EEG Based Communication System in Generalized & Customized Modes for Differently Abled Communities

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Abstract—**Differently abled people such as patients with Amyotrophic Lateral Sclerosis, brain stem stroke and spinal cord injury, encounter difficulty in communication due to the loss of muscle control and speech. Intelligent Brain Machine interfaces are devices which can be used to aid these severely affected people through the power of thought. In this research work, a Thought Controlled Communication System has been developed using seven English words which is considered to convey the basic needs of a patient. The proposed communication system records the Electroencephalography signal while mentally reading the words. The recorded EEG signals are pre-processed and segmented into four frequency bands. The band frequency signals are used to extract features using band power and power spectral density algorithms. In this analysis, two simple classifiers namely Multi Layer Neural Network and k-Nearest Neighbor have been used for recognizing the extracted features in both generalized and customized modes. The proposed classification system has been validated through simulation.**

Index Terms— **Band power; k-Nearest Neighbor; Multi Layer Neural Network; Power Spectral Density; Thought Controlled Vocabulary Classification**

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I. Introduction

COMMUNICATION is a fundamental human right and it is a process of conveying or expressing our thoughts, feelings and opinions to the external world. According to World Health Organization (WHO), communication disability is a lack of ability to perform an action which is normal for human beings, such as to speak, understand, read and write [1]. People who have intellectual disabilities or physically disabled with Motor Neuron Disease (MND), Amyotrophic Lateral Sclerosis (ALS), victims of spinal cord injuries are often paralyzed with voice and mobility impairments. Those most severely affected may lose all voluntary muscle control and experience difficulty in expressing their needs and thoughts to their care givers. However their sensory and cognitive abilities for such people often remain intact. Recent developments in augmentative communication system require a measure of voluntary muscle function of a patient to convey their needs in the absence of which Brain Computer Interface (BCI) can be used as an alternative communication system that does not depend on muscle control [2, 3].

Intelligent Brain Machine (IBM) interfaces are devices which allow the patient to interact with the computer and other machines through the power of thought. Using the sensory and cognitive abilities is a possible way to restore the communication of a patient with severe motor disorders. This is accomplished by providing the brain with a new, non-muscular communication channel using a direct intelligent brain computer interface. Through proper training, the patients can learn to control their brain activity in a predetermined fashion that is classified by a pattern recognition algorithm [3-6]. Recent improvements in thought controlled interfaces have been limited to control computer cursors, mouse and prosthetic devices [7-11]. However, a practical implementation of this approach is still not available. In this research work, as an initial step towards developing a communication system for differently abled communities, using Electroencephalography (EEG) called the Thought Controlled Vocabulary Classification (TCVC) system has been proposed. The proposed brain wave communication system utilizes the power of thinking of a patient to convey the potential needs or information to their listeners. The block diagram of the proposed thought controlled communication system is depicted in Fig. 1.

EEG is a tool, which can be used to detect the brain activity when cognitive tasks are performed. EEG signal can be measured directly from the cortical surface of the human head, to analyze a mental task. Since its discovery in 1875 by an English Physician Richard Caton, EEG signals have been used in clinical research to assess brain wave functions [8]. In early 90's EEG signals were acquired by implanted electrodes to design BCI for disabled people. After the introduction of non-invasive electrodes in 2000, lead to the research and development of thought controlled cursor movement BCI and Neuro-prosthetic arms. Currently this research work has been directed towards producing communication system through thought evoked signals [12, 13].

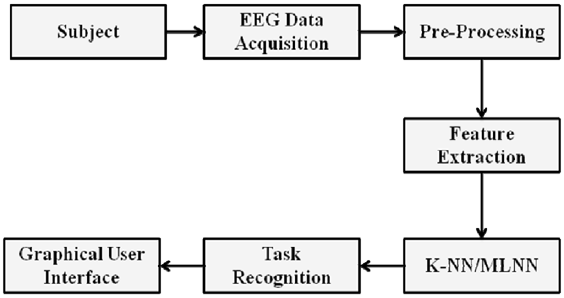

Fig. 1. Block Diagram of the TCVC System.

The main objective of this study is to develop a simple communication system, which can be used by movement and speech impaired people to communicate their needs to others. A simple experimental protocol is proposed wherein English words are shown to the subjects and the subjects are requested to mentally spell the words without any overt movements. EEG signals are recorded from various subjects, The EEG signals are recorded using a 'g.tec amplifier. The recorded signals are pre-processed using a fast fixed-point algorithm using independent component analysis, to detect and remove noise signals. The pre-processed EEG signals are segmented into frames of equal length and four frequency bands namely delta (0.1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (13-30 Hz) [8].

