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Estimation of Variations in EEG-based Emotions - A Framework

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ABSTRACT: EEG signals most prominently support in effective emotion recognition. It is presumed that these signals will also assist in estimating variations in emotion classes. An attempt has been made to estimate variations in spontaneous and posed neutral emotion using alpha band as stronger responses are reported in it for neutral emotion. For this purpose relative powers of selected electrodes are calculated to realize neural activation of brain points. Further, to establish ranges coefficient of variation is computed using relative power values of channels of interest for emotion classes. As a result, neural signatures of spontaneous neutral emotion are instituted to be more coherent as compared to posed neutral exhibition. The results are evaluated using existing datasets (DREAMER and SEED-IV) for spontaneous neutral and meditation practitioner's dataset for posed neutral emotion and outcomes are in compliance with established ranges.

Keywords: Absolute and Relative Power, Coefficient of Variation, Electroencephalogram, Estimation of variation, Posed Emotion, Power Spectrum, Spontaneous Emotion.

Abbreviations: CVs, Coefficient of Variations; EEG, Electroencephalogram; ICA, Independent Component Analysis.

I. INTRODUCTION

Estimating variations in human affective states specially; spontaneous and posed emotions using facial and/ or voice emotional expressions earned notable attention in past two decades [1, 2]. Emotion recognition using electroencephalograph (EEG) signals evidenced to be more reliable as these signals reflect inner affective state of the subject. These signals posses a superior spatial, temporal resolution and benefit of being hard to conceal or disguise [3]. The effect on emotion recognition accuracy is analyzed by varying the number of channels and diverse frequency bands using entropy and band energy features. The recognition accuracy for gamma frequency band instituted to be highest for 10, 14, 18 and 32-channels, regardless of the valence or arousal dimensions [4]. The channel specific nature of EEG signals is explore by decomposing EEG signals into sub bands using Flexible Analytic Wavelet Transform (FAWT). Information Potential (IP) is extracted as feature and two publicly available databases namely; SEED and DEAP are exercised for experimentation. The cross subject classification accuracies evaluated to be higher for random forest classifier than SVM [5]. The spectral relative powers for δ, θ, α, β, and γ frequency bands are computed for measuring correlation indices amongst neutral state and six prototypical emotions. The findings indicates that the correlation in brain activity and emotional states are significantly varying for various emotions [6]. However, the scope lies in estimating variations in spontaneous and posed emotions using EEG signals.

Neural signatures in frequency bands provides significant information to assess and estimate variations in emotional states. In this paper, we propose a framework to estimate variation in spontaneous and posed neutral emotion using frequency domain feature of EEG signals. The proposed framework along with background information on emotion elicitation, preprocessing and feature extraction is delineated in Section II. Section III deals with the experimental protocol and implementation detail integrated with modus operandi of EEG dataset collection. Section IV covers the results and discussion based on the relative power with respect to alpha band and coefficient of variation. We conclude with the future direction of work in Section V.

II. PROPOSED FRAMEWORK

We propose a framework to estimate variations in EEG based neutral emotion using relative power with respect to brainwaves frequency bands. Our framework consists of various phases such as data collection, preprocessing, feature extraction, and estimation phase as depicted in Fig. 1 and are discussed as follows:

Data Collection: The raw EEG signals act as an input in our framework. These are acquired from various locations of the brain corresponding to audio visual stimuli for spontaneous emotion and intentionally evoked emotion for posed one. Various EEG signal recording devices assist in acquiring raw EEG signals against presented stimuli or volitional exhibition. The acquired multi-channel EEG signals are represented as:

$$x(t) = \left[x^{Ch_1}(t),\ x^{Ch_2}(t), \dots, x^{Ch_n}(t)\right] \in R^{n \times N} \quad (1)$$

where $x(t)$ is multichannel primary EEG signals, t is the time index, n, N are the number of brain locations and sample points respectively, and $x^{Ch_i}(t)$ is the EEG signal of the i th channel and R is $n \times N$ dimensional real space [7]. The recorded raw EEG signals are contaminated with noise and various artifacts and require preprocessing.

