EEG-Based Emotion Feature Extraction Using Power Spectral Density

Minh Anh Tran
The University of Danang – University of Science and Technology
Danang, Vietnam
tmanh.8a@gmail.com

Le Hoa Nguyen*
The University of Danang – University of Science and Technology
Danang, Vietnam
ORCID: 0000-0002-3316-2394

Arjon Turnip
Department of Electrical Engineering Univesitas Padjadjaran
Jatinangor, Indonesia
turnip@unpad.ac.id

Cong Thanh Khoa Le
The University of Danang – University of Science and Technology
Danang, Vietnam
lecongthanhkhoas57@gmail.com

Nhu Quynh Luong
The University of Danang – University of Science and Technology
Danang, Vietnam
quynhluongnhu247@gmail.com

Van Buu Vo
The University of Danang – University of Science and Technology
Danang, Vietnam
buu26051990@gmail.com

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***Abstract*—Emotion recognition is an interesting area of study that has attracted much attention over the past decades. In this study, we address the problem of emotion feature extraction from electroencephalogram (EEG) signals. First, the public DREAMER dataset of EEG (i.e., experiment information, pre-processing, raw data, etc.) will be presented. Second, the detail procedure of EEG signal processing, including noise filtering, frequency band decomposition, etc., is described and finally, the power spectral density (PSD)-based feature extraction is proposed to investigate the correlation between PSD values and emotion states, and the obtained results are presented and discussed.**

***Keywords*—emotion state, electroencephalogram, feature extraction, power spectral density**

I. INTRODUCTION

Emotion is a significant psychological phenomenon in how people connect with one another. Therefore, emotion recognition is of great interest in developing brain-computer-interface (BCI) systems. It was revealed that electrical activities produced by neurons in the human's brain are correlated with emotional states. According to Rusell, human emotions can be categorized into valence and arousal [1]. Valence describes a pleasant or unpleasant feeling caused by a stimulus while arousal indicates the strength of a feeling. The range of valence is from negative to positive and that of arousal is from low to high. To fully describe emotional states, the dimensional model theory is used. Fig. 1 shows the two-dimensional model of emotion in which the values of valence dimension are set from negative to positive and the values of arousal dimension are set from low to high, to refer to the individual degree of emotional states. The origin presents the neutral emotion. This model is commonly used in many studies of human emotional states. However, other studies have also taken into account the three-dimensional model, in which, the third dimension that presents the dominance (i.e., the ability to self control emotion) is added [2].

In general, the brain signal-based emotion recognition process includes the following steps: brain data acquisition, data pre-processing, feature extraction, feature selection, and classification. To collect data from brain activity, various brain imaging techniques have been developed over the pass decades [3]. Among the brain imaging techniques mentioned above, EEG is the most widely used because of its low cost, portable, and high temporal resolution. EEG measures electrical impulses generated by the activity of neurons in the brain using various small, metal electrodes attached to the scalp.

Over the years, there have been many studies investigating the connection between emotional states and EEG signals. The obtained results reveal that emotional states can be recognized based on the features of EEG signals [2-6, 8-10,12-13]. This is particularly significant in human-machin-interaction (HMI) where emotion recognition is considered as an important part. To improve the quality of classification and thus the emotion recognition, emotional feature extraction plays a vital role. Many methods for extracting emotional features from EEG signals have been proposed throughout the years. Features are often extracted by analyzing the signal in the time or frequency domain. However, analysis in the time-frequency domain is also of interest [4]. In the study by Gao et al., emotional features extracted from STFT and wavelet transform (WT) techniques are fused to reflect time-frequency characteristics [5]. A time-frequency domain feature extraction technique called short-time Fourier transform (STFT) was used to obtain the power spectral of EEG signals for a specific frequency band within a time-varying window. This technique provides a good presentation of emotional features in both frequency and time domain [6]. Power spectral density (PSD) is also a common method that is widely used for feature extraction from EEG signals [2]. A review of current methods proposed for emotional feature extraction and classification from EEG signal was conducted by the authors in [4].

In the current study, we propose to use the PSD values calculated from EEG signals to extract features of two different emotional states, namely happiness and sadness. The DREAMER EEG dataset recorded from audio-visual triggered participants was used for analysis [2]. Topographic images of PSD distribution in different frequency bands (theta, alpha, beta) are constructed to clearly show the correlation between the PSD values and the emotional states at different areas of the brain.