The selected frequency band signals are then used to extract features using Band Power (BP) and Power Spectral Density (PSD) methods. The extracted features are associated to the corresponding vocabulary task and classified using Multi Layer Neural Network (MLNN). Further, the performance of the classification system is also compared using k-Nearest Neighbour (kNN) algorithm. Also, to measure the performance of each subject, customized TCVC system has been developed and the results are compared in section six.

II. Methodology

This section explains the selection of individuals, experimental setup and acquisition of EEG signals for vocabulary classification experiments.

A. Data Collection

In the work with the corpus of EEG based vocabulary classification system, different recording personnel are involved. Ten male subjects in the age group of 21-30 years took part in the study and the subjects were requested to fill-up the informed consent form. Most of the volunteers were Diploma and Post graduate students from the School of Mechatronic Engineering, University Malaysia Perlis. The subjects were chosen based on free of medication and central nervous system abnormalities and had no prior experience with EEG based communication systems. Before initiating the recording session, the volunteers were given a brief description about the purpose and objective of this research work and also the outcome of the experiment.

B. Experimental setup and protocol development

In the experimental setup, the EEG signals are studied with a standard EEG amplifier 'g.tec (Guger Technologies, Graz, Austria)' with electrode cap arrangement. The advantage of the electrode cap is that it uses individual electrodes for maximum electrode montage flexibility. Real-time processing was performed with a sampling frequency of 250 Hz under Matlab 7.10 and Simulink 5.0 (The MathWorks, Inc., Natick, USA). In this analysis, eight electrodes were placed at Parietal (P), temporal (T), central (C), occipital (O) and ground electrode locations of 10-20 system as illustrated in Fig. 2. [8, 14-15], eight channel electro-cap were connected through an amplifier whose band pass analog filters were set at 1.5 to 34 Hz. The main research interest in this work is to develop a simple communication system that is practical for use by a differently enabled person to communicate respectively. Hence, the protocol for the system was designed using seven vocabulary tasks, which address the basic needs, such as Food, Water, Help, Air-conditioner, Toilet, TV and Relax (normal), relax is used as the reference signal.

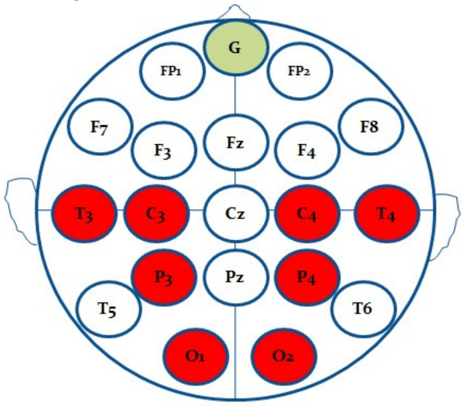

Fig. 2. International 10-20 electrode placement system.

The subjects are seated comfortably in a sound controlled booth with dim lighting. The subjects were requested to view the image which is displayed on the LCD monitor for ten seconds, and the LCD monitor is turned off. Then, the subject was requested to imagine the displayed image, and pronounce the word mentally. Simultaneously, the EEG signal was recorded for ten seconds during the imagination session. The sampling frequency is chosen as 250 Hz [16].

C. TCVC Database

The 'TCVC' database comprises of ten subjects, seven mental vocabulary task and ten trials per task. The system records the motor imaginary signal from the eight electrode positions such as T3, T4, C3, C4, P3, P4, O1 and O2 while the subjects were performing a vocabulary task. The electrodes are placed in such a way; it recognizes the electric potential of synchronized neuronal activity of the brain during recording. The subject executes seven different mental tasks while remaining in a totally passive state. No overt movements were made during the performance of the tasks. EEG signals were obtained from ten subjects using eight-channel Electro-Cap. The experiments were performed over two months. The subjects were requested to perform seven mental tasks and data from all electrodes were recorded for ten seconds during a given task and each task was repeated ten times per session. Thus the database has been built with 70 EEG signals per subject.

III. Pre-Processing Of EEG Signals

The recorded EEG signals on the scalp for various vocabulary mental tasks are usually contaminated with different kinds of interference waveforms such as artifacts, eye-blinks and eye ball movements. These recorded signals are the electrical potentials that are not originated in brain. Hence, detection and elimination of the artifacts is essential for the development of TCVC system [17-18]. This subsequent section of this paper briefly describes the pre-processing of the recorded EEG signals which includes pre-processing of EEG signals using Fast ICA algorithm, segmentation of frames and selection of frequency bands.

