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Performance Comparison of TEP and VEP Responses using Bispectral Estimation to Command an Intelligent Robot Chair with Communication Aid

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Abstract

This paper describes the classification of navigational tasks to command a navigation system incorporated with a communication device using thought and visually evoked potentials. To develop a navigation system with communication aid for the neuromuscular disorder community, simple protocol using TEP and VEP responses has been introduced in this research work. The developed protocol has seven basic tasks such as forward, left, right, yes, no, help and relax; these basic seven task are used to control the wheel chair navigation system and also perform voice communication using an oddball paradigm. The proposed system records the brain wave signals using a wireless EEG amplifier from ten subjects while the subjects were imagining and visualizing the seven different visual tasks. For each subject, the recorded brain wave signals are pre-processed to extract the six Electroencephalography rhythmic activities and segmented into frames of equal samples. Then, this study presents the higher order spectra based features to categorize the TEP and VEP tasks using bispectrum estimation algorithm. Further, statistical features such as the mean and entropy of the bispectral magnitude are extracted and formed as a feature set. To develop a customized classification system for individual responses, the extracted feature sets are classified using Multi layer neural networks and from the results it is observed that the entropy of bispectral magnitude feature using VEP based NN model has the maximum classification accuracy of 99.29% and the mean of bispectral magnitude feature using TEP based NN model has the minimum classification accuracy of 72.14%.

Keywords: Bispectrum Estimation, Customized-Intelligent Robot Chair with Communication Aid, Multi Layer Neural Network, Thought Evoked Potentials

1. Introduction

In daily life, every human being depends on their fundamental needs which includes moving around and communications with others to live a reasonable life. Neuromuscular Disorder (NMD) patients and differentially enabled communities have their walking abnormalities due to postural instability and difficulty in communication with others due to loss of muscle control and speech[1, 2]. Over the last few years, researchers have found that it is possible to provide a navigation system along with a communication aid for these patients using motor control and enable them to lead a normal life[3-5]. Hence, variety of Brain Machine Interface (BMI) applications have arisen and currently this research has been directed towards wheelchair navigation control and recognition of unspoken speech utterances without voluntary muscle functions [6-8].

Recently, several studies have examined Thought Evoked Perception (TEP) based design of robotic wheelchair control using human thoughts[9, 10], and communication systems using P300 speller and oddball paradigms[11]. Yet, the data acquisition protocols have shown a vital role in redefining the claimed action to command a navigation system or a communication system. The research work proposed by Kaufmann et al, involves

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positioning of four tactile stimulators and delivers navigation by concentrating their considerations on the desired tactile stimulus in an oddball paradigm to control the wheelchair. The results were validated through the participants navigating a virtual wheelchair[11]. Theresa M. Vaughan, Jonathan S. Brumberg and Anne Porbadnigk have developed several alternative communication systems using the recent developments in personal computers and new prosthetic methods to provide communication and control channels to individuals with difficulties in communication[8, 12, 13]. Despite, none of the systems have produced an expanded utilization of the BMI technology to facilitate both navigation and communication through a customized brain activity recording protocol. Thus, in this study it is proposed to develop a customized thought controlled Intelligent Robot Chair with Communication aid (IRCC), as an initial step towards the possibility of navigation and speech production using a simple thought response based protocol. Figure 1. Depicts the block diagram of the proposed customized classification system for robot chair control along with a communication aid.

The motivation towards this research is to establish a simple robot chair along with a communication aid, that can be used by an NMD, to control a wheel chair and to communicate their needs with others using TEP's and VEP's. A simple data acquisition protocol has been proposed to develop the thought and visually controlled custom-IRCC; the tasks (Forward, left, right, Yes, No and Relax) were initially simulated and the subjects were requested to imagine during the data acquisition process for TEP protocol and the subjects were requested to visualized the depicted simulation for VEP protocol. Further, the subjects were taught to pronounce the word loudly

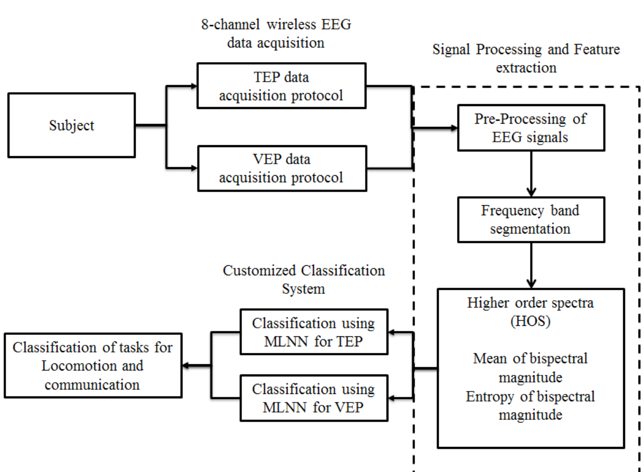


Figure 1. Block diagram of the proposed custom-IRCC using TEP and VEP response.