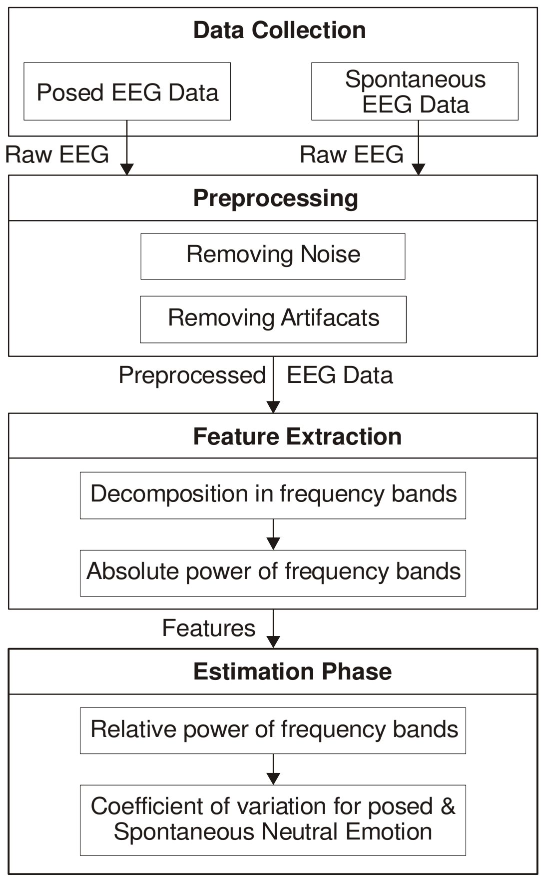

Fig. 1. Framework for Estimating Variations in Spontaneous and Posed Emotion.

Preprocessing: The preprocessing phase concerns with the transformation of raw EEG signals into standardized form thereby improving signal to noise ratio. The blind source separation method independent component analysis (ICA) is used to extract artifact free components from EEG signals [8]. The filtering techniques such as finite impulse response (FIR) filter and Butterworth filter help to remove noise and transforms raw EEG signals into standardize form. A general FIR filter of order Q, with each value of the output series as a weighted summation of the most recent input terms is represented as:

$$y(t) = b_0 x(t) + b_1 x(t-1) + \dots + b_Q x(t-Q) = \sum_{i=0}^{Q} (b_i . x(t-i)) \quad (2)$$

where *x(t)* is the multichannel input EEG signal, *y(t)* is the output signal, Q is the filter order; an Q th order filter has $(Q+1)$ terms, b_i is the filter coefficient for $0 \le i \le Q$. Thus, the raw EEG data is transformed into optimum noise free data in preprocessing phase [9].

Feature Extraction: Feature extraction is concerned with the transformation of input EEG signal to reduced set of most discriminatory information. EEG features are extracted in frequency domain, time domain or time-frequency domain. The power spectrum analysis method namely; Fast Fourier Transform (FFT) is used to transform pre-processed dataset into separate frequency bands. FFT is used to transform time domain EEG signal into frequency domain and split the signal into overlapping components. ICA assists in overcoming the problem of overlapping components by separating these components for each channel. The individual component provides precise reading of power spectrum activity corresponding to different frequencies. To extract a rhythmic signal of interest frequency band extrication is performed on the preprocessed EEG signals:

$$F_k(t) = \left[y^{Ch_1}(t),\ y^{Ch_2}(t), \dots, y^{Ch_n}(t)\right] \in R^{n \times N} \quad (3)$$

where $y^{Ch_i}(t)$ is the preprocessed EEG signal, $F_k(t)$ is the rhythmic signal of k th band, n, N are the number of brain locations and sample points respectively, and R is $n \times N$ dimensional real space.

Estimation Phase: Estimation phase deals with the estimation of variations in spontaneous and posed neutral emotion using frequency bands extracted in power spectrum activity. Each frequency band is allied with absolute and relative power. Absolute power is the integral of all power values within in its frequency range and hence, characterizes band power of EEG signal in specific emotion. It is expressed in microvolts (µ-volt) and contributes in assessing each frequency band. The absolute power with respect to each derived frequency band for each emotion is computed as follows:

$$AP_{fb}^{Ch_k} = \sum_{i=1}^{N} F_i^{Ch_k}(\mathrm{t}) \quad (4)$$

where $AP_{fb}^{Ch_k}$ is the absolute power with respect to a frequency band corresponding to k th channel, and N is the total number of sampling points.

The relative power of a EEG signal is the ratio of absolute power in a frequency band to the summation of absolute powers for over all frequency range. It is a unit less value and represents the percentage of signals reckoned by a particular band [10]. The relative power corresponding to desired frequency band is computed using absolute power derived from Eqn. (4) and represented as follows:

$$RP_{fb}^{Ch_k} = \frac{AP_{fb}^{Ch_k}}{AP_{\theta}^{Ch_k} + AP_{\alpha}^{Ch_k} + AP_{\beta}^{Ch_k} + AP_{\gamma}^{Ch_k}} * 100 \quad (5)$$

where $AP_{\theta}^{Ch_k}$, $AP_{\alpha}^{Ch_k}$, $AP_{\beta}^{Ch_k}$, and $AP_{\gamma}^{Ch_k}$ are the absolute powers of θ, α, β, and γ bands respectively for k th channel.