A. Interference removal using Fast ICA algorithm

In motor imaginary related experiments, identifying interference waveforms produced in EEG signals by other electrical potentials is a most important factor in EEG related research works. In case of EEG noise removal, classical methods are available such as rejection methods and subtraction methods [19-21]. However, removing artifacts using these methods entirely is impossible and leads to an unacceptable loss of EEG samples. In recent years, Independent component analysis (ICA) has been used as a method for blind source separation (BSS) and becomes a widely accepted tool for isolating the interference waveforms from the recorded EEG data. ICA based pre-processing method can be implemented using different metrics for statistical independence. Kachenoura, et al., presented a review on comparison of several ICA algorithms applied to BCI applications [22], which shows FastICA performs better than other algorithms and it uses kurtosis as a standard measure of non Gaussian expressions [23-24]. Hence in this research work, FastICA algorithm has been used as a pre-processing method to detect and eliminate the interference signals added to the recorded EEG signals [25].

B. Segmentation of frames

To analyze the motor imaginary signals a window is slid over the EEG mental vocabulary signal and the features over each frame are extracted. Overlapping windows offer better time resolution and can produce shorter delays in the detection, in order not to miss any possible imaginary events happening at the end of each frame and prolonging to the next one. A frame length of one second having 256 samples per frame has been chosen with an overlap of 0.5 sec (128 samples). Signal from each EEG channel was divided into segments of equal length.

The discrete time domain representation of the EEG signal is chosen as (X) and it is shown in Equation. 1. The first frame consists of the first N (256) samples. The second frame begins M (128) samples after the first frame, and overlaps it by (N – M) samples and so on. This process continues until all the EEG signals are accounted and is represented in Equation. 2.

$$\mathrm{X} = [\mathrm{X}_1, \mathrm{X}_2, \mathrm{X}_3, \ldots, \mathrm{X}_\mathrm{i}, \ldots, \mathrm{X}_\mathrm{N}] \quad (1)$$

where $\boldsymbol{X}$ is the EEG data

$\boldsymbol{X}_i$ is the i^{th} frame and it is represented as:

$$\boldsymbol{X}_i = [x_{i1}, x_{i2}, x_{i3}, \ldots, x_{ij}, \ldots, x_{256}] \quad (2)$$

where x_{ij} is the j^{th} signal of the i^{th} frame.

Thus the emphasized EEG signal is divided into number of frames and the framed signal is then used as an input to the frequency band selection algorithm

C. Selection of frequency bands

EEG brain wave signals are recorded for ten seconds at 250 Hz and each signal is blocked in to frames of equal length having 256 samples per frame. It has been suggested by Anderson et al [26] that frequencies above 40 Hz convey little information related to mental state; hence the segmented frame signals are processed using a band pass filter to remove all signals below 0.5 Hz and above 34 Hz. The segmented brain waves have been categorized into four basic groups: Delta (0.1-4 Hz), Theta (4-8 Hz), Alpha (8-13Hz) and Beta (13-30 Hz). The frequency bands signals for the normal and help tasks are depicted in Fig. 3(a) – 3(d).

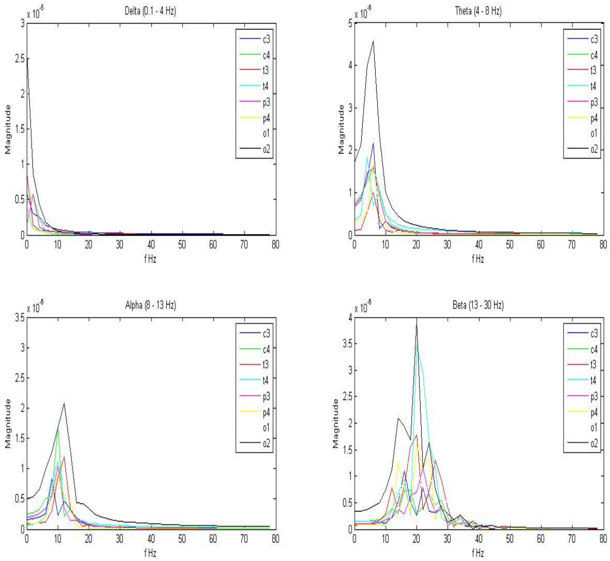

Fig. 3. a) Spectral band for Delta, b) Spectral band for Theta, c) Spectral band for Alpha and d) Spectral band for Beta

The selected frequency band is applied to each channel of the segmented brain wave signal and the features are extracted. The subsequent section of this paper explains the feature extraction methods used in this paper.

IV. Feature Extraction Using BP And PSD

Feature extraction is the process of identifying dominant characteristics from the EEG signal and representing the brain wave samples with minimum dimension and minimum loss of motor imaginary information. In this paper, two feature extraction methods namely band power and power spectral density methods were employed to study the motor imaginary vocabulary signals. The EEG signal obtained from each channel is divided into frames signals such that each frame has 256 samples. For each frame signal, Band pass filters are applied to extract the four frequency band signals. For each band signal, sum of the power values are extracted and a logarithmic transform is performed on the summed power value using Eq. 3. and Eq. 4. Therefore for eight channels we have 32 (8 X 4) features per frame.