This paper is structured as follows: In Section II, the information of the public DREAMER dataset is presented. Section III describes the EEG signal processing where the PSD values are calculated. Discussions and conclusions are given in Section IV.

II. DREAMER EEG DATASET [2]

The DREAMER dataset provides EEG signals that recorded from 23 participants (14 male and 9 female). Each participant was asked to watch 18 film clips to express their emotional reactions. These film clips were proposed by

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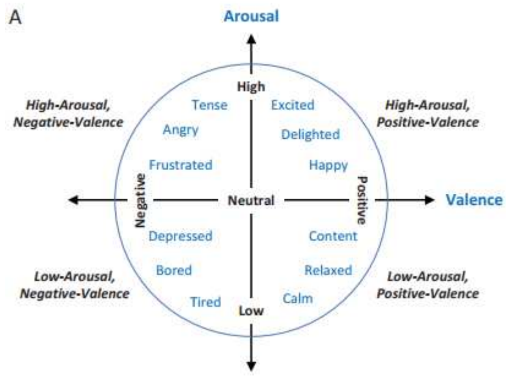

Fig.1. Two-dimensional model of emotion was proposed by Russel [1].

Gabert-Quillen et al. [7] that contain 9 emotional states (i.e., amusement, excitement, happiness, calmness, anger, disgust, fear, surprise, and sadness). Each film clip is 65 to 395 seconds long. However, to avoid duplication in emotional states, only recorded data for the last 60 seconds were used. In this expermiment, the EEG signals were acquired by using the Emotive EPOC system (128 Hz sampling rate, 14 channels, and 2 references). The detailed experiment is summarized as shown in Table 1. The EEG electrodes were placed in the head locations, as illustrated in Fig. 2. The DREAMER dataset is formatted in the form "DREAMER.mat" file in Matlab, which contains the following information: data (1x23 cell), sampling rate (128Hz), electrode locations, disclaimer, and others. The DREAMER dataset is made publicly available at http://zenodo.org.

III. EMOTION FEATURE EXTRACTION

A. Signal processing

The procedure for emotion feature extraction is proposed as shown in Fig. 3.

TABLE I. EXPERIMENT INFORMATION OF DREAMER DATASET [2]

Audio-visual stimuli	
Number of videos	18
Video content	Audio-Video
Video duration	65-393 s (mean = 199 s)
Experiment information	
Number of participants	23
Number of males/females	14/9
Age of participants	22-33 (mean = 26.6)
Rating scales	Arousal, Valence, Dominance
Recorded signals	14-channel, 128Hz

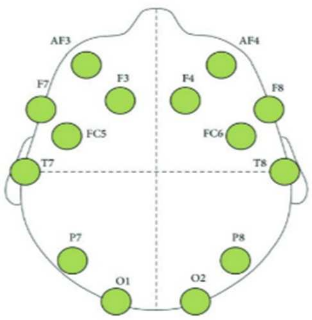

Fig. 1. The 10-20 topology for 14 EEG electrodes placement.

The procedure includes denoising, band decomposition, and feature extraction. An EEG signal is a small electrical signal with a magnitude ranging from tens to hundreds of microvolts that contains both noise and signals produced by the brain. This noise is caused by eyeball movement, heart activity (< 4 Hz), muscle contraction (> 30 Hz), and power line inteference (50 Hz or 60 Hz). However, as reported in [8] that the frequency band that carries information about emotional states was found in the range of 4-30 Hz. To remove noises, a bandpass filter with two cutoff frequencies of 4Hz and 30Hz was used. The filtered EEG signal may contain many frequency components, as depicted in Fig. 4. However, the common brain wave frequency bands of interest include delta wave (1-4 Hz), theta wave (4-7.4 Hz), alpha wave (7.5-13.5 Hz), beta wave (13.6-30 Hz), and gamma wave (30 – 50 Hz). These frequency bands carry different information about brain activity. It has been reported from previous studies that the correlation between different emotional states and frequency bands is different [9-10]. For example, the authors in [10] showed that EEG signals in the high frequency bands are more associated with positive emotions than negative ones. Therefore, in this study, the filtered EEG signals were then decomposed into theta, alpha, and beta sub-bands using the corresponding bandpass filters. The waveforms of theta, alpha, and beta rhythms are shown in Fig. 5. In addition, to clearly show the variations of induced responses generated by the human cortex that correspond to sub-bands of theta, alpha, and beta rhythms, the following constituents were used for further analysis

- Theta1 ($\theta 1$): 4–5.8 Hz, Theta2 ($\theta 2$): 5.9–7.4 Hz,
- Alpha1 ($\alpha 1$): 7.5–9.4 Hz, Alpha2 ($\alpha 2$): 9.5–10.7 Hz, Alpha3 ($\alpha 3$): 10.8–13.5 Hz,
- Beta1 ($\beta 1$): 13.6–25 Hz, Beta2 ($\beta 2$): 25.1–30 Hz.

