Articles in Press, J. Med. Biol. Eng. (Aug 20, 2014), doi: 10.5405/jmbe.1930

Title: Time-Varying Spectral Analysis of a Single EEG Channel: Application in an Affective Protocol

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Running Title: Emotional Differentiation on Single EEG Channel

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Abstract

Neural correlates of emotions have been widely investigated using noninvasive sensor modalities. These approaches are often characterized by a low level of usability and are not practical for real-life situations. The aim of this study is to show that a single EEG electrode placed in the central region of the scalp is able to discriminate emotional characterized events with respect to a baseline period. Emotional changes were induced using an imagery approach based on the recall of autobiographical events characterized by four basic emotions: "Happiness", "Fear", "Anger" and "Sadness". Data from 17 normal subjects were recorded on Cz position according to the International 10-20 System. After preprocessing and artifact detection phases, raw signals were analyzed through a time-variant adaptive autoregressive model to extract EEG characteristic spectral components. We considered 5 frequency bands, i.e. the classical EEG rhythms, namely the delta band (δ), [1-4] Hz, the theta band (θ), [4-6] Hz, the alpha band (α), [6-12] Hz, the beta band (β), [12-30] Hz, and the gamma band (γ), [30-50] Hz. The relative powers of the EEG rhythms were used as features to compare the experimental conditions. Our results show statistically significant differences when comparing the power content in the gamma band of baseline events versus emotionally characterized events. Particularly, we found a significant increase in gamma band relative power in 3 out of 4 emotionally characterized events, i.e. “Happiness” “Sadness” and “Anger". In agreement with previous studies, our findings confirm the presence of a possible correlation between broader high frequency cortical activation and affective processing of the brain. The present study shows that the use of a single EEG electrode represents a possible advantageous premise for the assessment of the emotional state with a minimally invasive set-up.

Keywords: Electroencephalogram (EEG), Emotions, Single EEG channel, Adaptive autoregressive model (AAR), Affective protocol.

1. Introduction

There is an increasing interest in developing systems that would automatically detect and distinguish emotions in a quantitative way. Emotions play an important role in the human experience influencing cognition, perception and everyday tasks such as learning, communication and decision making [1]. Beside qualitative methods, e.g. self-reports, startle responses and behavioral responses, quantitative approaches based on autonomic correlates and/or neurophysiological measurements have been recently proposed. As the brain is the centre of every human action, emotions can be detected through the analysis of physiological signals generated by the central nervous system [2,3] and the neurophysiological measurements might provide a direct means for emotion recognition [4]. The neural correlates of emotions have been investigated by a large body of researches using noninvasive sensor modalities, each one presenting unique spatial and temporal resolutions and spanning different level of usability. Functional Magnetic Resonance Imaging (fMRI) has been used to uncover cortical and subcortical nuclei involved in affective responses [5]. Magnetoencephalography (MEG) has been used to explore emotion-related neural signals in specific brain loci [6]. The cost and the laboratory environment of the experimental set-up do not allow these modalities being used for out-of-the-lab emotion recognition systems [7,8]. Electroencephalography (EEG) has been widely used to investigate the brain dynamics related to emotions since its high temporal resolution allows an early detection of response to emotionally characterized stimuli. The emotion identification from EEG has been performed using different features, in time and/or in frequency domain. Event Related Potential (ERP) components and spectral power at different frequency bands were related to underlying emotional states [4]. In the frequency domain, the spectral power in various frequency bands has been implicated in the emotional state. The alpha band power has been associated to discrete emotions such as happiness, sadness and fear [9]. Other studies analyzed the connection between gamma band and emotions: Li and Lu [10] analyzed the Event Related Desynchronization (ERD) at gamma band during emotional

stimuli presentation, also Müller et al. [11] and Keil et al. [12] reported the connection between gamma band activity and emotions when differential hemispheric activations were induced. The emotion identification from EEG has been performed also using mathematical transforms [13] or non linear quantities [14,15]. For a complete review of recent contributions to the field, please see [4]. Above mentioned studies employed up to 128 EEG channels. Such a large number makes these approaches impractical in real-life situations, resulting in long experimental set-up, a large discomfort for the subject and a huge computational need to handle the large amount of data. Therefore, attention has been focused to reach a feasible emotion classification using a reduced number of EEG channels. Min et al**.** [16] showed emotional response in physiological signals including EEG signals recorded from two channels, i.e. Cz and Fz International 10-20 System positions. Alpha and beta relative powers were used as features to distinguish conditions such as pleasantness, arousal, relaxation and unpleasantness. Mikhail and El-Ayat [1] performed a classification of four different emotions through brain responses elicited by facial expressions, using from 4 to 25 EEG channels. They showed a decrease in the accuracy by reducing the number of channels. A trade-off between the complexity of the set-up and the accuracy of the classification was reached using 4-6 channels.

