TWO CHANNEL EEG CLASSIFICATION OF IMAGINED SPEECH BRAIN WAVES USING MACHINE LEARNING TECHNIQUE

Sunandan Mandal[a], Kavita Thakur[a], Bikesh Kumar Singh[b], Heera Ram[c]
[a]School of studies in Electronics & Photonics, Pt. Ravishankar Shukla University, Raipur, Chhattisgarh, 492010, India
[b]Department of Biomedical Engineering, National Institute of Technology, Raipur, Chhattisgarh, 492010, India
[c]Kalyan Post Graduate College, Bhilai Nagar, Durg, Chhattisgarh, 490006, India

A B S T R A C T

Electroencephalography based brain wave analysis is the most common technique of imagined speech classification. The developed model of imagined speech can further help to improve the synthetic telepathy and speech prosthesis for person with having speaking disability. In this work, EEG signal is extracted from Wernicke's area and Broca's area of brain using two channel of EEG only. These areas are responsible for the speech articulation and comprehension. This EEG signals is further filtered into EEG rhythms namely delta, theta, alpha, beta, and gamma waves. In this study, the data acquisition is performed for imagined two words as "LEFT" and "RIGHT" only. The feature vectors of the EEG signals are classified using decision trees, discriminant analysis, SVM (support vector machines), logistic regression, k nearest neighbor, and ensemble classification. In this work, highest classification accuracy of 86.11% is achieved in gamma wave rhythm with fine k nearest neighbor and ensemble subspace k nearest neighbor classifier. The result of classification shows that the imagined speech can be classified with only two channel of EEG, which also reduces the system complexity.

Keywords: EEG, Imagined speech, Classification, Machine Learning, Classifier

1. Main text

Introduction

EEG is the most popular technique in functional Brain Imaging method. It measures the electrical activity during functioning of the brain [6]. Brain signals can be acquired by placing the electrode on the desire place on the scalp. Verbal speech communication is the normal approach of human and partial or complete loss of audible speech may be an obstacle to effective communication with human being. Imagined Speech recognition can help to give voice to thought of such individuals to express aspiration of mind with external world. Imagined Speech interpreted as thought that is uttered just in the mind without any muscle movement. For severely handicapped individuals, such as those with advanced amyotrophic lateral sclerosis (ALS) or locked in syndrome their condition prohibit normal communication adversely affecting their daily routine of life [1]. Such disable person can be benefited with imagined speech recognition. Electroencephalogram (EEG) based BCI (Brain Computer Interface) is the mechanism by which imagined speech can be recognized.

1.1. Related work

Porbadnigk et al. [2] investigated the EEG signals based imagined speech recognition. In this study total 21 subjects were participates and imagined 5 different words as "alpha", "bravo", "charlie", "delta" and "echo". Hidden Markov Model (HMM) based classifier was used. This work achieved an average recognition rate of 45.50%. DaSalla et al. [3] performed vowel speech imagery classification using spatial filtering. EEG signals were recorded during imagined English vowel |a|, |u| and no action state from three subjects. Spatial filter through CSP (Common Spatial Patterns) method and Low pass filter were used in preprocessing. Extracted feature vectors were further applied to classifier as state nonlinear SVM (Support

Vector Machine). Classification accuracies of pair-wise combination were gained between 68% and 78%. D'Zmura et al. [4] performed classifying of imagined speech through EEG. Here only four subjects participated in an experiment where two syllables |ba| and |ku| have to imagine during EEG recording with three different rhythms. Hilbert transform, Matched filter and Band pass elliptic filters were used in preprocessing method. Power Spectral densities and average power were the extracted features. Hilbert spectrum methods were performed by Deng et al. [5] for Imagined syllable classification from EEG signals. Data were recorded for seven subjects for imagined two syllable |ba| and |ku| with three different rhythms. Processing of EEG data were done using SOBI (Second Order Blind Identification) algorithm and HHT (Hilbert Huang transformation). In this work, multiclass LDA (linear discriminant analysis) based Bayesian classifier was used for classification. Classification accuracies were achieved between 51.33% - 72.67%.