Band energy $\boldsymbol{BE} = \left[e_1, e_2, e_3, \ldots, e_i, \ldots, e_N\right]$ (3)

where ***BE*** is the sum of the powered values and e_i is the frame power in the i^{th} frame and it is represented as:

$$e_i = \sum_{j=1}^{256} x_{ij}^2 \qquad (4)$$

Further, for each frame signal, power spectral density features are extracted using Welch's method. The frame signals are used to extract the four frequency band signals using the band pass filters. The segmented frequency band signals were analyzed using Welch's method, a hamming window is applied over each frame and Fast Fourier Transform (FFT) algorithm was used to compute the discrete Fourier transform (DFT) and its inverse. The sum of the absolute FFT values are the power spectral density (PSD) features [27]. The process is repeated for all the frequency bands of a task and for each subject. Therefore for eight channels we have 32 (8 X 4) features per frame. The band power and PSD features are extracted for ten such trials for each task and are used to train and test the classifier models. These feature vectors are then used to model the MLNN for the generalized system. Simultaneously, features sets corresponding to customized system 32 features x ten trials x seven tasks are formulated and used to develop customized neural network models.

V. Classification Using MLNN and k-NN

A. Multilayer neural network classifier

Artificial Neural Networks (ANN's) are biologically inspired tools for information processing and they are nonlinear in nature [28]. Classification motor imaginary vocabulary tasks basically falls on pattern recognition problem, and because artificial neural networks are good at pattern recognition, in recent years there has been a significant work that has established the idea of ANN as a useful technology for BCI applications [29-31]. In this analysis, a generalized TCVC system has been developed using MLNN, and customized MLNN models has been developed for each subject to measure and enhance the performance of each subjects in training.

The feature vectors formed for the customized (840 x 32 feature vectors) system and generalized (8400 x 32 features vectors) system using band power and PSD features are processed to label and then associated with the seven motor imaginary vocabulary classes. Also, the feature vectors are normalized using binary normalization method and partitioned into training set, and testing set. The training set has 672 x 32 samples and the testing set has the remaining 168 x 32 samples for the customized TCVC system of a subject and the training set has 6720 x 32 samples and the testing set has the remaining 1680 x 32 samples for the generalized TCVC system of all subjects.

The MLNN models are activated using logistic sigmoid activation function. The logistic sigmoid function can be scaled to have any range of the values that is appropriate for a given problem. The most common range is from 0.1 to 0.9. While training the neural network, a Mean Squared Error (MSE) tolerance of 0.1 is used. The learning rate and momentum factor for the models are chosen as 0.1 and 0.8 respectively. The values for learning rate, momentum factor and number of iterations are chosen by experimental observations in order to get better classification accuracy. The predicted task output is compared with the actual imaginary task output and the error is computed. The mean error is then back propagated to the hidden units and the weights are adjusted. This process is repeated until the mean squared error is less than the tolerance value [30]. Thus the output of the network is associated to the corresponding isolated word, and the word is pronounced through an audio speaker and displayed on the LCD screen. The MLNN for generalized mode and the customized mode are trained with 25 such trial weights and the number of epoch, network training parameters and the mean classification rate for all the models are shown in TABLE I to TABLE IV.

TABLE I
CLASSIFICATION PERFORMANCE FOR THE GENERALIZED MODE USING BP FEATURES

Classification rate for generalized system using band power features

Training Parameters		Testing Parameters	
		No of Hidden Neurons in the 1st Hidden Layer	No of Hidden Neurons in the 2nd Hidden Layer
No. of Epoch Set	4000		
No. of Hidden Layer	2	20	20
Training Tolerance	0	Testing Tolerance	0
Input Neurons	32	Output Neurons	3
Training Samples	6720		

No. of Trials	No. of Epocs			Training Time in Seconds			Classification Rate in Percentage		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1	115	121	128	658	694	731	84.5	85.1	86.0
2	155	169	183	701	745	789	85.2	85.6	86.4
3	112	153	194	728	830	933	85.3	**85.9**	87.1
4	158	256	351	687	821	956	85.0	85.6	86.2
5	162	191	221	719	787	856	83.3	**85.1**	85.7
Min	112	**121**	128	658	**694**	731	**83.3**	**85.1**	85.7
Mean	155	169	194	701	787	856	85.0	85.6	86.2
Max	162	**256**	351	728	**830**	956	85.3	**85.9**	**87.1**

TABLE II
CLASSIFICATION PERFORMANCE FOR THE GENERALIZED MODE USING PSD FEATURES

Classification rate for generalized system using PSD features

Training Parameters		Testing Parameters	
No. of Epochs Set	4000	No of Hidden Neurons in the 1st Hidden Layer	No of Hidden Neurons in the 2nd Hidden Layer
No. of Hidden Layer	2	20	20
Training Tolerance	0.009	Testing Tolerance	0.1
Input Neurons	32	Output Neurons	3
Training Samples	6720		