The aim of this work is to verify whether a single EEG electrode placed in the central region, i.e. on Cz position, could discriminate emotionally characterized events from a baseline condition. An imagery approach was used in an experimental protocol. Emotional responses were elicited by the recall of autobiographical events of four basic emotions, namely "Happiness", "Fear", "Anger" and "Sadness".

2. Materials and methods

2.1 Experimental protocol

Twenty one (21) healthy volunteers from the student body of IULM University of Milan took part at the experimental protocol. All participants had no history of neurological or psychiatric problems. The present experimental protocol, previously employed in other works [17,18], make use of a memory recall paradigm of emotionally characterized autobiographical episodes to trigger physiological responses. The considered emotions are "Happiness", "Fear", "Anger" and "Sadness". The protocol took place at the Behavior & Brain Lab at IULM University of Milan and consisted of two different phases. In the first phase, the subject told a psychologist two recent emotionally characterized autobiographical episodes for each target emotion. During the recall, the psychologist took notes about the episodes. For each target emotion the psychologist asked the subject to judge the most intense episode: these very episodes were selected as emotional stimuli for the second phase of the protocol. Subjects unable to recall any episode related to the target emotion were excluded from the protocol. The second phase took place the day after. After arriving at the Lab, the subject was asked to sit in front of the eye-tracker provided of a grey screen monitor, at a fixed distance of 70 cm, in a room with constant illumination conditions. First, three minutes of a "Baseline", i.e. a resting period, were recorded. During this phase the subject was asked to sit still and to relax. Subsequently, the psychologist helped the subject to recall the formerly selected episode which was related to the first target emotion. When the subject nodded he/she was experiencing the emotion, his/her physiological signals were recorded for 3 minutes. This phase is defined "Autobiographical Recall". Later on, a “washout” period of at least 3 minutes was provided to allow the subject to relax and clear his/her mind. Finally, the recall of the next emotional episode could start. The order of the target emotions was randomly chosen for every subject. Figure 1 shows a graphical representation of the experimental protocol.

[Figure 1 here]

2.3 Physiological signals recording

To track the brain activity, a single-channel EEG was recorded. The electrode was placed in Cz position, according to the 10-20 International System, while the reference electrode was placed on the left earlobe. The Electromyographic (EMG) signal was acquired on the *Corrugator Supercilii* muscle. EEG and EMG were recorded through a Flexcomp Infinity^{TM} encoder (Tought Technology Ltd; Montreal, Canada) at a sampling rate of 2048 Hz. Pupil Dilation (PD) signals were recorded using the SensoMotoric Instruments RED250^{TM} Eye-Tracker. Prior to start the "Baseline" and each "Authobiographical Recall", calibration of the eye-tracker was performed. Other physiological signals were acquired during the second phase, but their analysis was not included in the present study. Further details on the acquired signals can be found in [17].

2.4 Signal pre-processing and artifacts detection

For computational purposes, the EEG signals were low-passed and resampled at 100 Hz. Before the analysis of the EEG signals, artifacts detection was performed. Muscle contraction related to eye movements is the main artifact for the EEG signals because it produces a sudden change in the electric field around the eyes, which affects the scalp electric field [19]. In particular, the electric potentials due to eye-blinking can be larger than the EEG and can propagate across most of the scalp, covering and adulterating brain signals [20]. To detect eye-blinking artifacts, we took advantages of simultaneously recorded PD signals, while EMG signals of the *Corrugator* muscle were used for other undifferentiated muscle activity: the PD signal permits to precisely detect eye-blinking occurrences, while the EMG signal tracked the activity of the *Corrugator Supercilii* muscle, which is mostly involved in the frowning response. Aligning EMG and PD signals, we observed a narrow correspondence between eye-blinking events and EMG activity peaks, as shown in Fig. 2. According to this observation, we used the eye-blinking detection performed by the eye-tracker to automatically identify and exclude the relative EEG segments. A visual check of the signals was performed to correct possible misdetections.

[Figure 2 here]

2.5 EEG analysis

EEG power spectral density (PSD) was computed using an Adaptive Autoregressive (AAR) method. Florian and Pfurtscheller [21] claimed that autoregressive (AR) approaches are more advisable than traditional techniques based on Fourier Transform, as the frequency resolution does not depend on the length of the time series. AR models are suited to stationary signals only, an assumption in general not valid for EEG signals [21]. To circumvent this limitation AAR methods have been proposed [22]: at each new available observation the set of AR parameters is updated to track the statistical changes occurred in the observed data. For each AR update, a window of the signal is used by assuming the hypothesis that the segment within the window is stationary.