Next, Brigham and Kumar [6] performed Subject Identification from imagined speech EEG signals. For this investigation, total six subjects were guided and two syllables |ba| and |ku| were selected. From two syllables each of them imagined by subject during data acquisition. Hilbert transform, Matched filter, Band pass elliptic filters were applied during data preprocessing. From the processed EEG signals autoregressive (AR) coefficients are extracted and further fed to the Linear SVM and k-NN classifier for subject identification. Again the same research team Brigham and Kumar [7] reported speech imagery classification for EEG signals. EEG signals were recorded for 7 subjects and instructed to simple imagine speaking of two syllables |ba| and |ku|. Data were preprocessed using Modeling EEG Signal, Independent Component Analysis, Hurst exponent, Band pass filter range between 4-25Hz and subspace based Wiener filter. For feature extraction Univariate AR model coefficients was applied after preprocessing and Euclidean distance based 3-Nearest Neighbor classifier was utilized for classification. Chi et al. [8] reported positive result for classifying imagined phonemes on basis of EEG signals. In this work ten English –language phonemes used that are |aa|, |ae|, |l|, |r|, |nasal-m|, |nasal-n|, |uu|, |ow|, |s| and |z| and two relax trials. Total 5 subjects were chosen for data recording. Features were extracted and classified with Naive Bayes and LDA methods. Classification performance levels were reached 80% correct. Zabidi et al. [9] proposed successful discrimination of imagined writing of letter |A|, |B| and |D| from EEG signals. EEG signals for imagined writing were collected from one subject and 120 sets per letter. The EEG signals were bandpassed with frequency range 8 -30Hz. Autoregressive model was used to extract feature from EEG signals. Features were classified through Multilayer Perceptron (MLP). Average classification accuracies were between 80.79% - 96.25%.

Classification of EEG based speech imagery with Chinese word pronounced as “zuo” in third tone and “yi” in first tone were performed by Wang et al. [10]. In this work 8 healthy subjects were chosen and 150 trials from each subject were taken. Band pass filter (0.1Hz and 100Hz), CSP (Common Spatial Patterns) method were applied on EEG data during preprocessing. Feature like Covariance matrices, Eigenvectors and Eigenvalue extracted. SVM classifier was applied for classification. The classification accuracies were between 73.65% and 95.76%. Matsumoto M. [11] performed speech imagery with 4 subjects of two Japanese vowels |a| and |u|. CSP based filters were applied during preprocessing of signals. Classification was done by SVM with Gaussian kernel and classification accuracy was obtained 73-92% for pair wise combination. Arafat and Kanade [12] carried out EEG based imagined speech classification with 2 subjects of two word “left” and “right”. Preprocessing were done using Hilbert transform, matched filter, bandpass elliptic filter. Mean, Standard Deviation and Energy was feature selected for classification. The Euclidean distance based Nearest Neighbors Classifier was employ for classification. Kamalakkannan et al. [13] classified 5 English vowel and recorded EEG data from 13 subjects. IIR notch filter of second order and wavelet decomposition method are applied in preprocessing. Mean, Variance, Average Power, and Standard deviation are the feature extracted and classified using BPANN (back propagation artificial neural network). This work achieved average classification accuracy of 44%. Zhao and Rudzicz [14] used 7 phonemic/syllabic prompts (|iy|, |uw|, |piy|, |tiy|, |diy|, |m|, |n|) and 04 words (|pat|, |pot|, |knew|,

|gnaw|) with 12 participants for imagined as well as articulated speech. In pre-processing method band pass filter and laplacian filter are used to noise removal of EEG data. Various statistical features like Mean, Maximum, Minimum, Median, Standard deviation, Variance, Maximum±Minimum, Sum, Skewness, Spectral Entropy, Energy, kurtosis were extracted. Deep-belief network and non linear SVM were used for classification. They achieved accuracy of 95% between different states.