for the 'Help' task. The EEG signals are recorded for 12 seconds for each trial per task and are trimmed to 10 seconds during the pre-processing stage for uniformity. In the pre-processing, the recorded brain wave signals were band-passed filtered in the frequency range of 0.5 to 100 Hz and segmented into six frequency bands Delta (δ), theta (θ), alpha (α), beta (β), Gamma 1 ($\gamma 1$) and Gamma 2 ($\gamma 2$). Thus, frequency band signals are segmented into frame segments of 512 samples and used to extract the features using Higher Order Spectra (HOS) technique. The general motivation behind the use of bispectrum estimation is to detect and characterize the nonlinear properties of the navigational tasks, and they are potentially better to estimate the deviations from Gaussianness (normality)[14]. Thus, in this study, the third order statistics bispectrum based feature extraction method has been implemented to extract the features from each frame of frequency band signals over each electrode position and the features such as the Mean of bispectral magnitude (M) and the bispectral entropy features (E) were extracted. The non-linear features were extracted and associated with the corresponding TEP and VEP tasks. Then, the feature set of each subject modeled using a supervised learning-Multi Layer Neural Network (MLNN) classifier and the classification performance was validated. The research methodology and the developed model results are explained in the subsequent sections of this paper.

2. IRCC Database and Preprocessing

In the development of custom-IRCC database, ten healthy participants (eight male, aged 21-30 years and two female, aged 24 years) were participated. The proposed study has been registered and approved from National Medical Research Registration (NMRR ID: NMRR-13-51-14570) and obtained Ethical approval from The Medical Research and Ethics Committee (MREC), Ministry of Health Malaysia. (Ref:(7)dlm.KKM/NIHSEC/800-2/2/2Jld2P13-179). All the experiments were performed as per the obtained ethical procedures and the consent from all the 10 subjects were obtained before performing the data acquisition procedures. Then, the subjects were requested to imagine these tasks during the data acquisition process. The data recording sessions were implemented in the lab environments at school of Mechatronic engineering, University Malaysia Perlis. The following section describes the data acquisition protocol, principle of EEG recording and the formation of IRCC database to develop a customized classification system using Thought Evoked Potentials (TEP) and Visually Evoked Potential (VEP).

2.1 TEP, VEP Tasks and IRCC Database

In the experimental setup, 'g-mobilab+' 8-channel EEG data acquisition system was used to record the thought responsed brain wave signals[15]. The system consists of an electrode cap with nine differential screwable electrodes, a bio-signal amplifier and a wireless data acquisition system connected to the MATLAB® interactive programming environment. In the data acquisition protocol, three primary tasks, such as Left, Forward and Right hand movement control are included to address the navigation control of the robot chair and also to categorize the isolated words in an oddball paradigm. Further, three additional tasks have been included to use in emergency circumstances and to address the basic needs of a human being, help, yes, no tasks. Relax signal has been used as the reference signal in this experiment. The EEG signals are recorded while the subject was settled comfortably and remained in totally static posture. No overt actions were made during the 12.0 seconds of the data acquisition process. Figure 2 and Figure 3 depicts the tasks that were implemented using the TEP responses and VEP responses to command an IRCC.

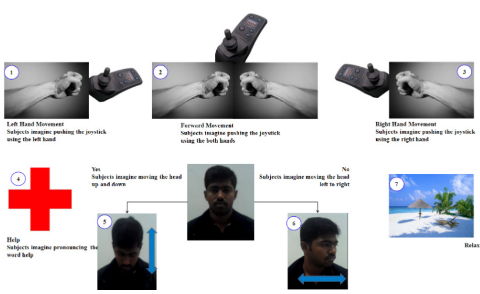


Figure 2. Preliminary representation of the tasks (10.0 s) for subject to conduct the asynchronous data acquisition process.

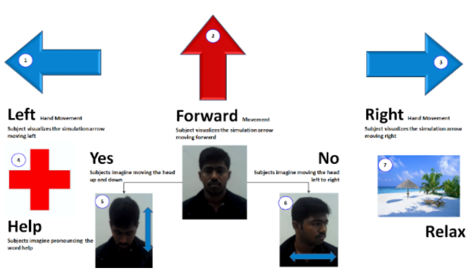


Figure 3. Representation of the tasks (12.0 s) for subject to conduct the VEP data acquisition process.

The system records the brain wave signals from the eight electrode positions such as Temporal (T3, T4), central (C3, C4), parietal (P3, P4) and occipital (O1, O2) with one common electrode on the left ear lobe while the subjects were performing the seven different tasks respectively. The specified electrode positions represent the area of the sensorimotor cortex region with different patterns of brain activation during navigational and conversational tasks. The proposed IRCC system captures the brain wave patterns in order to identify the rhythmic activity for the seven different thoughts of an individual. Thus, during data collection, the EEG signals were recorded at a sampling rate of 256 Hz from a grid of 8 Ag/AgCl scalp electrodes which were placed on the scalp according to the international 10-20 lead system[16]. The electrodes are placed on the scalp of the selected locations and tested for level of impedance using g-tec impedance checker and maintained below 10 KΩ throughout the experiment.