2.5.1 AAR model

Let us remind the vector representation of a generic linear AR model:

$$y(t) = \Phi(t)^T a + w(t) \qquad (1)$$

where $w(t)$ is a zero-mean Gaussian noise, $\boldsymbol{a}$ is the vector of the parameters $a_1, a_2 ... a_p$, where p is the model order, and $\Phi(t)^T = [\Phi(t-1), \Phi(t-2), ..., \Phi(t-p)]$ is the observation vector. The corresponding predictor is given by

$$\hat{y}(t) = \phi(t)^T a \qquad (2)$$

where $\hat{y}(t) = \hat{y}(t \mid t-1)$ is the estimated vector and $y(t)$ is the discrete time series. The difference between the measured value $y(t)$ and its prediction $\hat{y}(t)$ is the prediction error, also called *a priori* error, because it is based on the parameters vector defined at the previous estimation step.

The analytical formulation of the prediction error is

$$\varepsilon(t) = y(t) - \hat{y}(t) = y(t) - \boldsymbol{\Phi}(t-1)^T \hat{\boldsymbol{a}}(t-1) \qquad (4)$$

Once computed $\varepsilon(t)$, the model coefficients are updated using a Recursive Least Squares (RLS) identification. A forgetting factor $\lambda \in (0,1)$ is introduced in the RLS formulation: the coefficients $\hat{\boldsymbol{a}}(t-1)$ obtained at the previous sample are updated adding an innovation term dependent on the estimation error $\varepsilon(t)$, which is weighted according to a gain vector $\boldsymbol{K}(t,\lambda)$, i.e. a vector of weights depending on the forgetting factor λ and the inverse of the autocorrelation matrix of the time series [23]. The λ defines a decay factor $T = 1/(1-\lambda)$ of the weights, and can be interpreted as the memory of the update step: more recent values of the prediction error contribute more than older ones. A compact formulation of the update is given by

$$\begin{cases} \hat{\boldsymbol{a}}(t) = \hat{\boldsymbol{a}}(t-1) + K(t,\lambda)\varepsilon\, t \\ \varepsilon(t) = y(t) - \boldsymbol{\Phi}(t)^T \hat{\boldsymbol{a}}(t-1)\,. \end{cases} \qquad (4)$$

In conclusion we obtain an updating formulation of the autoregressive model, which tracks the dynamical variations of the signal. The factor λ is selected as a trade-off between preserving the fast dynamics of the signal and preventing the model to be influenced by artifacts. From each $\boldsymbol{a}(t)$ we computed the power spectral density (PSD) and the single spectral components. The general form of the parametric estimation of PSD through an AR model is

$$S(f) = T * H(z)\sigma^2 H(z^{-1}) \qquad (5)$$

where $z = exp(j2\pi f)$, σ^2 is the variance of the prediction error and $H(z)$ is defined as $H(z) = \dfrac{1}{A(Z)} = \dfrac{1}{1 + a(1) * z^{-1} + \ldots + a(p) * z^{-p}}$ (6)

The spectral components are computed according to the residual method [24,25]. Each component is attributed to a given frequency band when the central frequency of its peak lays within the frequency band itself. We considered 5 frequency bands, i.e. the classical EEG characteristic rhythms: the delta band (δ), [1+-4] Hz, the theta band (θ), [4-6] Hz, the alpha band (α), [6-12] Hz, the beta band (β), [12-30] Hz, and the gamma band (γ), [30-50] Hz. All the components

laying in the same frequency band are summed up to compute the total power of the rhythm. AAR identification and correspondent spectral decomposition were computed for each sample of the entire signal. Figure 3 shows an example of time-frequency representation of EEG PSD.

[Figure 3 here]

For each rhythm we computed the relative power, i.e. the ratio between the average power in a certain band and the total variance of the signal. The main steps of the method here performed are summarized in Fig. 4.

[Figure 4 here]

2.6 Statistical analysis

The relative powers of the EEG rhythms were used to compare the experimental conditions. A Lilliefors test [26] and a Levene test [27] were performed to verify the hypotheses respectively of normality and homogeneity of the variance. As the hypothesis of normality was rejected and the hypothesis on the homogeneity of the variance was accepted, we accordingly performed a nonparametric statistical test for the analysis of variance, i.e. the Kruskal-Wallis test. As *post-hoc* analysis we performed the Wilcoxon sign rank test to test the differences between the "Baseline" and each emotionally characterized event.

3. Results

17 out of 21 subjects were analyzed, as 4 subjects were affected by too many artifacts. Table 1 shows the median values and the first and third quartiles of the relative powers of EEG signals in each frequency band and for each emotion.