Iqbal et al. [15] carried out EEG based imagined speech classification of two vowel sound |a|, |u| and no action. In this work they preprocessed EEG data with bandpass filter in range of 1-45 Hz and Variance, Entropy, Signal Energy are the feature extracted. Linear, quadratic and nonlinear SVM classifiers are applied to discriminate of classes. The classification accuracies were obtained in range of 77.5-100%. Idrees and Farooq [16] performed EEG based imagined speech classification of English vowel sound |a|, |u| and ‘rest’. For recognize the 3 classes two algorithm ‘pair wise’ and ‘combination of tasks’ were proposed and tested on 3 subjects. For each task 50 trials has been taken from each subject. In this work, 11 statistical features were extracted. Classification accuracies were achieved 70-82.5% in pair wise algorithm and 85-100% in ‘combination of tasks’ with linear classifier. Mohanchadra and Saha [17] performed subvocalized speech classification on 3 subjects. Instead of syllables or vowel they have selected five words like “water”, “help”, “thanks”, “food”, and “stop”. For each word 50 trials has been taken from each subject. The EEG signals are filtered using 0.5-40Hz band pass filter. SVM classifier has been utilized by them. Training and testing of classifier were done by 5 fold CV (cross-validation) technique. Classification accuracies were achieved in range of 60-92%.

P300 speller based cognitive state response classification of Devanagari script were report by Chaurasiya et al. [18]. The data were collected from nine healthy subjects. EEG signals of subjects were filtered with Chebyshev type I bandpass filter of 8^{th} order with 1 to 10 Hz cut-off frequency range. In this work, weighted ensemble SVM was achieved an average accuracy of 94.2%.

Further, Idrees and Farooq [19] also performed imagined speech classification of English vowel sound |a|, |u| and ‘rest’ using 3rd and 4th level of wavelet decomposition method in preprocessing of data to get beta, delta and theta rhythms of EEG. Energy sum and energy’s waveform length feature were extracted from detail coefficients of 3rd level wavelet decomposition. For ’combination of tasks’ this work achieved classification accuracy 81.25-98-75%. Similarly, energy sum is feature extracted from approximation coefficients of 4th level wavelet decomposition and for ‘pair wise classification’ achieved classification accuracy 65-82.5%. Linear classifier was applied for classification. Rojas et al. [20] perform imagined speech classification of two Spanish vowels |a| and |e| using SVM classifier. Preprocessing of data were done by apply Blackman –Tukey Transform, IIR Butterworth pass band Filter. Feature extraction and selection were performed by symbolic aggregate approximation. The algorithm developed was able to distinguish the two imagined vowels with 85.29% accuracy. Min et al. [21] performed vowel imagery decoding using ELM (extreme learning machine) with EEG. EEG signals were recorded for five native Korean subjects. They imagined different vowels |a|, |e|, |i|, |o| and |u|. The EEG data was bandpass filtered with 1-100Hz and an IIR notch filter was also applied to remove the power line noise. Statistical feature like Mean, skewness, standard deviation and variance were extracted and sparse regression model applied for feature selection. LDA, SVM-R, ELM-L and ELM-R were the classifier applied in this study. In this work, ELM and its variants showed better performance than other classifier.

Material & methods

1.2 Data acquisition of imagined speech

In the present work, two channels Biopac MP45 system is used for recording of brain activity during imagined speech. From the literature survey it has found that both Wernicke’s area and Broca’s area of brain mainly process the speech articulation and comprehension. One of the areas is in the posterior-superior temporal lobe, called Wernicke’s area, and another one is placed in the posterior-inferior frontal gyrus, called Broca’s area [10]. Both the area is positioned in the left hemisphere of the brain. In this work, we place the electrode of the EEG to that particular area. The dataset is recorded from two right handed healthy control subjects.

1.3 Experimental Protocol

During the recording session subjects were seated on a comfortable arm chair. An LCD monitor was placed in front of subject with 1 m distance. Before recording, the purpose and instructions of the experiment were explained to subjects. Two words “Left” and “Right” have been selected for this study. Target stimuli were presented in a sequence and predefined duration as depicted in Figure 1. Total nine trials (repetition) were performed by each subject for each word.

The time varying visual cues were used for experimental protocol. Firstly Relax shows for 15 seconds on the LCD screen which indicate the subject to take relax. Further ready will display on the screen for 10 seconds which indicate that next slide shows stimulus for 5 seconds of respective imagined word. After that the screen will dark for 10 seconds, this time subject will have to imagine. Further process is same for next imagine speech. The sampling rate is put to 1000 sample per second for both the channels.

1.4 Pre-processing and Feature extraction

The captured EEG data contaminated with physiologic artifacts like Electromyogram (EMG) artifacts from facial muscle contractions and Electrooculogram (EOG) artifacts from eye blinking, Glossokinetic artifact from tongue activity, Skin artifact and ECG artifact, to remove these artifacts the EEG data was preprocessed. After the recording session, the complete recorded signals were visually scrutinized to remove the artifacts.

