) has used Multiclass CSP (mCSP) features with SVM as classifier. Zhang *et al.* (2013) used Complex CSP feature and SVM as classification technique. Hardik *et al.* (2018) used the adaptive learning classifier, given the name Self-Regulated Interval Type-2 Neuro-Fuzzy Inference System (SRIT2NFIS), while using mCSP as feature. Table 3 indicates that the best average classification accuracy (78.48%) have been achieved by our proposed approach as compared to latest research approaches. The statistical significance of classification accuracy using t-test and calculating p-value for proposed approach and benchmark approaches has also been shown in Table 3.

Our approach exhibits comparatively best results due to the fact that we are considering short duration power spectrum of a signal using Mel Frequency Cepstrum (MFC). The benefit of using quadratic kernel for SVM is that it can handle nonlinear data transformation. Experimental results have revealed that using minimum 12 MFCCs results in the best classification accuracies. The EEG signal pattern can differentiate among movements of different limbs.

Table 2: *True positive and false negative rates-subject 9.*

	Class	Percentage of predicted class by Q-mSVM				True positive rate	False negative rate
		Left hand	Right hand	Both feet	Tongue		
True class	Left hand	79%	21%	-	-	79%	21%
	Right hand	21%	67%	13%	-	67%	33%
	Both feet	-	-	96%	4%	96%	4%
	Tongue	21%	-	-	79%	79%	21%

Table 3: *Classification accuracy of proposed approach as compared to other approaches.*

BCI Competition Data Set-2008 Graz Data Set A					
Classification Accuracy in %					
Subjects	**Grosse-Wentrupp and Buss (2008)**	**Zang et.al (2013)**	**Hardik Meishri et al. (2018)**		**Proposed Approach**
	mCSP with SVM	ComplexCSP with SVM	mCSP with SVM	mCSP with SRIT-2NFIS	MFCC with Q-mSVM
1	48.1	61.5	68.75	74.65	83.91
2	27.3	32.1	41.67	45.48	66.99
3	70.6	68.6	66.31	74.31	75.27
4	21.4	27.1	37.98	39.58	70.74
5	22.7	34.3	25	32.99	79.49
6	32.4	35.3	36.62	37.9	76.8
7	52.3	48	52.97	54.17	83.66
8	65.8	65.6	65.55	66.32	80.69
9	34.2	41.8	64.58	66.31	88.19
Mean	41.64	46.01	51.04	54.63	78.48
S.D	18.34	15.65	16.15	16.27	6.72
p-value with proposed approach			0.0001	0.0001	

For example, movement of left hand will result in activity of right side motor cortex while movement of right hand will generate activity in left side motor cortex.

This activity can be picked up by the sensors recording the signals from the scalp of a subject. Our feature extraction technique normalized MFCC has successfully differentiated the activity generated in the motor cortex and Q-mSVM worked as the best classifier in comparison to the latest research techniques. Figure 6 shows the comparison of percentage classification accuracies of our research approach with latest research approaches in terms of maximum and minimum values.

Conclusion and Recommendations

This research article proposes the use of MFCC as features for classification of four distinct motor imageries (EEG signals). Cepstral Coefficients is widely employed in speech recognition and seismological operations. The higher percentage classification accuracy achieved in our proposed technique is attributed to novel feature extraction approach MFCC coupled with Q-mSVM classifier. Experiments were performed on publicly available EEG signal data set (BCI Competition 2008-Graz dataset A). We also employed Linear Multi-class Support Vector Machine and Cubic Multi-class Support Vector Machine which generated comparable results. Our proposed architecture was compared with state of art approach which reveals that proposed system can considerably surpass existing approaches with mean classification accuracy of 78.48 percent and standard deviation of 6.72. The state of art approaches includes mCSP, Complex CSP, mCSP with SVM and mCSP with SRIT2NFIS. The past compared approaches exhibit maximum mean classification accuracy equal to 54.63%. MFC represents the short-term power spectrum of a signal. This power spectrum is a linear cosine transform of log power spectrum on a nonlinear mel scale of frequency.

The feature extraction method has resulted in better discriminative representation of data which helps the classification algorithm to draw optimal discriminative hyperplane for multiclass classification. Since the frequency bands are logarithmically positioned in MFCC, it approximation for human system response is more concise as compared to any other system. Representing the pattern of human limb movements through feature extraction was successfully achieved in this research. Our feature extraction technique, MFCCs take into account all the trials and extracts 12 mel frequency coefficients for the window used for feature extraction. These coefficients give the maximum and best representation of data and result in highest average percentage classification accuracy (overall 78.48% and 88.19% for subject # 9). Our proposed scheme of detecting the four-class human limb movement detection based on MFCCs and Quadratic Multi-Class Support Vector Machine has produced improved results classification in comparison to other latest research techniques. Moreover, our research has also augmented the fact that use of MFCC is not limited to the domain of speech recognition or analyzing sound signal, but it can be affectively and successfully used for Brain Computer Interface applications.

Towards the future work, this feature extraction and classification technique can be utilized for driving a wheelchair or an artificial human limb. The further work can be extended to the use of an embedded system rather than a computer.

Novelty Statement

Use of Mel frequency cepstral coefficients as features have been used on EEG signal classification for improved classification accuracy.

Author's Contribution

All authors contributed in interpretation, processing of data followed by feature extraction and classification, drafting and revising the article for intellectual content and final approval of the version to be submitted for publishing.

Conflict of interest

The authors have declared no conflict of interest.

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