B. PSD calculation for feature extraction

Power spectral density (PSD) is a common signal processing technique that describes the distribution of signal power over frequency. In other words, PSD shows the strength of the energy of the signal as a function of frequency. PSD values can be used to evaluate the action of wave bands when the volunteers watched the stimuli film clips. To estimate the PSD value of the sampled EEG signal, the Welch method was applied [11]. The procedure is described as follows:

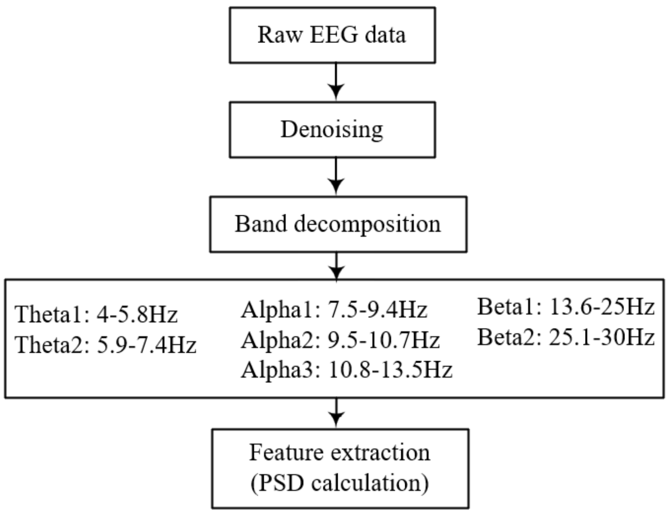

Fig. 3. The procedure of EEG feature extraction.

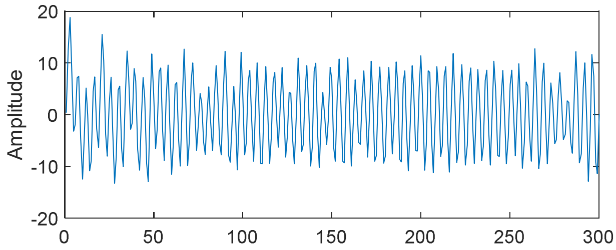

Fig. 4. A sample of EEG signal after denoising.

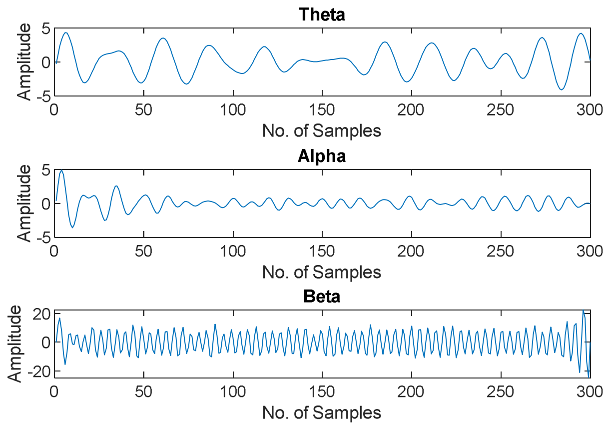

Fig. 5. Theta, alpha, and beta EEG signal waveforms, respectively, after band decomposition.

- The sampled EEG signal $x(k)$, $k = 0,1,2,\cdots,N-1$, is divided into L overlapping segments (an overlap of 50% is applied). The data of the lth segment is denoted as $x_l(n)$, where $n = 0,1,2,\cdots,\frac{l-1}{N/2}$ and $l = 1,2,\cdots,L$.
- The specified window function $w(n)$ is applied to each segment.
- Calculate the fast Fourier transform for each windowed segment as

$$A_l(\omega) = \sum_{n=0}^{N-1} x_l(n) w(n) e^{-j\omega k}, \quad \omega = \frac{2\pi}{N} n.. \tag{1}$$

- Calculate the PSD value for each windowed segment as

$$P_l(\omega) = \frac{1}{NU} \left| A_l(\omega) \right|^2, \tag{2}$$

where U denotes the normalization of the power of the window $w(n)$, i.e.,

$$U = \frac{1}{N} \sum_{n=0}^{N-1} \left| w(n) \right|^2 . \tag{3}$$

- Finally, the Welch estimate of PSD is obtained by the evarage of these $P_l(\omega)$, $l = 1,2,\cdots,L$, i.e.,

$$P_w(\omega) = \frac{1}{L} \sum_{l=1}^{L-1} P_l(\omega) . \tag{4}$$

PSD values of EEG signals recorded from 14 channels for each frequency sub-bands (i.e., theta1, theta2, alpha1, alpha2, alpha3, beta1, beta2) are calculated.