No. of Trials	No. of Epocs			Training Time in Seconds			Classification Rate in Percentage		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1	129	136	143	737	777	819	81.1	**81.7**	82.6
2	174	189	205	785	834	884	85.8	86.4	87.3
3	120	164	208	780	890	1000	86.1	**86.7**	87.9
4	185	300	411	804	961	1119	86.7	**86.8**	87.1
5	186	220	254	827	905	984	84.1	85.9	86.5
Min	120	**136**	143	737	**777**	819	**81.1**	**81.7**	82.6
Mean	174	189	208	785	890	984	85.8	86.3	87.1
Max	186	**300**	411	827	**961**	1119	86.7	**86.7**	**87.9**

From TABLE 1, it is observed that the MLNN model has two hidden layers and each layer consists of 20 hidden neurons. Since the number of training samples were 6720 samples, to minimize the training time and to avoid the overfit on training, two hidden layers has been chosen for the generalized mode. It is inferred that the network model has the mean minimum epoch of 121 and the mean maximum epoch of 256. Further, the network model has been trained with a mean minimum training time of 694 seconds and mean maximum training time of 830 seconds. The performance of the classification system has the mean minimum classification accuracy of 85.06 % and the mean maximum classification accuracy of 85.89 %. The overall maximum classification accuracy of 87.08 % has been obtained for the generalized system using band power feature.

From TABLE II, it is observed that the MLNN model has two hidden layers and each layer consists of 20 hidden neurons. Since the number of training samples were 6720 samples, to minimize the training time and to avoid the overfit on training, two hidden layers has been chosen for the generalized mode. It is inferred that the network model has the mean minimum epoch of 136 and the mean maximum epoch of 300. Further, the network model has been trained with a mean minimum training time of 777 seconds and mean maximum training time of 961 seconds. The performance of the classification system has the mean minimum classification accuracy of 81.73 % and the mean maximum classification accuracy of 86.73 %. The overall maximum classification accuracy of 87.92 % has been obtained for the generalized mode using PSD features.

TABLE III MLNN CLASSIFICATION PERFORMANCE FOR THE CUSTOMIZED MODES USING BP FEATURES

Classification rate for customized mode using band power features

Training Parameters		Testing Parameters	
No. of Epochs Set	4000	No of Hidden Neurons	
No. of Hidden Layer	1		20
Training Tolerance	0.009	Testing Tolerance	0.1
Input Neurons	32	Output Neurons	3
Training Samples	672		

Subject Id	No. of Epocs			Training Time in Seconds			Classification Rate in Percentage		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1	36	51	65	65	71	78	94.1	95.2	95.8
2	55	99	143	71	185	300	94.1	94.1	94.6
3	34	76	121	28	70	87	92.9	94.6	94.6
4	45	145	248	61	211	364	**92.3**	**93.5**	94.6
5	45	93	123	57	148	198	95.2	95.2	95.8
6	30	87	143	43	134	225	95.8	95.8	96.4
7	124	129	135	135	160	184	96.4	97.0	**98.2**
8	57	102	147	73	191	309	**97.0**	97.0	97.0
9	35	78	125	29	72	90	95.8	**97.6**	97.6
10	46	149	255	63	217	375	95.2	96.4	97.6
Min	30	**51**	65	28	**70**	78	**92.3**	**93.5**	94.6
Mean	45	96	139	62	154	212	95.2	95.5	96.1
Max	124	**149**	255	135	**217**	375	97.0	**97.6**	**98.2**

TABLE IV MLNN CLASSIFICATION PERFORMANCE FOR THE CUSTOMIZED MODES USING PSD FEATURES

Classification rate for generalized system using PSD features

Training Parameters		Testing Parameters	
No. of Epocs Set	4000	No of Hidden Neurons	
No. of Hidden Layer	1		20
Training Tolerance	0.009	Testing Tolerance	0.1
Input Neurons	32	Output Neurons	3
Training Samples	672		

Subject Id	No. of Epocs			Training Time in Seconds			Classification Rate in Percentage		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1	60	109	159	77	202	327	94.1	96.4	97.0
2	37	84	134	31	76	95	94.1	95.2	95.8
3	49	160	275	67	230	397	92.9	95.8	95.8
4	49	102	137	62	161	216	92.3	**94.6**	95.8
5	33	96	159	47	146	246	95.2	96.4	97.0
6	136	142	150	147	174	201	95.8	97.0	97.6
7	62	112	164	80	208	337	96.4	98.2	**99.4**
8	39	86	138	31	79	98	97.0	98.2	98.2
9	51	164	284	69	237	409	95.8	**98.8**	98.8
10	33	56	72	31	76	85	95.2	97.6	98.8
Min	33	**56**	72	31	**76**	85	**92.3**	**94.6**	95.8
Mean	49	106	154	64	168	231	95.2	96.7	97.3
Max	136	**164**	284	147	**237**	409	97.0	**98.8**	**99.4**

