A Real Time Set Up for Retrieval of Emotional States from Human Neural Responses

Rashima Mahajan, Dipali Bansal, Shweta Singh

***Abstract*—**Real time non-invasive Brain Computer Interfaces have a significant progressive role in restoring or maintaining a quality life for medically challenged people. This manuscript provides a comprehensive review of emerging research in the field of cognitive/affective computing in context of human neural responses. The perspectives of different emotion assessment modalities like face expressions, speech, text, gestures, and human physiological responses have also been discussed. Focus has been paid to explore the ability of EEG (Electroencephalogram) signals to portray thoughts, feelings, and unspoken words. An automated workflow-based protocol to design an EEG-based real time Brain Computer Interface system for analysis and classification of human emotions elicited by external audio/visual stimuli has been proposed. The front end hardware includes a cost effective and portable Emotiv EEG Neuroheadset unit, a personal computer and a set of external stimulators. Primary signal analysis and processing of real time acquired EEG shall be performed using MATLAB based advanced brain mapping toolbox EEGLab/BCILab. This shall be followed by the development of MATLAB based self-defined algorithm to capture and characterize temporal and spectral variations in EEG under emotional stimulations. The extracted hybrid feature set shall be used to classify emotional states using artificial intelligence tools like Artificial Neural Network. The final system would result in an inexpensive, portable and more intuitive Brain Computer Interface in real time scenario to control prosthetic devices by translating different brain states into operative control signals.

***Keywords*—**Brain Computer Interface (BCI), Electroencephalogram (EEG), EEGLab, BCILab, Emotiv, Emotions, Interval features, Spectral features, Artificial Neural Network, Control applications.

I. INTRODUCTION

AUTOMATED analysis of the physiological signals like EEG has become more extensive during the last three decades for the development of BCIs to include areas like lie detection, stress and emotion measurement [1]. This sparked some interest in investigating whether an emotion could be recognized merely seeing the physiological response. Although emotional information could also be retrieved from other modalities like subject's face expressions, speech, text, gestures, etc. However, these can be consciously altered. This led to the development of emotion detection methods based on human physiological signals such as heart rate, skin conductance, cardiac activity, neural responses (EEG), etc. Recent researches on the human EEG reveal that brain activity plays a major role in the assessment of emotions [2]. Further, recognizing emotional states from neural responses is an effective way of implementing affective brain computer interfaces [3]. BCI systems create a communication channel between the brain and computer by acquiring, analyzing and classifying neural activities under certain stimulations, and generate control signals for real world applications in areas including clinic, psychiatry, security, military, law enforcement, and telecommunications. Therefore, automatic emotion recognition from EEG signals is obtaining more attention nowadays. An EEG signal represents an electrical activity of brain with its amplitude ranges from 10 to 100 microvolt whereas frequency lies in the range of 1 to 100Hz. Brain waves are characterized by five frequency sub bands, defined as; delta waves (1-4 Hz), theta waves (4-8 Hz), alpha waves (8-13 Hz), beta1 waves (13-18 Hz), beta2 waves (18-30 Hz), and gamma waves (>30 Hz) [4]. These EEG signal frequency bands are associated with the neural activity and tend to change under different emotional environment [5]. Thus, by capturing these variations and analyzing them, it is possible to characterize the correlated emotional state.

Area of affective computing has been extensively explored in the context of human neural responses. Some previously published works utilizes statistical features of EEG for automated emotion recognition [1], [6], [7], discrete wavelet transform (DWT) [8], [9] and lifting based wavelet transforms in fusion with spatial filtering to extract emotion related features of EEG in order to classify happiness, sadness, disgust, and fear emotions using Fuzzy C-Means clustering [10]. DWT based techniques are not so favorite due to large feature set. Another research investigates the application of optimization techniques including different sizes of sliding windows, normalization approaches, filtering methods and dimensionality reduction algorithms on time and frequency domain features of EEG signal to distinguish pleasant, neutral, and unpleasant emotional states using support vector machines (SVM) [11]. This is followed by methods that involve the application of short time Fourier Transform and Fast Fourier Transform to the acquired EEG signals to classify feelings of joy, sadness, anger, and pleasure/fear using SVM but with low accuracy [12], [13]. The fusion of EEG with other physiological signals such as skin conductance, blood volume pulse (BVP) and respiratory rate has been explored successfully to classify calm-neutral and negative excited emotions using Genetic Algorithm (GA) and Elman neural

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network. The whole feature set comprises of linear features of EEG in conjunction with chaotic invariants like approximate entropy, fractal and correlation dimension [2]. Further a set of algorithms classify human emotions by estimating power spectrum density followed by the extraction and comparison of five EEG power bands with the standard EEG sub bands using Bayesian network [14] and SVM [15], respectively.