In this work, EEG signals were pre-processed using some inbuilt feature of Biopac Student Lab pro software. This software provides band pass filter which can separate the EEG signals into delta wave, theta wave, alpha wave, beta wave, and gamma wave. The magnitudes of these waves are further used as feature for analysis of EEG signal. Figure 2 shows the snapshot of different EEG rhythms of channel 1 during recording.

1.5 Classification

In this analysis, the feature vectors of the EEG signals were classified using decision trees, discriminant analysis, SVM, logistic regression, k-nearest neighbors, and ensemble classification. The implementations used for these classifiers are the ones provided by MATLAB. The Classification Learner app of MATLAB trains models of different classifier to classify data.

1.6 Proposed approach

The proposed approach for imagined speech brain waves classification using ML (machine learning) technique is shown in figure 3. This prototype model includes two parts, divided by dotted line. The left part of the model shows offline system while in the right side of figure depicts an online system. The noise removal and feature extraction are common steps in both offline and online system. In feature extraction section delta, theta, alpha, beta, and gamma brain waves are extracted from EEG signals. The amplitudes of these brain waves are further used as feature for training and testing the system. In the present work the online system is used supervise training of different classifier. During the online mode, the testing of EEG signal is done with the generated machine learning parameter.

1.7 Performance evaluation

In the present work, the proposed approach is studied with different classifier. In order to quantify the performance of all classifier confusion matrix based accuracy parameter is calculated. Table 1 shows the confusion matrix for two class problem. Symbol μ_{TP}, μ_{FP}, μ_{FN} and μ_{TN} are representing true positive, false positive, false negative and true negative respectively. Formulations of some performance measures which can be calculated from confusion matrix are as follows.

Table 1: Layout of confusion matrix for two class problem

Actual class	**Recognized class as positive (1)**	**Recognized class as negative (0)**
Positive(1)	μ_{TP}	μ_{FN}
Negative(0)	μ_{FP}	μ_{TN}

Result & Discussion

In this study, only two words are imagined "LEFT" and "RIGHT". After preprocessing of EEG signals of imagined speech are divided into training and testing part using 5-fold Cross Validation data division protocol. Total twenty three different classifiers are trained using training data set. Further the classifiers are tested using testing data set and Table 2 shows the overall accuracy of different classifier.

Table 2 Accuracy of classifier models for different EEG frequency range

Classifier Model	Accuracy (%)				
	Delta	**Theta**	**Alpha**	**Beta**	**Gamma**
Complex TREE	**83.33**	**80.56**	69.44	50.00	80.56
Medium TREE	**83.33**	**80.56**	69.44	50.00	80.56
Simple TREE	**83.33**	**80.56**	69.44	50.00	80.56
Linear Discriminant	52.78	50.00	55.56	61.11	55.56
Quadratic Discriminant	55.56	55.56	58.33	55.56	66.67
Logistic Regrassion	61.11	63.89	69.44	52.78	19.44
Linear SVM	41.67	47.22	72.22	63.89	55.56
Quadratic SVM	61.11	52.78	**75.00**	**75.00**	77.78
Cubic SVM	72.22	55.56	69.44	72.22	83.33
Fine Gaussian SVM	47.22	44.44	52.78	47.22	77.78
Medium Gaussian SVM	38.89	47.22	52.78	50.00	58.33
Coarse Gaussian SVM	44.44	44.44	50.00	44.44	50.00
Fine KNN	61.11	50.00	66.67	72.22	**86.11**
Medium KNN	41.67	50.00	47.22	47.22	44.44
Coarse KNN	44.44	44.44	44.44	44.44	44.44
Cosine KNN	50.00	55.56	58.33	58.33	47.22
Cubic KNN	44.44	47.22	47.22	52.78	47.22
Weighted KNN	41.67	50.00	58.33	47.22	77.78
Ensemble Boosted Tree	44.44	44.44	44.44	44.44	80.56
Ensemble Bagged	50.00	69.44	63.89	66.67	83.33
Ensemble Subspace Discriminant	61.11	52.78	58.33	58.33	83.33
Ensemble Subspace KNN	50.00	61.11	66.67	72.22	**86.11**
Ensemble Rusboosted	55.56	44.44	50.00	50.00	80.56

Classification accuracy of 83.33 % is achieved using complex, medium and simple tree classifier in delta wave of EEG. Similar result found in theta wave with 80.56% classification accuracy using complex, medium and simple tree classifier. Quadratic SVM classifier shows 75% classification accuracy in both alpha and beta wave of EEG. In this work, highest classification accuracy of 86.11% is achieved in gamma wave range with fine k nearest neighbor and ensemble subspace k nearest neighbor classifier.