During the TEP data acquisition of each task, the subjects were requested to view the simulation of the specific task on the LCD monitor as depicted in Figure 2(1) to Figure 2(7) for 10.0 seconds. The simulation depicts the movement of a wheelchair joystick using the left hand, both hands and right hand movement for the left, forward and right directions respectively. For the additional tasks like 'yes' and 'no', the visual presents a volunteer performing head movements up-down and left-right movements and for 'help' task, the subject was requested to pronounce imaginarily the word 'help' respectively. Then the LCD monitor is turned off and a blank screen was presented for 2.0 s. Meanwhile, the subject was requested to perform the tasks asynchronously as shown in the simulation. During the VEP data acquisition of each task, the subjects

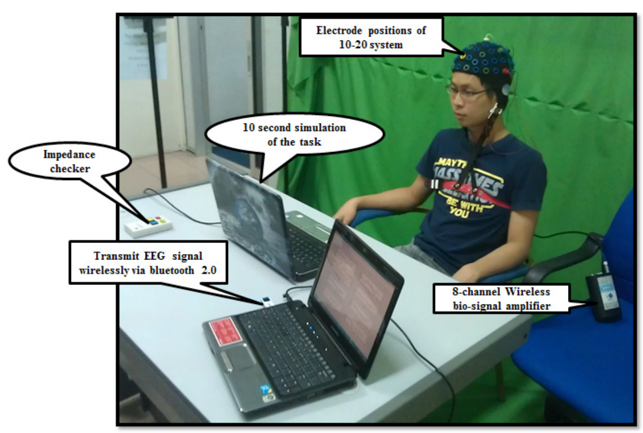


Figure 4. Experimental setup during the acquisition of tasks to comand custom-IRCC.

were requested to view the simulation of the specific task on the LCD monitor as depicted in Figure 3(a) to Figure 3(g) until recording all the trials. The additional tasks are repeated similarly as represented in the TEP tasks. Then, the subject performs a specified task and the EEG signals were recorded for 12.0 s from the specified electrode positions. Ground electrode and reference electrodes are placed in the Cz position and left earlobe locations of 10-20 system respectively. Figure 4 represents the experimental setup during the data acquisition process.

The recorded EEG signals are contaminated with unknown noise component lying within a 60 Hz frequency range. A simple first order IIR notch filter was designed for removing the power line noise from the recorded EEG signals. The center frequency of the filter, F0 was chosen to be at exactly 50 Hz and the bandwidth, ΔF was set as 4Hz[17]. The above acquisition process was repeated 10 times for each task and the subject was requested to take a rest break for ten minutes after completing each task. The same procedure was repeated by all the ten subjects and using the recorded signals a database named IRCC database was created. The IRCC database consists of data pertaining to 10 trials. Further, the IRCC database was validated through hypothesis testing using Analysis of Variance (ANOVA) technique performed by 10 subjects for 10 trials.

2.2 Segmentation of EEG Rhythmic Activity and Frames

The 16-bit digitized signals with 256 Hz sampling frequency were trimmed to segregate the intermediate 10s signals from 12s signal. The trimmed raw signals are filtered to remove the artifacts and EMG's below 0.5 Hz and above 100 Hz using 6th order band pass filters[17]. The segmented brain waves are categorized into six traditional bands: Delta (δ) 0.1 – 4 Hz, Theta (θ) 4 – 8 Hz, Alpha (α) 8 – 16 Hz, Beta (β) 16 – 32 Hz, Gamma 1, (γ1) (32-64 Hz) and Gamma 2, (γ2) 64 – 100 Hz. Thus, each frequency band signals are segmented into frames such that a frame length of 2s having 512 samples per frame along with an overlap of 1s (m = 256 samples). Thus, the first frame consists of n = 512 samples. The second frame was initiated after a lap of m−1 samples such that the second frame overlaps with the n−m samples of the first frame. This procedure was repeated until all the frequency band signals were counted. Then, each frame is considered as an input to extract the bispectral features also known as polyspectral representations of higher order statistics.

3. Statistical Feature Extraction using Bispectrum Estimation

3.1 Bispectrum Estimation

In various BMI applications, EEG signals have been analyzed using power spectra in several distinctive frequency bands. Power spectrum estimation provides the statistical descriptions of a Gaussian signal. In case of non-gaussianity or non-linear mechanisms, higher order spectra can be used to determine the higher order moments or complaints which provide additional information on the phase characteristics and realistic information of the EEG signal[18, 19]. In this paper, bispectrum $B(f1, f2)$ analysis has been employed to study the brain wave patterns of the visual stimuli. The bispectrum estimation is particularly the third-order statistics of a signal, which represents the Fourier transform of the third order correlation with highly interdependent frequency components[19]. The mathematical representation of the bispectrum estimation is expressed in Equation (1).

$$B\left(f_1, f_2\right) = E\left[X\left(f_1\right)X\left(f_2\right)X^*\left(f_1+f_2\right)\right] \qquad (1)$$

Where $X(f)$ is the DFT at frequency samples $x(nT)$. The frequency (f) may be normalized by the Nyquist frequency to lie between 0 and 1. $X^*\left(f_1+f_2\right)$ denotes the complex conjugate and therefore the bispectrum obtained using equation (1) is a complex valued function which represents the product of three Fourier co-efficients. In this feature extraction process, the non-redundant region or the positive bispectrum sequence $(\Omega) = 0 \le f_2 \le f_1 \le \left(f_1 + f_2\right) \le 1$ was used to extract the mean and entropy features.