TABLE I
COMPARISON OF EEG HEADSETS BY DIFFERENT MANUFACTURERS

Specifications	Emotiv EEG Neuroheadset [26]	Neurosky Mindwave [27]	Xwave with Neurosky [28]	Muse [29]
Channels	14	1 (1-ref, 1-gnd)	1 (1-ref, 1-gnd)	4
Sampling rate	128 Hz	512 Hz	-	220-500 Hz
Resolution	16-bits	12-bits	8-bits	-
Bandwidth	0.2-45 Hz	3-100 Hz	3-100 Hz	2-50 Hz
Dynamic range	$256mV_{pp}$	1 mV_{pp}	-	2 mV_{pp}
Coupling mode	AC coupled	-	AC Coupled	AC Coupled
Cost	$750	$99.99	$90	$269
Battery type	Li-poly	AAA	Lithium	Lithium
Battery life	12hrs	8hrs	6hrs	4.5hrs
Remarks	Capture 4 mental States, 5- EEG bands	Capture 2 mental states	Extracts 8-EEG band data	Detects positive and negative emotions, 5 bands of brain waves

These linear feature extraction techniques suppress the phase information related to the morphology of non-linear and non-stationary EEG waves [16] and thus are less accurate. A group of researchers presented a technique to detect and classify emotions from human EEG signals using higher order crossings analysis and achieved higher classification rates to classify the emotions into six categories [17]-[20]. Another recent research involves the use of higher order spectral features of EEG to develop an emotional stress recognition system using LDA classifier and achieved noticeable high classification accuracy [21]. These latest findings reveal the importance of higher order spectral analysis in affective computing.

Work done earlier mainly involves the use of linear or non-linear features of EEG. This paper proposes a real time portable set up for retrieval of emotional states from human neural responses by capturing both temporal (linear) and spectral (non-linear) variations in EEG attained from corresponding lobes of the brain using Emotiv EEG Neuroheadset under external emotional stimulations.

II. DESIGN CONSIDERATIONS

The basic design for construction of real time and portable set up for EEG based automated emotion recognition incorporates the set of subsystems namely, stimuli modalities, human subjects, EEG acquisition unit, signal processing unit.

A. Stimuli Modalities Selection

Development of an efficient emotion detection module based on real time human neural responses primarily involves the construction of emotion specific EEG signal dataset from healthy volunteers by external stimulation, to make them experience the emotional states of interest. As the literature findings indicate that emotional state is reflected in human neural responses it reflects high chances of EEG reactivity to evoked emotion when the induction method is active for the subject. Primary development procedure includes the selection of efficient and reliable emotion induction stimuli as this would be the key to repetition of experiment. Different stimuli modalities include audio, visual or combination of both. The labeled database of visual stimuli and audio stimuli for emotion induction are International Affective Picture System (IAPS) [22] and International Affective Digitized Sounds (IADS) [23], respectively. It has been reported that EEG data acquired with visual stimuli are relatively difficult to classify in comparison to audio and audio-visual modalities [24] whereas combined audio-visual stimuli outer performs the other two [2], [6], [25]. Therefore, experiments with fusion of both audio and visual stimuli to evoke human emotions shall be realized in order to attain best emotion classification rates.

B. Subjects

To construct emotion specific EEG signal dataset twenty healthy volunteered right-handed male subjects between the ages of 20-30 years shall be selected. Each participant equipped with EEG acquisition unit shall be made to sit in a quiet and electromagnetic interference free environment to acquire emotion elicited neural responses in terms of EEG.