Conclusion and Future Work

In the present work, we have tried various classification techniques for classifying imagined speech. We first recorded the EEG signals, which itself was a complicated and time-taking process. The mental state of the subjects plays a crucial role in the study. If the participant is distracted and unable to concentrate on the task then the recordings will be affected adversely. We have investigated if there is possible to achieve satisfactory results with lesser training time and fewer electrodes. Here we achieved maximum classification accuracy of 86.11% using fine K nearest neighbour classifier without extracting any time or frequency domain attributes. For enhance the performance we can extract the time and frequency domain attributes before classification. Further research will help the control the machine through brain waves. As state in most of the research work the primary goal of the research in the field imagined speech recognition is to help to improve quality of life the people with speaking disability like ALS (amyotrophic lateral sclerosis), locked in syndrome (LIS), paralysis, laryngectomy etc. May be in future astronaut/cosmonaut will communicate in space through just imagined speech. War place also create such condition where communication should be secure from enemy. This type of communication system is called as synthetic telepathy system that may be the future use of imagined speech

2. Illustrations

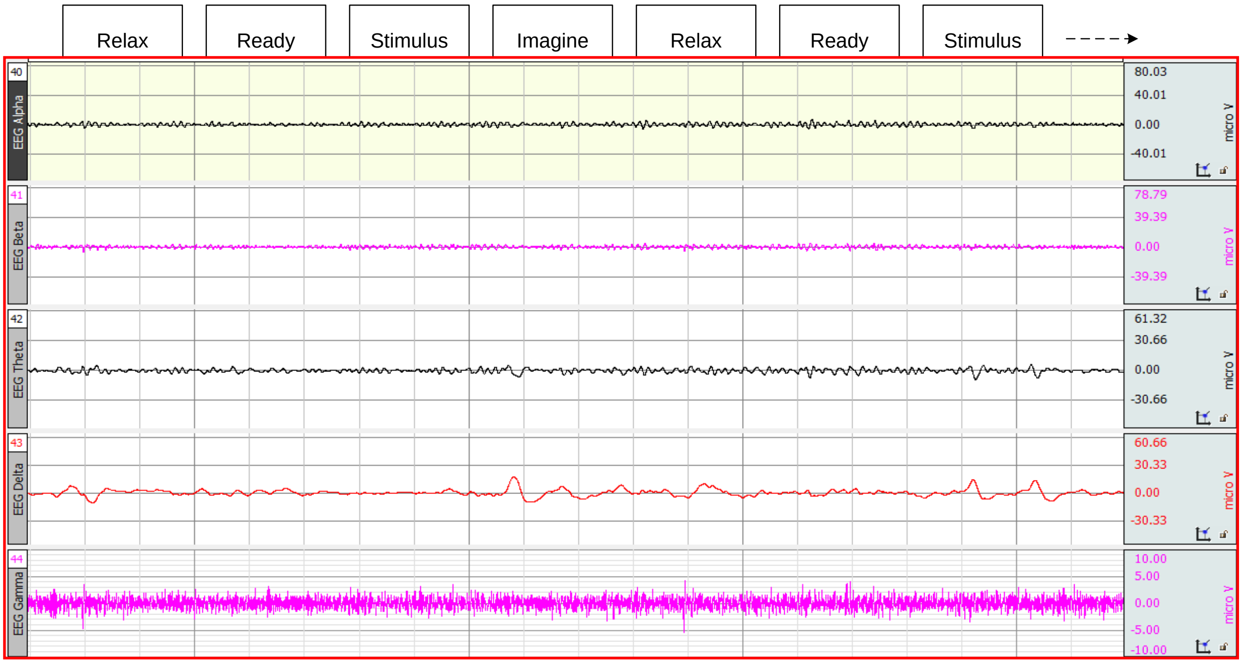