Hence, the EEG signal acquired from each channel was used to extract the six frequency band signals, namely Delta (δ), theta (θ), alpha (α), beta (β), Gamma 1 (γ1) and Gamma 2 (γ2) and segmented into frames such that each frame has 512 samples. The positive fourier coefficients of $B(f_1, f_2)$ was estimated using the i^{th} frame of each channel. Thus, the bispectrum sequence for $B_\delta^{ij}\left(f_1, f_2\right)$ was obtained from δ band, where i and j are the frame numbers and an electrode channel number respectively. Similarly, the bispectrum sequence for $B_\theta^{ij}\left(f_1, f_2\right)$, $B_\alpha^{ij}\left(f_1, f_2\right)$, $B_\beta^{ij}\left(f_1, f_2\right)$, $B_{\gamma1}^{ij}\left(f_1, f_2\right)$ and $B_{\gamma2}^{ij}\left(f_1, f_2\right)$ were also computed.

From the estimated sequences, two statistical features, namely, Mean of bispectral magnitude (M) and bispectral entropy (E) features are computed to characterize the distribution of bispectrum sequence as represented in equation (2-5). Therefore, for eight channels we have 48 (6 × 8) features per frame. The statistical features are extracted from all the trials and are used to form the feature set. Simultaneously, the features are derived from each task and the corresponding feature set consisting of 700 samples are formulated and used to train and test the classifier models correspond to the TEP and VEP tasks.

$$M^{ij} = \{M^{ij}_{\delta}(f_1,f_2), M^{ij}_{\theta}(f_1,f_2), M^{ij}_{\alpha}(f_1,f_2), M^{ij}_{\beta}(f_1,f_2), M^{ij}_{\gamma 1}(f_1,f_2) \text{ and } M^{ij}_{\gamma 2}(f_1,f_2)\} \quad (2)$$

$$E^{ij} = \{E^{ij}_{\delta}(f_1,f_2), E^{ij}_{\theta}(f_1,f_2), E^{ij}_{\alpha}(f_1,f_2), E^{ij}_{\beta}(f_1,f_2), E^{ij}_{\gamma 1}(f_1,f_2) \text{ and } E^{ij}_{\gamma 2}(f_1,f_2)\} \quad (3)$$

where, M and E represents the mean and entropy (bispectral magnitude of the (Ω) in the i^{th} frame of the j^{th} electrode channel position.

$$E = -\sum_n pnlog(pn) \quad (4)$$

where

$$pn = \frac{|B(f_1,f_2)|}{\sum_{\Omega}|B(f_1,f_2)|},$$
$$\Omega = region\ of\ the\ bispectral\ magnitude \quad (5)$$

4. Multilayer Neural Network Classifier for Classification of Seven Tasks

Multi layer neural networks are biologically inspired tools used for information processing and they are nonlinear in nature[20]. Classification of TEP and VEP responses to categorize the navigational tasks basically falls on pattern recognition problem. In this analysis, customized IRCC system has been developed for each individual using MLNN for Multi-class pattern classification. The feature vectors derived from each subject (700 × 48 feature vectors) using TEP responses were processed and then associated with the seven TEP classes and the feature vectors derived from each subject (700 × 48 feature vectors) using VEP responses were processed and then associated with the seven VEP classes. Further, the feature vectors were normalized using binary normalization method and partitioned into training and testing sets[21]. The training set has 560 × 48 (90% of master data set) and the testing set has the remaining 140 samples for the classification of the motor-imagery vocabulary tasks accordingly.

In this work, the MLNN models were organized with 48 input neurons, 18 hidden neurons and three neurons in the output layer. As the logistic sigmoid function scales any range of values between 0.1 an 0.9, in the designed MLNN models, logistic sigmoidal function was used to activate the neurons in the hidden and output layer. The Mean Squared Error (MSE) tolerance of 0.1 was used for training the neural network. In order to improve the performance rate, the learning rate, momentum factor and number of iterations were chosen based on the experimental observations in different trials. The learning rate and momentum factor for the models were chosen as 0.1 and 0.8 respectively. The generalization capability of the model was validated by performing 10 trials for training and testing method. The network models were trained using Levenburg Marquth Model. The MLNN model for spectral features were trained with ten trial weights for each subset. On the first subset, the network model was trained using 8/10 of the feature set and the classification rate was estimated using 2/10 subset of the remaining feature set. This process was repeated until all the 2/10 subset are used for the validation set[22]. Further, the network training parameters, mean classification rates are shown in are shown in Table 1 to Table 4.

5. Result and Discussion

In this paper, the EEG brain wave signals were pre-processed and blocked into number of frames and the frequency band features, namely delta, theta, alpha, beta, gamma 1 and gamma 2 were extracted. A simple feature extraction algorithm based on bispectral estimation was employed to extract the statistical features such as Mean and entropy of the bispectral magnitude and associated with one of the TEP tasks. The extracted features are classified using MLNN classifier for the customized IRCC classification systems using TEP and VEP. The classification performance of the developed models are summarized in Table 1 and 2.