[Table 1 here]

We can observe that there are significant differences in the gamma band for "Baseline" versus "Happiness", "Anger" and "Sadness", respectively. These differences are also shown in Fig. 5. It is

possible to observe that the median value of "Happiness" is higher than in "Baseline" condition. The same trend can be found when "Baseline" is compared with "Anger" and "Sadness", respectively.

[Figure 5 here]

Figure 6 shows the PSD for the subject "sbj57". Each line represents the mean spectrum computed in each experimental condition. It can be seen that an higher power value is observed in the gamma band during "Happiness", "Anger" and "Sadness" with respect to "Baseline".

[Figure 6 here]

Figure 7 shows the inter-subject variations of the relative power of gamma band during "Baseline" versus the other experimental conditions but “Fear”. In particular, the relative power during "Happiness" is higher than during "Baseline" for 16 out of 17 subjects. Similarly, the comparison between "Anger" and "Baseline" shows the same trend in 13 out of 17 participants. During "Sadness" 12 out of 17 subjects experienced an increase in the gamma power with respect to "Baseline".

[Figure 7 here]

4. Discussion

In this work we explored the prospect of using a single channel EEG, i.e. Cz, to evaluate the effect of emotionally characterized stimuli when compared with a neutral stimulus. Several studies had tried to recognize emotions from EEG signals with a number of electrodes that varies from 3 [28] to 128 [12,29]. Our results show the possibility to distinguish the elicitation of basic emotions, i.e. "Happiness", "Anger" and "Sadness", from the "Baseline" condition using a single EEG channel. We found that differences between baseline and emotions are located in the gamma band. This result is in agreement with previous studies in which a connection between high frequency components in EEG signals, i.e. gamma rhythm, [30-50] Hz, and emotions have been documented: Müller [11] and Keil [12] suggested that emotions are represented in wide cortico-limbic network rather than in particular regions of the brain and that during processing of emotional stimuli such a

network produces wide spread rather than focal cortical activity at high frequencies; Li and Lu [10] used EEG signals to classify emotional reactions evoked by pictures of facial expressions representing different emotions, and gamma band was found to be related to pictures of "Happiness" and "Sadness". These approaches required a large number of electrodes for emotion detection, 62 in the latter study [10] and 128 in the former [11,12]. These findings are in agreement with our results which evidence an increase in gamma band, more evident for “Happiness” than for “Sadness” and “Anger”. Müller [11] and Keil [12] supported also the hypothesis of a localized EEG activity due to positive and negative emotions: they observed the involvement of the left hemisphere in positive valence, and the right hemisphere in negative valence at gamma band activity. For this reason, it would be difficult to perform a discrimination among emotions using a single EEG electrode and it would be necessary to use at least two electrodes, one for each brain side. Our findings suggest that the activity collected from a central lobe electrode can distinguish neural activation of emotional stimuli from neural activation of a neutral condition: a future development of this work will be the use of two electrodes placed in the left and in the right side of the central lobe. This would lead to a further confirmation of the present study and to investigate whether it is possible to improve the actual results taking into account the asynchronous activity of the brain. The results obtained in our study can be a useful premise for the assessment of the emotional states through the use of a minimally invasive system, particularly in application such as human-computer interaction, communication, marketing research and user experience, which can take advantage from a quantitative representation of emotions in a minimal sensory set-up.

5. References

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Figure Caption:

Figure 1: A graphical representation of the protocol. Data were recorded during gray colored boxes. After recording the "Baseline" event, during the "Autobiographical Recall" the subject was addressed to recall the most vivid episode of the target emotion that he/she has reported in the first phase of the study. When the subject nodded to experience again the target emotion, the recording of physiological data was performed for 3 minutes. A “washout” period of at least 3 minutes was provided before starting the next “Autobiographical recall”.

Figure 2: Artifacts Detection of EEG signal (in red) from PD (in green) and EMG (in blue) signals. Eye-blink events and ocular artifacts are set at 0 in the PD signal.

Figure 3: Time-frequency representation of EEG PSD computed for 2 seconds during the "Happiness" recording for the subject "sbj05".

Figure 4: Block diagram of the steps performed for the analysis of the EEG signal. The subscript indices indicate the EEG bands (i), and the emotions (j).

Figure 5: Boxplots of "Baseline", "Happiness", "Fear", "Anger" and "Sadness" relative power of the gamma band.

Figure 6: An example of PSD for the subject "sbj57". Each plot represents the comparison between the PSD during "Baseline" condition (in black) and one of the emotional condition. "Happiness" is

depicted in green at top left, "Fear" in red at top right, "Anger" in blue at bottom left and "Sadness" in purple at bottom right.

Figure 7: Variations of the relative power of the gamma band from "Baseline" to "Happiness" (plot at the left), from "Baseline" to "Anger" (plot at the middle) and from "Baseline" to "Sadness" (plot at the right).