The Coefficient of Variation (CV) is computed using the relative power $RP_{fb}^{Ch_k}$ values obtained from Eqn. (5) for spontaneous and posed neutral emotion. The CV_{EC} for emotion classes (spontaneous and posed) is expressed as follows:

$$CV_{EC}(\%) = \frac{\sqrt{\frac{\sum_{i=1}^{k}\left(RP_{fb}^{Ch_i} - \overline{RP_{fb}^{Ch_i}}\right)^2}{k}}}{\overline{RP_{fb}^{Ch_i}}} * 100 \quad (6)$$

where $\sqrt{\frac{\sum_{i=1}^{k}\left(RP_{fb}^{Ch_i} - \overline{RP_{fb}^{Ch_i}}\right)^2}{k}}$ is the standard deviation of relative power values with respect to k channels and $\overline{RP_{fb}^{Ch_i}}$ is mean of relative power values.

III. EXPERIMENTAL SET UP AND EXECUTION

Human emotional expressions are broadly classified as posed and spontaneous and these emotions are inherently varied in numerous aspects. [11]. In order to estimate the variation in spontaneous and posed neutral emotion, an experiment is designed to capture EEG data. The Emotiv Epoc+ wireless headset is used to record the raw EEG data. The headset contains 14 electrodes namely; AF3, AF4, F7, F8, F3, F4, FC5, FC6, T7, T8, P7, P8, O1 and O2 with two reference nodes behind ears. The sampling rate of headset is 128 samples/ sec with 16 bit analog to digital convertor. The electrode positioning is based on International 10-20 electrode placement system [12]. The experiment is performed using EEGLAB tool on MATLAB 13a on Windows 10.

The raw EEG signals are recorded in European Data Format (.edf file) from 24 healthy subjects (three groups of 8 subjects each). These groups are comprised of namely; Subjects with no acting experience, Subjects with preliminary acting experience, and Subjects with advance acting experience. It is presumed that the group with advanced acting experience will enact the posed emotion aptly. The recording of 60 seconds of each subject for each emotion is used for experimentation. Spontaneous neutral emotion is evoked by exposing subjects to an audio-visual clip for emotion elicitation whereas for posed neutral emotion subjects are directed to voluntarily exhibit it. Moreover, the raw data from 8 subjects (highly experienced meditation practitioners) is also captured for posed neutral emotion.

For estimating classes of neutral emotion, we intend to remove noise and artifacts from raw EEG signals using band-pass filter between 1-50 Hz in preprocessing. ICA is used to separate individual component for each channel. The preprocessed dataset of 24 subjects (based on aforementioned groups) and 8 subjects (meditation practitioners) is collected and decomposed into frequency bands (δ, θ, α, β, γ) using FIR filter for power spectrum analysis. The delta band (1-4 Hz) is discarded to eliminate artifacts such as eye blinking/ movement, pulses and neck movement, as these are most prominent below 4 Hz. Relative power with respect to alpha band is computed using Eqn. (5) from extracted frequency bands and used for analysis. Based on valance-arousal model and event-related spectral perturbation (ERSP) maps, stronger responses are reported in alpha band for neutral emotion [13]. The facial micro expressions along with EEG signals are used to predict user's expressed emotion based on optimal EEG features. The features are extracted from specific time and frequency domain. The literature establish that the channels FC5, P7, P8, T8 and FC6 are most relevant for neutral emotion based on ReliefF over Random forest algorithm [14]. Further, CV is computed using Eqn. (6) for spontaneous and posed neutral emotion to assess variability of relative power values around mean for selected electrodes.

IV. RESULTS AND DISCUSSION

We have attempted to analyze and validate the variations in spontaneous and posed neutral emotion using some cases based on our framework. And, we discuss them as follows:

Case I: Inexperienced Group

The Group I comprises of subjects with no acting experience. The subjects are exposed to an audio visual stimuli to induce spontaneous neutral emotion whereas posed emotion is enacted intentionally. The relative powers of selected electrodes in Case I for spontaneous neutral emotion, as highlighted in Table 1, are higher as compared to posed neutral emotion. It is apparent that in spontaneous exposition, subjects underwent neutral state spontaneously while exposed to a stimuli as compared to posed exhibition. Further, CV for spontaneous and posed neutral emotion are observed as 19.16% and 25.34% respectively implying the coherent neural activation of selected electrodes in spontaneous exposition as compared to posed exhibition.