From Table 1, the results obtained using TEP responses shows that the network model has a minimum classification accuracy of 72.14%, 82.14%, 82.86%, 77.14%, 87.14%, 73.57%, 85.71%, 87.86%, 80.00% and 88.57% for the

Table 1. Mean classification performance for the IRCC system using MLNN classifier with the mean of bispectral magnitude using TEP response

MLNN Classification results using mean of bispectral magnitude features										
No. of training Samples		560	No. of hidden neurons		12	Output Neurons	3	Training Tolerance		0.001
No. of testing Samples		140	Input Neurons		48			Testing tolerance		0.1
Trial Number	Subjects									
	Subject I (%)	Subject II (%)	Subject III (%)	Subject IV (%)	Subject V (%)	Subject VI (%)	Subject VII (%)	Subject VIII (%)	Subject IX (%)	Subject X (%)
1	81.43	82.14	86.43	77.14	88.57	85.00	85.71	90.00	80.00	92.14
2	80.00	85.71	86.43	83.57	87.14	81.43	87.14	87.86	85.71	88.57
3	73.57	85.00	89.29	84.29	95.71	78.57	90.00	94.29	87.86	95.71
4	80.71	89.29	82.86	90.00	92.86	87.14	95.71	89.29	92.14	95.00
5	79.29	86.43	91.43	84.29	92.14	80.00	87.14	92.14	87.14	92.86
6	72.14	85.71	92.14	85.71	92.86	73.57	87.14	93.57	87.86	94.29
7	80.71	87.14	87.14	82.14	92.86	82.86	89.29	89.29	85.71	95.00
8	80.00	85.71	87.86	86.43	95.71	83.57	89.29	91.43	88.57	95.71
9	85.71	87.14	88.57	86.43	94.29	90.00	91.43	92.86	89.29	95.00
10	75.71	82.14	82.86	86.43	90.71	81.43	87.86	88.57	88.57	95.71
Min %	72.14	82.14	82.86	77.14	87.14	73.57	85.71	87.86	80.00	88.57
Mean %	78.93	85.64	87.50	84.64	92.29	82.36	89.07	90.93	87.29	94.00
Max %	85.71	89.29	92.14	90.00	95.71	90.00	95.71	94.29	92.14	95.71

Table 2. Mean classification performance for the IRCC system using MLNN classifier with the entropy of bispectral magnitude using TEP response

MLNN Classification results using entropy of bispectral magnitude features										
No. of training Samples		630	No. of hidden neurons		18	Output Neurons	3	Training Tolerance		0.0001
No. of testing Samples		70	Input Neurons		48			Testing tolerance		0.1
Trial Number	Subjects									
	Subject I (%)	Subject II (%)	Subject III (%)	Subject IV (%)	Subject V (%)	Subject VI (%)	Subject VII (%)	Subject VIII (%)	Subject IX (%)	Subject X (%)
1	82.86	83.57	87.86	78.57	90.00	86.43	87.14	91.43	81.43	93.57
2	81.43	87.14	87.86	85.00	88.57	82.86	88.57	89.29	87.14	90.00
3	75.00	86.43	90.71	85.71	97.14	80.00	91.43	95.71	89.29	97.86
4	82.14	90.71	84.29	91.43	94.29	88.57	94.29	90.71	93.57	97.14
5	80.71	87.86	92.86	85.71	93.57	81.43	88.57	93.57	88.57	94.29
6	73.57	87.14	93.57	87.14	94.29	75.00	88.57	95.00	89.29	95.71
7	82.14	88.57	88.57	83.57	94.29	84.29	90.71	90.71	87.14	96.43
8	81.43	87.14	89.29	87.86	97.14	85.00	90.71	92.86	90.00	97.14
9	87.14	88.57	90.00	87.86	95.71	91.43	92.86	94.29	90.71	95.00
10	77.14	83.57	84.29	87.86	92.14	82.86	89.29	90.00	90.00	93.57
Min %	73.57	83.57	84.29	78.57	88.57	75.00	87.14	89.29	81.43	90.00
Mean %	80.36	87.07	88.93	86.07	93.71	83.79	90.21	92.36	88.71	95.07
Max %	87.14	90.71	93.57	91.43	97.14	91.43	94.29	95.71	93.57	97.86

Table 3. Mean classification performance for the IRCC system using MLNN classifier with the mean of bispectral magnitude using VEP response