From TABLE III, it can be inferred that the network model has a mean minimum epoch of 51 and a mean maximum epoch of 149. Further, the network model was trained with a mean minimum training time of 70 seconds and mean maximum training time of 217 seconds. The performance of the classification system has a mean minimum classification accuracy of 93.45 % for subject 4 and a mean maximum classification accuracy of 97.62 % for subject 9. The overall maximum classification accuracy of 98.21 % has been obtained for subject 7 in the customized system using band power features.

From TABLE IV, it is observed that the MLNN model using PSD features has single hidden layer with 20 hidden neurons. It is inferred that the network model has the mean minimum epoch of 56 and the mean maximum epoch of 164. Further, the network model has been trained with a mean minimum training time of 76 seconds and mean maximum training time of 237 seconds. The performance of the classification system has the mean minimum classification accuracy of 94.64 % for subject 4 and the mean maximum classification accuracy of 98.81 % for subject 9. The overall maximum classification accuracy of 99.40 % has been obtained for subject 7 in the customized mode using PSD features

B. k-Nearest Neighbor classifier

kNN is a simple classifier, supervised learning algorithm and suitable for pattern classification. The k-NN classifier is also called as lazy algorithm because the testing sample has been assigned to the nearest neighborhood based on the minimum Euclidean distance [32]. In this research, the feature vectors derived for the customized (840 x 32 feature vectors) system and generalized (8400 x 32 features vectors) system using band power and PSD features are used to classify using the kNN algorithm. The extracted features are processed to label the outputs and then associated with the seven motor imaginary vocabulary classes. The feature vectors are normalized using binary normalization method and partitioned into training set, and testing set. Such that, the training set has 672 x 32 samples and the testing set has the remaining 168 x 32 samples for the customized TCVC system of a subject and the training set has 6720 x 32 samples and the testing set has the remaining 1680 x 32 samples for the generalized TCVC system of all subjects. The classifier model identifies the testing samples based on majority voting of kNN query. The kNN category is calculated by finding the Euclidean minimum distance between each testing sample with the corresponding training sample using the Eq. 5.

$$\left(ED_{X,Y}\right) = \sum_{i=1}^{F} \sqrt{(X_i + Y_i)^2} \quad (5)$$

where X and Y are the training feature vectors and testing feature vectors, F represents the 32 features for each frame signal corresponding to four filter bands. The value of k is chosen as six, as it shows the better classification accuracy than the one to ten through experimental observations. Thus the output of the classifier is associated to the corresponding isolated word, and the word is pronounced through an audio speaker and displayed on LCD screen. The kNN classifier for generalized system and the customized systems are trained with 25 such trial weights and classification rate for all the models are shown in TABLE V to TABLE VIII.

TABLE V kNN PERFORMANCE FOR THE GENERALIZED SYSTEM USING BP FEATURES

TABLE V: kNN Classification rate for generalized system using band power features

Input Neurons	32		
Output Neurons	3		
Training Samples	6720		
	Classification Rate in Percentage		
value of k	Min	Mean	Max
1	89.94	90.89	92.08
2	89.94	90.89	92.08
3	89.64	90.65	92.08
4	89.76	90.42	92.14
5	88.69	90	91.07
6	**90.95**	**91.85**	**93.81**
7	85.6	88.57	91.19
8	90.54	91.43	92.92
9	87.68	**88.51**	90.06
10	87.8	88.87	90.3
Min	**85.6**	**88.51**	90.06
Mean	89.17	90.21	91.64
Max	90.95	**91.85**	**93.81**

From TABLE V, it is observed that the kNN model using band power features has the mean minimum classification accuracy of 88.51 % and the mean maximum classification accuracy of 91.85 %. It is inferred that the k value of 6 has the maximum classification accuracy of 93.81 % and the minimum classification accuracy of 85.6 % is obtained for for the *k* value 7 compared to the classification accuracy of other *k* values.