Case II: Preliminary Acting Experience Group

The subjects of Group II possess preliminary acting experience of 2-3 years to enact an emotion. The subjects are presented with an audio visual stimuli to spontaneously evoke neutral emotion. Subjects volitionally elicited neutral emotion based on enacting experience. From Table 1, it is evident that relative powers of selected electrodes as highlighted in Case II for spontaneous emotion are higher in comparison to posed exposition. This suggests that subjects felt neutral emotion spontaneously resulting in higher neural activation of selected electrodes as compared to posed exposition. The CV for spontaneous and posed neutral emotion are observed as 20.66% and 24.86% respectively establishing the consistent neural activation of selected electrodes in spontaneous neutral emotion in contrast to posed exhibition.

Case III: Experienced Group.

The subjects of Group III possess 5-7 years of acting experience. An audio visual stimuli is used to evoke spontaneous neutral emotion in subjects. The subjects enacted posed neutral emotion based on acquired acting experience. It is apparent that relative powers in Case III for spontaneous neutral emotion as highlighted in Table 1 are higher as compared to posed neutral emotion.

It establishes that subjects experienced neutral emotion spontaneously resulting in higher neural activation of selected electrodes as compared to posed exposition. The coefficient of variation for spontaneous neutral emotion is premeditated as 19.11%, whereas for posed neutral emotion as 23.39%, thereby suggesting the rational neural activation of selected electrodes in spontaneous evocation is more consistent than posed elucidation.

Table 1: Estimation of Variations in Neutral Emotion using Alpha Band.

Cases & Datasets		Classes of Neutral Emotion	Relative Power					CV (%)
			FC5	P7	P8	T8	FC6	
1.	Group I	Spontaneous	26.94	40.81	35.65	38.39	26.98	19.16
		Posed	22.67	22.3	29.52	16.5	16.3	25.34
2.	Group II	Spontaneous	28.37	41.93	33.49	39.16	25.47	20.66
		Posed	21.83	23.67	30.29	16.78	17.43	24.86
3.	Group III	Spontaneous	25.13	38.39	34.32	37.41	26.46	19.11
		Posed	23.45	22.87	28.44	17.48	15.82	23.39
4.	DREAMER (Group I)	Spontaneous	28.4	24.09	29.15	17.79	29.34	19.17
	DREAMER (Group II)	Spontaneous	29.69	27.93	27.24	17.47	22.57	19.84
	SEED-IV (Group I)	Spontaneous	23.42	18.41	15.18	15.11	21.98	20.29
	SEED-IV (Group II)	Spontaneous	17.36	22.28	15.17	16.65	23.34	19.11
5.	Meditation Practitioners	Posed	33.77	28.4	33.99	21.02	36.6	20.18

Case IV: Existing Neutral Emotion Class Datasets.
We use existing datasets DREAMER and SEED-IV for compliance of our experimental results [15, 16]. Two groups of eight subjects each are selected at random from aforementioned datasets respectively for spontaneous neutral emotion only. As shown in Case IV of Table 1, CVs for spontaneous neutral emotion are observed as 19.17% (Group I), 19.84% (Group II) for DREAMER dataset and 20.29% (Group I), 19.11% (Group II) for SEED-IV dataset respectively. As these CVs are in range obtained in our experimental results 19% to 21% approximately for spontaneous neutral emotion, it is evident that our experimental results are coherent.

Case V: Meditation Practitioners Group.
An experiment is carried out to observe the effect of meditation on volitionally experiencing neutral state. It is presumed that the meditation practitioners must have better control on emotional states. The subjects are directed to pose neutral emotion intentionally with eyes open. In this case, it is observed that CV computed as 20.18% for posed neutral emotion as depicted in Table 1. And hence, it has been complied with the range of spontaneous neutral emotion from 19% to 21%. Thus, we result into the fact that the meditation practitioners have effectively posed neutral emotion and voluntarily underwent neutral state without any stimulus.

V. CONCLUSION

We have presented a novel framework to estimate variations in spontaneous and posed neutral emotion using EEG signals. An experiment has been carried out to capture EEG signals from heterogeneous groups for this purpose. The estimated ranges for variations in alpha band (since it is dominant in neutral emotion) have been tested using existing datasets and meditation practitioners. Further, estimated ranges in alpha band for neutral emotion will help researchers as baseline to discriminate spontaneous and posed emotions using EEG Modality.

Conflict of Interest. The authors declare no conflict of interest associated with this work.

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