MLNN Classification results using mean of bispectral magnitude features										
No. of training Samples		560	No. of hidden neurons		12	Output Neurons	3	Training Tolerance		0.001
No. of testing Samples		140	Input Neurons		48			Testing tolerance		0.1
Trial Number	Subjects									
	Subject I (%)	Subject II (%)	Subject III (%)	Subject IV (%)	Subject V (%)	Subject VI (%)	Subject VII (%)	Subject VIII (%)	Subject IX (%)	Subject X (%)
1	83.57	84.29	88.57	79.29	86.43	87.14	87.86	89.29	82.86	91.43
2	77.86	90.00	88.57	85.71	89.29	83.57	89.29	90.00	85.71	91.43
3	75.71	87.14	91.43	86.43	92.14	80.71	92.14	96.43	89.29	91.43
4	82.86	91.43	85.00	93.57	95.00	82.14	97.86	91.43	95.00	91.43
5	75.71	88.57	93.57	82.14	94.29	81.43	89.29	94.29	89.29	90.71
6	74.29	87.86	94.29	87.86	89.29	75.71	89.29	90.00	90.00	96.43
7	82.86	89.29	89.29	84.29	95.00	85.00	91.43	93.57	87.86	93.57
8	82.14	87.86	90.00	88.57	97.86	80.00	91.43	93.57	90.71	95.71
9	87.86	89.29	86.43	88.57	96.43	82.14	93.57	95.00	91.43	97.14
10	79.29	84.29	85.00	88.57	92.86	83.57	90.00	90.71	90.71	96.43
Min %	74.29	84.29	85.00	79.29	86.43	75.71	87.86	89.29	82.86	90.71
Mean %	80.71	88.21	88.93	87.14	93.57	82.14	90.71	92.50	89.64	92.50
Max %	87.86	91.43	94.29	93.57	97.86	87.14	97.86	96.43	95.00	97.14

Table 4. Mean classification performance for the IRCC system using MLNN classifier with the entropy of bispectral magnitude using VEP response

MLNN Classification results using entropy of bispectral magnitude features										
No. of training Samples		560	No. of hidden neurons		12	Output Neurons	3	Training Tolerance		0.001
No. of testing Samples		140	Input Neurons		48			Testing tolerance		0.1
Trial Number	Subjects									
	Subject I (%)	Subject II (%)	Subject III (%)	Subject IV (%)	Subject V (%)	Subject VI (%)	Subject VII (%)	Subject VIII (%)	Subject IX (%)	Subject X (%)
1	85.00	85.71	90.00	80.71	87.86	88.57	89.29	90.71	84.29	92.86
2	79.29	91.43	90.00	87.14	90.71	87.14	90.71	91.43	87.14	92.86
3	77.14	88.57	92.86	87.86	93.57	82.14	93.57	97.86	90.71	97.86
4	84.29	92.86	86.43	95.00	96.43	83.57	94.29	92.86	96.43	97.14
5	77.14	90.00	95.00	83.57	95.71	82.86	90.71	95.71	90.71	92.14
6	75.71	89.29	95.71	89.29	90.71	77.14	90.71	91.43	91.43	97.86
7	84.29	90.71	90.71	85.71	96.43	86.43	92.86	95.00	89.29	95.00
8	83.57	89.29	91.43	90.00	99.29	81.43	92.86	95.00	92.14	97.14
9	89.29	90.71	87.86	90.00	99.29	83.57	95.00	96.43	92.86	95.00
10	80.71	85.71	86.43	90.00	94.29	85.00	91.43	92.14	92.14	93.57
Min %	75.71	85.71	86.43	80.71	87.86	77.14	89.29	90.71	84.29	92.14
Mean %	82.14	89.64	90.36	88.57	95.00	83.57	92.14	93.93	91.07	95.00
Max %	89.29	92.86	95.71	95.00	99.29	88.57	95.00	97.86	96.43	97.86

subject I to X respectively. It is also observed that the network model has the maximum classification accuracy of 85.71%, 89.29%, 92.14%, 90.00%, 95.71%, 90.00%, 95.71%, 94.29%, 92.14% and 95.71% for the subject I to X respectively. The overall maximum classification accuracy of 95.71% has been obtained from the customized model for Subject V, VII and X and the overall minimum classification accuracy of 72.14% has been obtained for subject I using the mean of the bispectral magnitude features.

From Table 2, the results obtained using TEP responses shows that the network model has a minimum classification accuracy of 73.57%, 83.57%, 84.29%, 78.57%, 88.57%, 75.00%, 87.14%, 89.29%, 81.43% and 90.00% for the subject I to X respectively. It is also observed that the network model has the maximum classification accuracy of 87.14%, 90.71%, 93.57%, 91.43%, 97.14%, 91.43%, 94.29%, 95.71%, 93.57% and 97.86% for the subject I to X respectively. The overall maximum classification accuracy of 97.86% has been obtained from the customized model using Subject X and the overall minimum classification accuracy of 73.57% has been obtained for subject I using the entropy of the bispectral magnitude features.

From Table 3, the results obtained using VEP responses shows that the network model has a minimum classification accuracy of 74.29%, 84.29%, 85.00%, 79.29%, 86.43%, 75.71%, 87.86%, 89.29%, 82.86%, 90.71% for the subject I to X respectively. It is also observed that the network model has the maximum classification accuracy of 87.86%, 91.43%, 94.29%, 93.57%, 97.86%, 87.14%, 97.86%, 96.43%, 95.00%, 97.14% for the subject I to X respectively. The overall maximum classification accuracy of 97.86% has been obtained from the customized model using Subject V and VII and the overall minimum classification accuracy of 74.29% has been obtained for subject I using the mean of the bispectral magnitude features.