Figure 2- Graph of EEG rhythms during recording

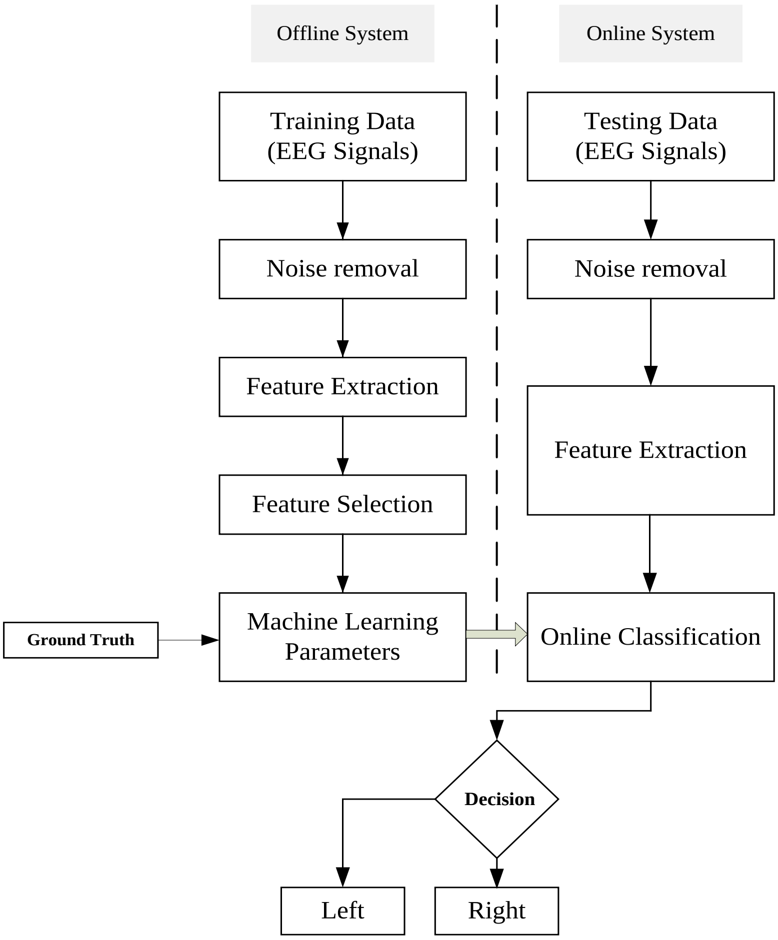

Figure 3- Architecture of proposed approach

3. Equations

Accuracy: It is a measurement which indicate the system ability to correctly classified both for positive and negative cases during the testing of the model

$$Accuracy(\%) = \frac{\mu_{TP} + \mu_{TN}}{\mu_{TP} + \mu_{FN} + \mu_{TN} + \mu_{FP}} \times 100 \quad (1)$$

Sensitivity: It is a measurement which indicate that ability to correctly classified positive cases from total positive cases during the testing of the model

$$Sensitivity(\%) = \frac{\mu_{TP}}{\mu_{FN} + \mu_{TP}} \times 100 \quad (2)$$

Specificity: It is similar to the sensitivity but it shows correctly classification of negative cases from total negative cases.

$$Specificity(\%) = \frac{\mu_{TN}}{\mu_{TN} + \mu_{FP}} \times 100 \quad (3)$$

Area under receiver operating characteristic curve (AUC): It is calculated average value of sensitivity and specificity.

$$AUC(\%) = \frac{1}{2}\left(\frac{\mu_{TP}}{\mu_{TP} + \mu_{FN}} + \frac{\mu_{TN}}{\mu_{TN} + \mu_{FP}} \right) \times 100 \quad (4)$$

Matthew's correlation coefficient (MCC): The performance of classifier is calculated using MCC which also consider the balance of positive and negative cases.

$$MCC(\%) = \frac{\mu_{TP} \times \mu_{TN} - \mu_{FP} \times \mu_{FN}}{\sqrt{(\mu_{TP} + \mu_{FP})(\mu_{TP} + \mu_{FN})(\mu_{TN} + \mu_{FP})(\mu_{TN} + \mu_{FN})}} \times 100 \quad (5)$$

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