C. Selection of Acquisition Unit

The next step is to explore the availability and features of commercially available EEG headsets required to acquire emotion specific neural responses. Table I compares and highlights features of various commercial EEG headsets like Emotiv EEG Neuroheadset [26], Neurosky Mindwave headset [27], Xwave with Neurosky [28], and Muse headset [29]. Major innovations and up gradations has been made in the key areas such as cost, portability, low power consumption, lengthened battery performance, increased bit rate, better resolutions, quick response, wireless connectivity and thus enhanced efficiency and reliability of acquisition units.

The comparison of headsets present commercially for EEG acquisition justifies the selection and suitability of Emotiv EEG Neuroheadset to this research as it possesses higher bit rate, better resolution and comparatively more user-friendly interface.

TABLE II
COMPARISON OF FEATURES OF VARIOUS EEG SIGNAL PROCESSING AND ANALYSIS TOOLBOXES

Toolbox	Implementation Software	Objective	Features
FieldTrip [30]	MATLAB	To test differences between averaged evoked responses entire scalp and time dimensions, provides flexible combination of high and low level functions according to requirement.	No GUI, User can interact directly with MATLAB functions, Rich feature set for real time and offline EEG preprocessing, event related responses, spectral analysis, connectivity analysis.
EEGLab [31]	MATLAB	To investigate single trial response variability.	Provides functions for Independent Component Analysis of EEG, event related potentials (ERPs), power spectrum, event related cross coherence and inter-trial coherence.
BCILAB [32]	MATLAB	Plugin of EEGLab, online/offline analysis, possesses ability to classify brain states based on statistical learning (LDA, Bayesian classifier).	Signal processing, feature extraction, common spatial patterns, slow cortical potentials, spectrum analysis and non-linear classification.
LIMO EEG [33]	MATLAB	To analyze evoked responses over all space and time dimensions, provide robust parametric tests.	First level analysis with maximum statistics, spatial temporal clustering-1D, 2-D, ERPs, followed by second level statistical analysis.
BioSig [34]	C/C++, MATLAB/Octave	Accepting/generating signals in multiple data formats for EEG preprocessing, visualization, feature extraction and classification.	Provides vast features including time, frequency and time-frequency transformations, common spatial pattern classification, blind source separation.
PyEEG [35]	Python	Feature extraction and feature vector mapping.	Provides a total set of 21 frequency domain and non-linear features.
OpenVIBE [36]	C++	Supports online signal processing and classification	Provides a platform to acquire, filter, process and classify EEG signals.

D.Selection of EEG Signal Processing Toolbox

Once the EEG acquisition unit is finalized an appropriate MATLAB based advanced brain mapping toolbox would be selected to primarily process and analyse the acquired EEG signals. Data control and signal processing algorithms are then explored on the acquired signal. To start with the development the first task is to review the different standalone and MATLAB based brain mapping toolboxes available for BCI research (FieldTrip [30], EEGLab [31], BCILAB [32], LIMO EEG [33], BioSig [34], PyEEG [35], OpenVibe [36]) and identify the right kind of signal processing platform that provides quality set of features, programmability, and flexibility. Table II compares the features of various EEG signal processing toolboxes. EEG Lab toolbox and its plugin BCILAB provides a perfect environment and platform for analysis, detection and classification of emotional states from acquired EEG signals.

Detailed materials required and method to be used in this work is explained in the subsequent section.

III. Materials and Methods

This research proposes the design set up of cost effective and portable real time system for acquisition and analysis of neural responses to classify human emotional states. Block diagram of the EEG based real time human emotion assessment system is sketched in Fig. 1. The proposed system consists of stimuli generator to elicit the emotional state of interest, EEG acquisition unit (Emotiv EEG Neuroheadset) to acquire brain activity in the form of EEG, Bluetooth receiver for wireless reception of EEG signals, signal processing and feature extraction module to characterize variations in EEG under different emotional states followed by the classifier to classify the human emotions.