From Table 4, the results obtained using VEP responses shows that the network model has a minimum classification accuracy of 75.71%, 85.71%, 86.43%, 80.71%, 87.86%, 77.14%, 89.29%, 90.71%, 84.29%, 92.14% for the subject I to X respectively. It is also observed that the network model has the maximum classification accuracy of 89.29%, 92.86%, 95.71%, 95.00%, 99.29%, 88.57%, 95.00%, 97.86%, 96.43%, 97.86% for the subject I to X respectively. The overall maximum classification accuracy of 99.29% has been obtained from the customized model using Subject V and the overall minimum classification accuracy of 75.71% has been obtained for subject I using the entropy of the bispectral magnitude features.

From the results, it is observed that Subject V has the maximum classification accuracy of 99.29% using VEP based MLNN and entropy of the bispectral magnitude features and Subject I has the minimum classification accuracy of 72.14% using TEP based MLNN and mean of the bispectral magnitude features. The following section presents the comparison study on mean classification performance, training time and number of epochs for the developed MLNN models.

5.1 Comparison of Mean Classification Accuracy

From Figure 5, it can be inferred that the network model using TEP responses has an average mean classification accuracy of 78.93%, 85.64%, 87.50%, 84.64%, 92.29%, 82.36%, 89.07%, 90.93%, 87.29% and 94.00% for the subject I to X using MLNN with Mean of bispectral entropy based classifier. It is also observed that the network model using TEP responses has an average mean classification accuracy of 80.36%, 87.07%, 88.93%, 86.07%, 93.71%, 83.79%, 90.21%, 92.36%, 88.71% and 95.07% for the subject I to X using MLNN entropy of the bispectral magnitude based classifier. Further, it can be also inferred that the network model using VEP responses has an average mean classification accuracy of 80.71%, 88.21%, 88.93%, 87.14%, 93.57%, 82.14%, 90.71%, 92.50%, 89.64%, 92.50% for the subject I to X using MLNN with Mean of bispectral entropy based classifier. It is also observed that the network model using VEP responses has an average mean classification accuracy of 82.14%, 89.64%, 90.36%, 88.57%, 95.00%, 83.57%, 92.14%, 93.93%, 91.07%, 95.00% for the subject I to X using MLNN entropy of the bispectral magnitude based classifier. Further, the overall mean maximum classification accuracy of 95.07% has been obtained with MLNN based on Mean features for Subject

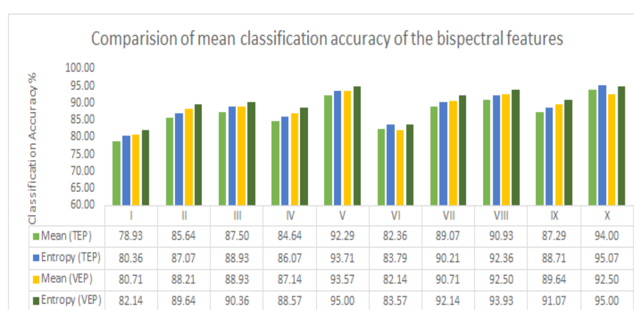


Figure 5. Comparison of mean classification accuracy for the MLNN using mean and entropy features.

V and X and the overall mean minimum classification accuracy of 78.93% has been obtained with MLNN based on entropy features for Subject I. From the results, it is inferred that MLNN entropy features based classifier has better classification accuracy for TEP and VEP responses and subject I has less performed during the thought evoked data acquisition of IRCC.