Table Captions:

Table 1: Median and 1st and 3rd quartiles of the relative powers of each EEG characteristic band. Statistically significant differences between "Baseline" and emotions were bold typed. Asterisks (*) indicate p-values<0.01, while pounds (#) indicate p-values<0.05.

Figures:

Figure 1

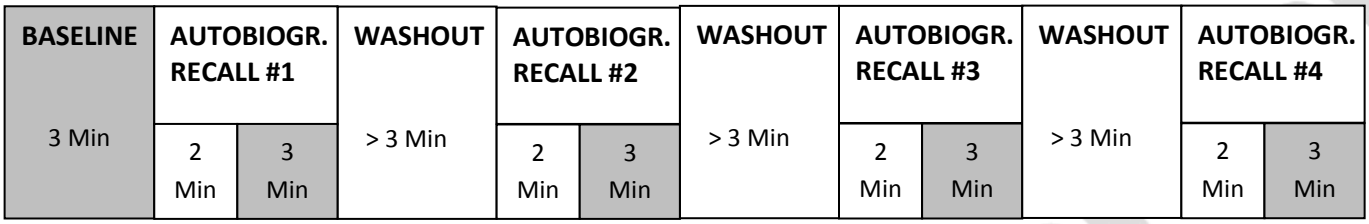


Figure 2

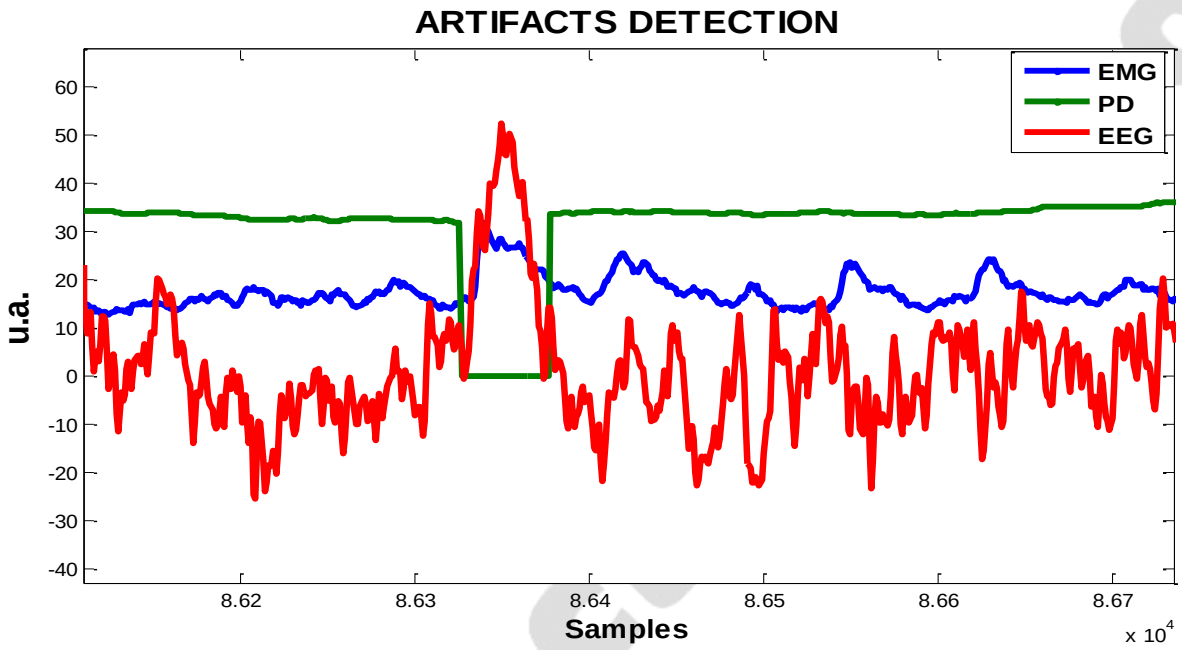


Figure 3

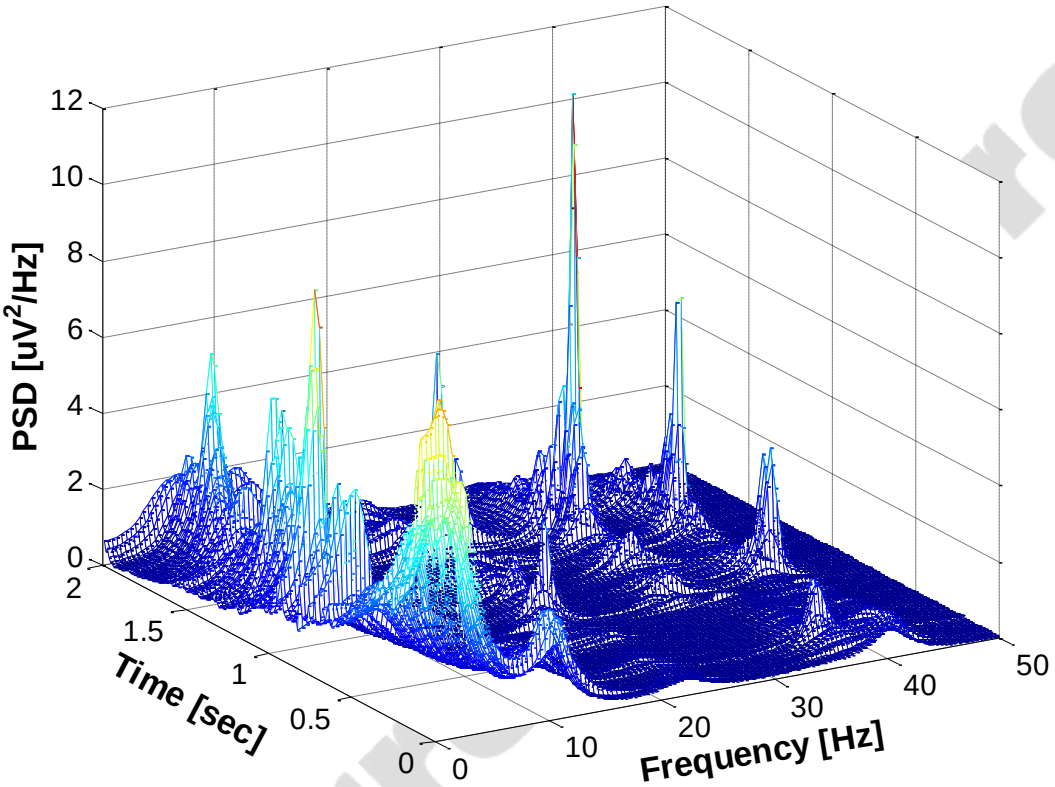


Figure 4

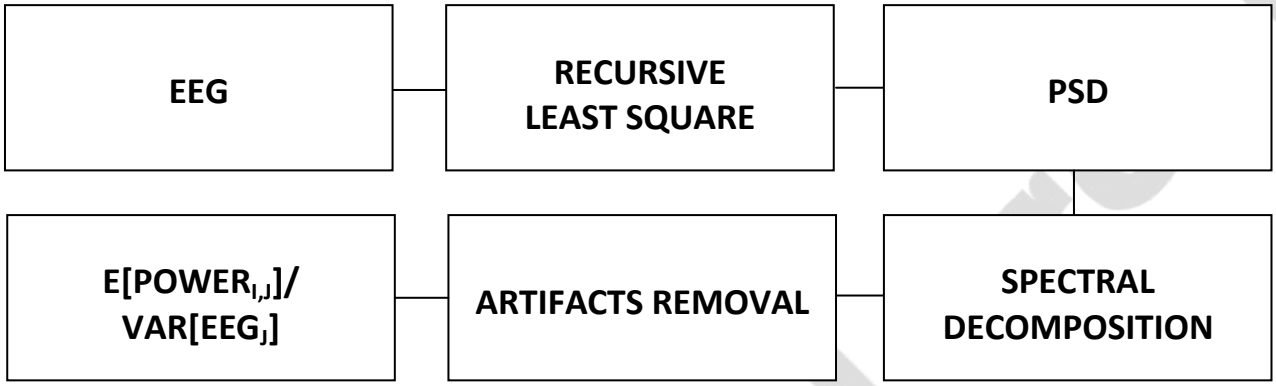


Figure 5

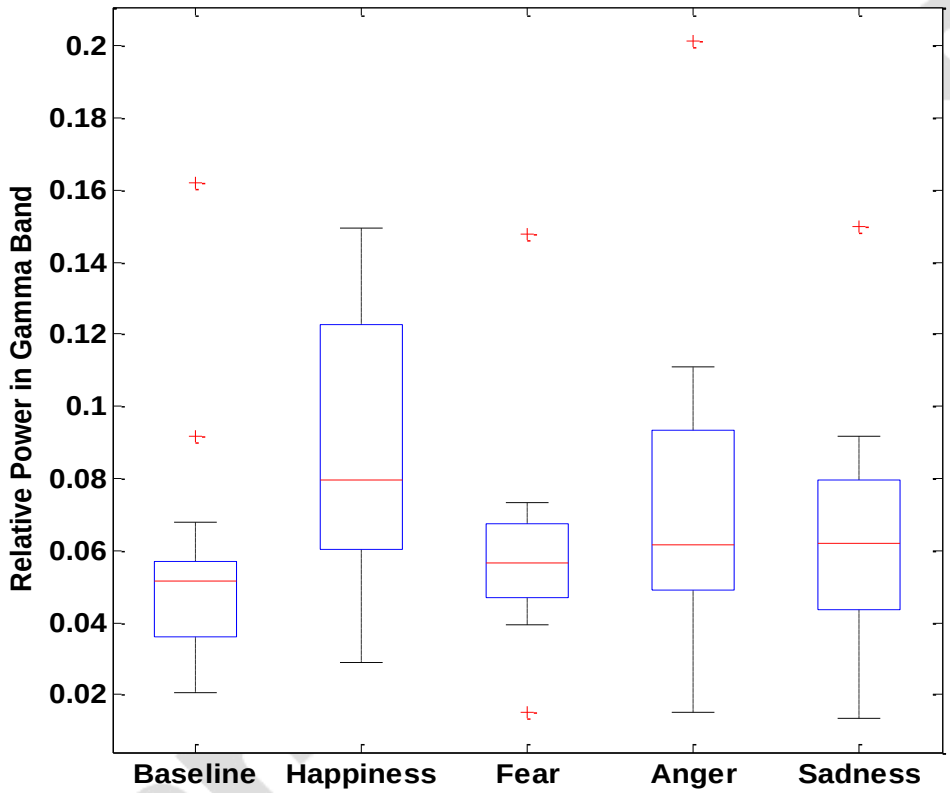


Figure 6

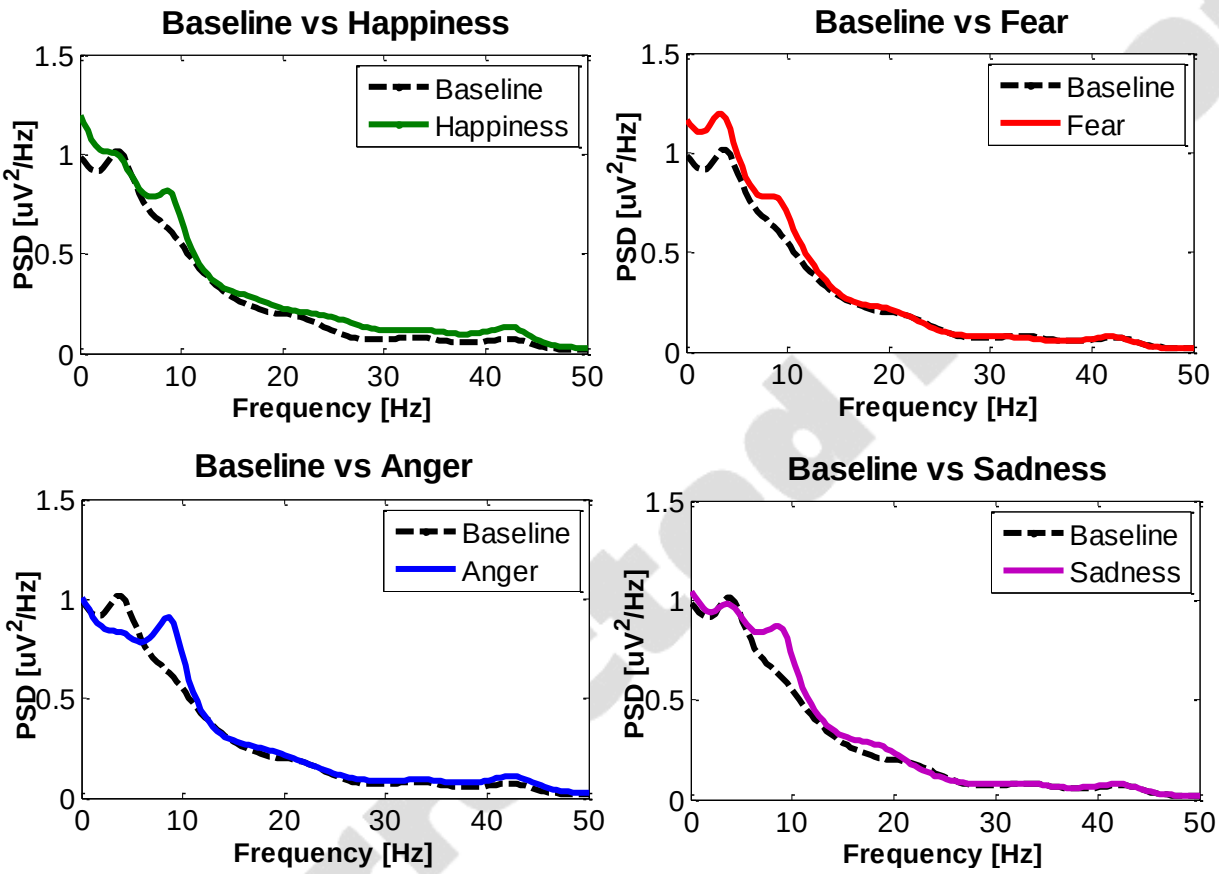
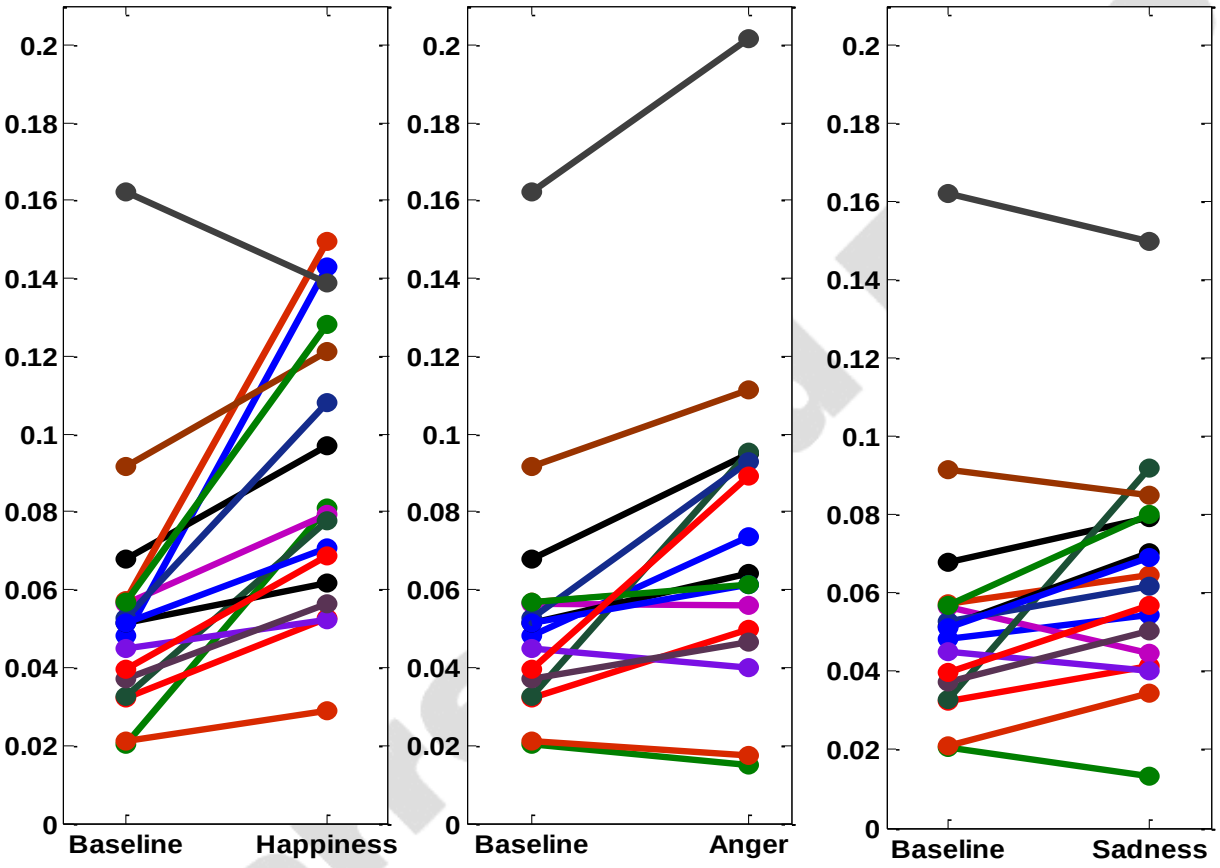


Figure 7



Tables

	Baseline	Happiness	Fear	Anger	Sadness
delta δ	0.688 (0.595,0.788)	0.671 (0.565,0.759)	0.664 (0.533,0.746)	0.618 (0.565,0.733)	0.647 (0.554,0.699)
theta θ	0.513 (0.424,0.655)	0.483 (0.421,0.589)	0.508 (0.420,0.563)	0.500 (0.435,0.545)	0.466 (0.433,0.639)
alpha α	0.433 (0.383,0.540)	0.448 (0.397,0.557)	0.465 (0.412,0.557)	0.500 (0.415,0.630)	0.511 (0.422,0.616)
beta β	0.166 (0.154,0.249)	0.175 (0.146,0.253)	0.197 (0.127,0.260)	0.204 (0.136,0.273)	0.196 (0.132,0.248)
gamma γ	0.051 (0.036,0.057)	**0.080 (0.060,0.123)** *	0.057 (0.047,0.068)	**0.061 (0.049,0.094)** *	**0.062 (0.044,0.080)** #