A. EEG Signal Acquisition

Real time EEG potentials shall be acquired from subject's scalp using cost effective and portable EEG Neuroheadset unit EMOTIV. It shall acquire neural signals of subject generated in response to distinct audio-visual emotion stimulators using 14-channel electrode sensors (AF3, AF4, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 with 2 reference electrodes CMS and DRL) arranged at standard positions on scalp as shown in Fig. 2 (a). The acquired EEG signal shall be transmitted to a data receiver laptop through the Bluetooth dongle. The EEG dataset shall be recorded at a sampling frequency of 128Hz and saved as .edf (European data format) file. The name of the electrode refers to the region of the cerebral cortex as depicted in Fig. 2b above which the electrode is located, F corresponds to the frontal lobe (involved in thoughts/conscious, deliberated movements) and T the temporal lobe (involved in speech reception), O the occipital lobe (signal reception from eye retinas) and P the parietal lobe (sensory signal reception) with C corresponds to central lobe [37]. It has been also observed by continuously monitoring that emotional changes are more associated with frontal scalp regions and thus can be maximum captured at frontal channels i.e., AF3, AF4, F3, F4, FC5 and FC6.

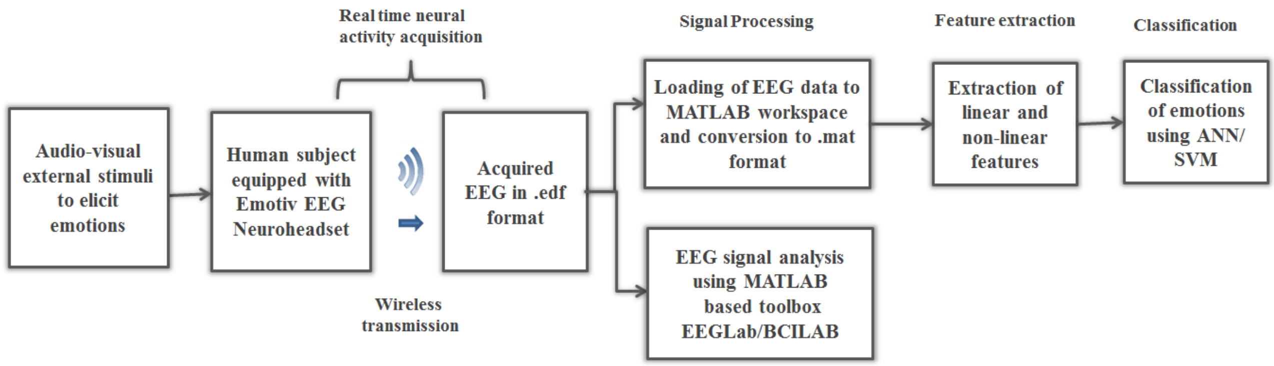

Fig. 1 Block diagram of the proposed portable and wireless EEG based real time human emotion recognition and classification system

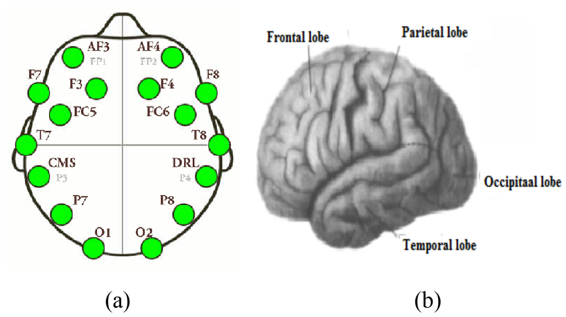

Fig. 2 (a) Emotiv EEG channels and their positioning layout [26], (b) Lobes of cerebral cortex [37]

B. EEG Signal Processing and Algorithm Development

Preliminary signal processing of real time acquired EEG shall be done using EEGLab/BCILAB in MATLAB workspace and EDF Browser application software platforms. Independent Component Analysis (ICA) algorithm of EEGLAB shall be explored to identify distinct emotional states from the neural signals attained through scalp channels. Activity of the distinct Emotiv headset channels during certain emotion shall be identified by plotting their channel activity spectra plots. The event-related EEG-dynamics and relative comparison information shall be retrieved by plotting channel's event related potentials (ERPs). The understanding obtained from primary signal processing results using predesigned toolboxes shall be applied to develop an efficient MATLAB based algorithm for EEG based emotion recognition by extracting an informational feature set from human neural responses (EEG).

Further physiological signals including EEG exhibit nonlinear behavior [16]. Considering this an attempt shall be made to extract linear temporal and non-linear spectral features of EEG. All the possibilities for fusion of linear and non-linear features shall be tested to capture the finest variations in human EEG responses under respective emotional stimuli. The combination of the best discriminative and low-dimensional feature set leading to the best classification results using artificial intelligence tools shall be selected.