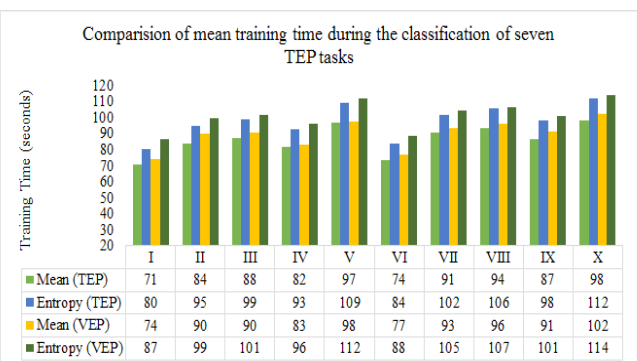
5.2 Comparison of Mean Training Time

From Figure 6, it can be inferred that the network model using TEP responses has an average mean training time of 71 seconds, 84 seconds, 88 seconds, 82 seconds, 97 seconds, 74 seconds, 91 seconds, 94 seconds, 87 seconds and 98 seconds for the subject I to X using MLNN mean based classifier. It is also observed that the network model using TEP responses has an average mean training time of 80 seconds, 95 seconds, 99 seconds, 93 seconds, 109 seconds, 84 seconds, 102 seconds, 106 seconds, 98 seconds and 112 seconds for the subject I to X using MLNN entropy based classifier. It can be also inferred that the network model using VEP responses has an average mean training time of 74 seconds, 90 seconds, 90 seconds, 83 seconds, 98 seconds, 77 seconds, 93 seconds, 96 seconds, 91 seconds and 102 seconds for the subject I to X using MLNN mean based classifier. It is also observed that the network model using VEP responses has an average mean training time of 87 seconds, 99 seconds, 101 seconds, 96 seconds, 112 seconds, 88 seconds, 105 seconds, 107 seconds, 101 seconds and 114 seconds for the subject I to X using MLNN entropy based classifier. Further, the overall mean maximum training time of 114 seconds has been obtained with VEP-MLNN entropy based classifier for Subject X and the overall mean minimum training time of 71 seconds has been obtained with TEP-MLNN mean based classifier for Subject I. From the results, it is inferred that MLNN mean based classifier has less training time for all the ten subjects.

From Figure 7, it can be inferred that the TEP based network model has an average mean training epochs of 142 epochs, 161 epochs, 167 epochs, 159 epochs, 180 epochs, 139 epochs, 171 epochs, 176 epochs, 166 epochs and 182 epochs for the subject I to X using MLNN mean based classifier. It is also observed that the TEP based network model has an average mean training epochs of 157 epochs, 177 epochs, 183 epochs, 174 epochs, 212 epochs, 161 epochs, 186 epochs, 192 epochs, 181 epochs and 201 epochs for the subject I to X using MLNN entropy based classifier.

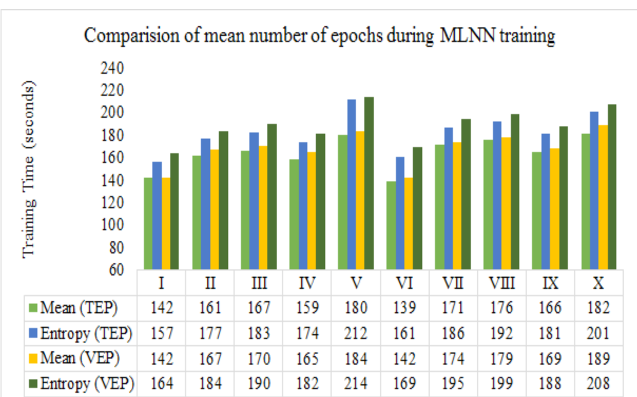
5.3 Comparison of Mean Number Of Epochs

It can be inferred that the VEP based network model has an average mean training epochs of 142 epochs, 167 epochs, 170 epochs, 165 epochs, 184 epochs, 142 epochs, 174 epochs, 179 epochs, 169 epochs and 189 epochs for the subject I to X using MLNN mean based classifier. It is also observed that the VEP based network model has an average mean training epochs of 164 epochs, 184 epochs, 190 epochs, 182 epochs, 214 epochs, 169 epochs, 195 epochs, 199 epochs, 188 epochs and 208 epochs for the subject I to X using MLNN entropy based classifier. Further, the overall mean maximum training epochs of 212 epochs has been obtained with TEP-MLNN entropy based classifier for Subject V. The overall mean minimum training epochs of 139 epochs has been obtained



	I	II	III	IV	V	VI	VII	VIII	IX	X
Mean (TEP)	71	84	88	82	97	74	91	94	87	98
Entropy (TEP)	80	95	99	93	109	84	102	106	98	112
Mean (VEP)	74	90	90	83	98	77	93	96	91	102
Entropy (VEP)	87	99	101	96	112	88	105	107	101	114

Figure 6. Comparison of mean training time for the MLNN using mean and entropy features.



	I	II	III	IV	V	VI	VII	VIII	IX	X
Mean (TEP)	142	161	167	159	180	139	171	176	166	182
Entropy (TEP)	157	177	183	174	212	161	186	192	181	201
Mean (VEP)	142	167	170	165	184	142	174	179	169	189
Entropy (VEP)	164	184	190	182	214	169	195	199	188	208

Figure 7. Comparison of mean number of epochs for the MLNN using mean and entropy features.

with TEP-MLNN mean based classifier for Subject VI. From the results, it is inferred that MLNN mean based classifier has less number of epoch iterations for all the ten subjects.

6. Conclusions

The regards to the objective of this study, a customized robot chair with communication aid (IRCC) has been developed using higher order spectral algorithm and Multi layer neural network using TEP and VEP responses. The proposed system uses the TEP based task signals recorded from ten subjects and are blocked into frames of equal samples. Six frequency band has been chosen to study the spectral representation of the mental tasks and the features were extracted. The extracted feature vectors based on bispectral estimations are distinguished easily. The feature vectors are associated with the corresponding output targets and are classified using, MLNN classifiers in customized modes.

The test results obtained from this analysis open many possible areas of applications and improvements in thought controlled robot chair navigation and communication system for differentially enabled communities. The network parameters and the study on mean training time shows the proposed IRCC system can be developed for an NMD patient with simple experimental setup. In the future analysis, non-linear feature extraction algorithms, classification algorithms and online training sessions so as to be used to improve the recognition accuracy of the IRCC system. Further, it is propitious to explore useful characteristics of brain wave pattern signals based on effective feature extraction and classification methods.

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