TABLE VI kNN PERFORMANCE FOR THE GENERALIZED SYSTEM USING PSD FEATURES

TABLE VI. kNN Classification rate for generalized system using PSD features

Input Neurons	32		
Output Neurons	3		
Training Samples	6720		
	Classification Rate in Percentage		
value of *k*	Min	Mean	Max
1	88.27	89.7	90.83
2	88.27	89.7	90.83
3	88.15	89.29	90.65
4	89.05	90.3	91.25
5	89.76	90.65	92.02
6	**92.14**	**92.98**	**94.11**
7	89.35	90.24	91.55
8	90.6	91.67	93.15
9	88.1	**88.93**	90
10	88.15	89.17	89.94
Min	**88.1**	**88.93**	89.94
Mean	89.2	90.27	91.4
Max	92.14	**92.98**	**94.11**

From TABLE VI, it is observed that the kNN model using PSD features has the mean minimum classification accuracy of 88.93 % and the mean maximum classification accuracy of 92.98 %. It is inferred that the *k* value of 6 has the maximum classification accuracy of 94.11 % and the minimum classification accuracy of 88.1 % is obtained for the *k* value 9 compared to the classification accuracy of other *k* values.

TABLE VII kNN CLASSIFICATION PERFORMANCE FOR THE CUSTOMIZED MODE USING BP FEATURES

kNN Classification rate for customized system using BP features

Input Neurons	32		
Output Neurons	3		
Training Samples	672		
Subject Id	Classification Rate in Percentage		
	Min	Mean	Max
1	86.9	88.1	91.07
2	91.07	92.86	94.05
3	88.69	90.48	92.86
4	**84.5**	**86.9**	89.88
5	92.86	94.05	95.24
6	91.07	93.45	95.24
7	92.86	94.64	95.83
8	89.88	91.67	94.64
9	93.45	**94.6**	**96.4**
10	91.07	92.86	95.83
Min	**84.5**	**86.9**	89.88
Mean	91.07	92.86	94.94
Max	93.45	**94.6**	**96.4**

TABLE VIII kNN CLASSIFICATION PERFORMANCE FOR THE CUSTOMIZED MODE USING PSD FEATURES

TABLE VIII: kNN Classification rate for customized system using PSD features

Input Neurons	32		
Output Neurons	3		
Training Samples	672		
Subject Id	Classification Rate in Percentage		
	Min	Mean	Max
1	88.1	89.88	91.67
2	91.07	92.26	94.05
3	91.67	92.86	94.05
4	**86.9**	**88.1**	90.48
5	92.86	94.64	95.24
6	92.26	94.64	95.83
7	93.45	95.24	97.02
8	91.67	92.86	95.83
9	94.05	**95.83**	**97.62**
10	89.29	91.67	94.64
Min	**86.9**	**88.1**	90.48
Mean	91.67	92.86	94.94
Max	94.05	**95.83**	**97.62**

From TABLE VII it is observed that the kNN model using band power features has the mean minimum classification accuracy of 86.90 % for subject 4 and the mean maximum classification accuracy of 94.64 % for subject 9. It is inferred that the network model has the maximum classification accuracy of 96.43 % and minimum classification accuracy of 84.52 %.

From TABLE VIII, it is observed that the kNN model using PSD features has the mean minimum classification accuracy of 88.10 % for subject 4 and the mean maximum classification accuracy of 95.83 % for subject 9. It is inferred that the network model has the maximum classification accuracy of 97.62 % and minimum classification accuracy of 86.90 %. The following section presents the comparison of results and confusion matrix for the average maximum classification for both generalized and customized TCVC systems.

VI. Classification Using MLNN And K-NN

In this paper, the EEG brain wave signals are pre-processed and blocked into number of frames and the frequency band power features namely delta, theta, alpha, and beta are extracted. A simple feature extraction algorithm based on band power and power spectral density methods has been used to extract the features and are associated it to one of the motor imaginary vocabulary task. The extracted features are classified using multi layer neural network and kNN classifier for both generalized and customized classification systems.

From the results shown in TABLE I to TABLE VIII, it is observed that the network models have classification accuracy in the range of 85.06% to 92.08% for the generalized classification system and 85.7% to 89.76% for the customized classification system. The comparison of band power features and PSD features corresponding to MLNN and kNN classifiers are depicted in Fig. 4 and Fig. 5.

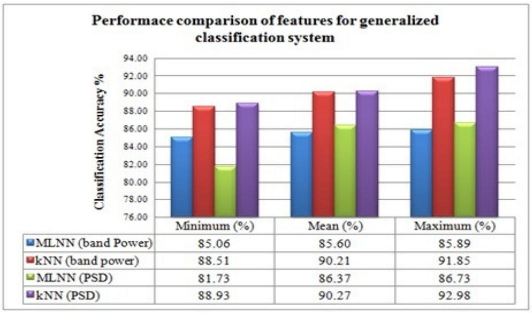

Fig. 4. Comparison of classification accuracy for the generalized classification system