C. Classification of Emotions

Once the neural responses are mapped into a feature set an appropriate artificial intelligence tool would be selected and trained to classify distinct emotional states. The training procedure shall involve the labeling of emotions according to subject's feedback. Several classification algorithms have been proposed such as Bayesian statistical classifier [14], [38], Support vector machine [11]-[13], [15], *k*-nearest neighbor [8], [10], [39] Linear Discriminant Analysis (LDA) [21], [24] and Artificial neural network (ANN) models [40], [41]. Out of these defined classifiers support vector machines and artificial neural network classifiers outer perform the others in terms of processing time, flexibility, availability of multiple architectures, size of training vector requirement and suitability for both linear and non-linear modalities, hence shall be implemented in the proposed research.

Finally the control interface stage consisting of neural decoder and translation algorithm could be developed to translate the classified emotions from EEG signals into meaningful commands for various control applications for rehabilitation. Fig. 3 is the experimental set up for Emotiv EEG Neuroheadset based real time system for acquisition and analysis of EEG signals to interpret human emotional states.

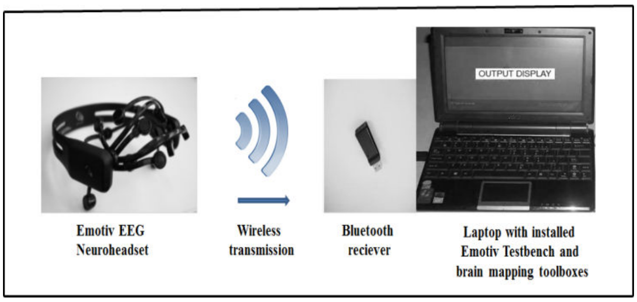

Fig. 3 Experimental set up for acquisition and analysis of EEG signals for emotion assessment

IV. Discussion

Real time affective Brain computer interfaces that could be used for rehabilitative control need to be designed carefully. A compromise could have been made between efficiency and reliability to size, cost, hardware potential and power requirements by the system. In comparison to earlier used EEG acquisition system, Emotiv EEG Neuroheadsets have sufficient power for long-lasting use [26]. The relative advantages and disadvantages of the different EEG acquisition units have been discussed in detail. The design proposed in this work shall ensure sophisticated real time processing of neural signals using free of cost accessible advanced brain mapping toolboxes in conjunction with Emotiv that requires less power, is compact in size, portable, possesses higher information rate and resolution and is cost effective. It has also been reported that EEG data acquired with combination of audio-visual stimuli exhibits higher classification rates [2], [6], [25]. Different brain mapping toolboxes have been surveyed in context of their ability to analyze and thus construct the most informational feature set from human neural responses (EEG) corresponding to elicited emotional states. The feature vector must also be compact in size in order to reduce complexity and computational load associated with feature extraction and classification stage. The classification stage classifies the signals by training the classifier using labeled emotional feature set. The selection of the best discriminative features is therefore essential to achieve effective emotion classification rates in order to accurately decode the subject's intentions.

Therefore, an effort shall be attempted to develop a more efficient and robust technique to detect and classify human emotions automatically by merely analyzing the brain activity of subject using MATLAB based algorithms without compromising with the accuracy while reducing complexity and response time of the system. The efforts shall also be directed towards investigating the combinations of feature sets of real time attained EEG signals in the attempt to increase the classification rate to interpret human mental states in order to enrich human-computer interface

V. Conclusion

Design of real time Brain computer interfaces is crucial for successful analysis of neural responses for rehabilitation. An attempt has been made to present a review of construction protocols and neural feature sets considered for development of existing BCIs. Documentation of the existing BCIs design process shall lead towards designing of a brain computer interface for human emotion recognition with refinement of existing ones using additional feature set. A design set up of real time, cost-effective and portable EEG based affective BCI using Emotiv EEG Neuroheadset has been proposed. The arrangement discussed in this paper would result in an inexpensive established solution to real time implementation of BCIs for acquiring and analyzing EEG signals to discriminate human emotions with reduced complexity and response time of the system. The designed system can be further programmed towards the development of a neuroscientific and medical tool to assist complete or partial paralyzed patients suffering from voluntary motor disorder such as speech loss, amputation or psychiatric disorders in order to restore or maintain a quality life.

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