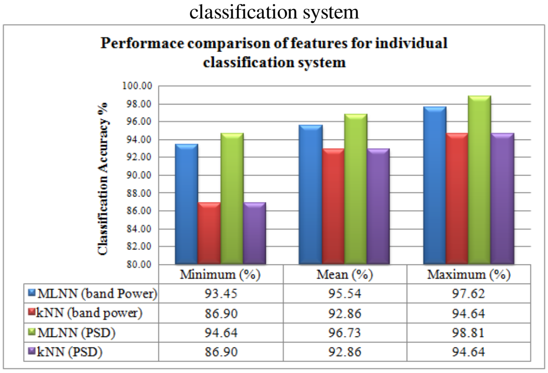

Fig. 5: comparison of classification accuracy for the customized classification system

Fig. 4, it is observed that average maximum classification accuracy of 90.27 % is obtained using PSD features and kNN classifier. The average minimum classification accuracy of 85.60 % is obtained using the band power features and MLNN classifier. Also, maximum classification accuracy of 92.98 % has been obtained using PSD feature and kNN classifier for the generalized TCVC system.

From Fig. 5, it is observed that average maximum classification accuracy of 96.73 % is obtained using PSD features and MLNN classifier. The average minimum classification accuracy of 92.86 % is obtained for both band power features and PSD features using kNN classifier. The maximum classification accuracy of 98.81 % has been obtained using PSD feature and MLNN classifier. Further, the developed classifier models were analysed to identify the actual and predicted classifications by developing a confusion matrix. The confusion matrices for the developed systems are explained in next section.

A. Confusion matrix

A confusion matrix is a visualization tool which contains information about actual and predicted classifications done by a classification system. The confusion matrices for the generalized system (average maximum classification accuracy of 90.27 % obtained using PSD features and kNN classifier) and customized system (subject 9, average maximum classification accuracy of 96.73 % is obtained using PSD features and MLNN classifier) are depicted in TABLE IX and TABLE X.

TABLE IX AND TABLE X
CONFUSION MATRIX FOR THE GENERALIZED SEVEN CLASS TCVC SYSTEM AND CONFUSION MATRIX FOR CUSTOMIZED TCVC SYSTEM

TABLE IX: Confusion Matrix for Seven Class Classifier (Generalized System)

Task	Food	Water	Help	Aircon	Toilet	TV	Relax	Accuracy %
Food	216	0	0	0	0	0	2	90
Water	2	211	1	2	0	0	1	87.92
Help	2	1	218	0	2	1	0	90.83
Aircon	0	2	0	216	2	3	2	90
Toilet	0	1	0	1	217	0	0	90.42
TV	2	0	2	0	0	215	0	89.58
Relax	0	2	0	0	1	0	223	92.92
						Minimum		87.92
						Mean		90.27
						Maximum		92.92

TABLE X: Confusion Matrix for Seven Class Classifier (Subject 6)

Task	Food	Water	Help	Aircon	Toilet	TV	Relax	Accuracy %
Food	23	0	0	0	0	0	0	95.83
Water	0	22	0	0	0	0	1	91.67
Help	0	0	24	0	0	0	0	100
Aircon	0	0	0	22	0	0	0	91.67
Toilet	0	0	0	0	23	0	0	95.83
TV	0	0	0	0	0	24	0	100
Relax	0	0	0	0	0	0	24	100
						Minimum		91.67
						Mean		96.73
						Maximum		100

From TABLE IX, it is inferred that maximum classification accuracy of 92.92 % is obtained for the 'realx' task and the minimum classification accuracy of 87.92 is obtained for 'water' task of the generalized TCVC system. The obtained results are the features extracted from PSD method and classified using kNN classifier.

From TABLE X, it is inferred that maximum classification accuracy of 100 % is obtained for the 'realx', 'tv' and 'help' task and the minimum classification accuracy of 91.67 % is obtained for 'water' and 'air-conditioner' task of the customized TCVC system. The obtained results are the features extracted from PSD method and classified using MLNN classifier.

VII. Conclusion

The regards to the objective of this research work, a simple thought controlled vocabulary classification system has been developed using spectral features and classifier algorithms. The use of the brain wave as a source of information does improve the performance of the motor imaginary vocabulary tasks classification from. The proposed system uses independent component analysis technique to remove the interference wave forms and enhance the characteristics of recorded EEG signal. Four frequency bands has been chosen to study the spectral representation of the mental tasks and the spectral features namely band power and power spectral density features extracted from each frame signal. The extracted feature vectors based on frequency band selection shows the features are distinguished easily. The feature vectors are associated to the corresponding output targets and are classified using MLNN and kNN classifiers, and the results are compared. The test results obtained from this analysis open many possible areas of applications and improvements in thought controlled communication system for differently enabled communities. In the future analysis, more EEG signals from different peoples, other statistical feature extraction algorithms, classification algorithms and online training sessions may used to improve the recognition accuracy of the thought controlled vocabulary classification system. Further, it is propitious to explore useful characteristics from EEG signals based on effective feature extraction and classification methods.

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