In this study, to find correlations between PSDs of EEG signals in different sub-bands with the affective state of humans, we focus our analysis on two opposite emotional states that are happy state and sad state. According to the emotion model depicted in Fig. 1, these two emotional states are high valence and low valence, respectively. Therefore, only EEG signals generated by happy and sad film clips were used for analysis. To this end, the average PSD value of each frequency sub-band at each channel is calculated as follows (an example of theta1 sub-band at channel AF3 is used to illustrate).

$$PSD_{\theta_1}^{AF3}(i) = \frac{1}{n} \sum_{j=1}^{n} PSD_{\theta_1}^{AF3}(i)(j) \tag{5}$$

$$PSD_{\theta_1}^{AF3} = \frac{1}{N} \sum_{i=1}^{N} PSD_{\theta_1}^{AF3}(i) \tag{6}$$

where i index indicates the subject ith, and j index indicates the jth happy (or sad) stimuli (i.e., happy or sad film clips).

IV. RESULTS AND DISCUSSIONS

The average values of the PSD of each frequency sub-band at each channel are summarized in Table 2, where significant values of PSD (PSD $\geq$ 0.15) are bolded. The threshold value of PSD = 0.15 was chosen to distinguish between low correlation and high correlation levels. Furthermore, to visualize the correlations between emotional states and PSD values at different locations in the human brain, topographical head heat maps were constructed, as shown in Fig. 6. In these maps, the color bar presents the PSD ranging from the smallest to the highest values. The obtained results (in Table 2 and Fig. 6) show that:

- Strong correlations were observed between valence (two emotional states) and EEG signals at all frequency sub-bands. This finding was also documented in the work of Koelstra et al. [12].
- Theta 1, alpha3, and beta1 sub-bands carry more information for both the happy state (high valence) and the sad state (low valence) than theta2, alpha1, alpha2, and beta2 sub-bands. This finding is consistent with the work of Chernykh et al. [13].
- In high and low valence (happy state and sad state respectively), neurons in the brain were found to be more active (high value of PSD) at channels AF3, T7, O1, O2, P8, T8, FC6, F4, F8, and AF4.
- For most frequency sub-bands, the PSD values of the happy state are larger than those of the sad state. This means that the correlation between the PSD value and EEG signals at high valence is more significant than that at low valence.

V. CONCLUSION

The current study proposes the use of the power spectral density technique to extract emotional features from EEG signals. The public DREAMER dataset containing EEG signals recorded from 23 participants was used for the analysis. The signal processing procedure, including noise filtering and frequency band decomposition, was applied before calculating the PSD value. The obtained results clearly show that there is a strong correlation between emotional states (i.e., happy, and sad) and the PSD value of the EEG signals. In addition, all frequency sub-bands of EEG signals correlate with emotional states at different levels. Therefore, PSD-based features can be applied for further analysis to detect human emotion through EEG signals.

TABLE II. THE AVERAGE VALUES OF PSD CALCULATED FROM DIFFERENT FREQUENCY SUB-BANDS OF EEG SIGNALS AT ALL CHANNELS

EMOTION	WAVE	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
	THETA1	**0.39**	0.14	0.13	0.09	0.07	0.07	**0.41**	**0.15**	**0.16**	**0.29**	**0.3**	**0.25**	**0.43**	**0.42**
	THETA2	**0.17**	0.07	0.06	0.04	0.04	0.03	**0.3**	0.08	0.09	0.12	0.14	0.13	**0.28**	**0.25**
	ALPHA1	0.14	0.06	0.07	0.04	0.05	0.03	0.03	0.1	0.12	0.14	0.14	0.13	**0.22**	**0.18**
HAPPY	**ALPHA2**	0.07	0.03	0.05	0.02	0.04	0.02	0.014	0.08	0.11	0.12	0.1	0.1	0.14	0.1
	ALPHA3	0.12	0.07	0.07	0.05	0.09	0.03	**0.27**	**0.15**	**0.17**	**0.23**	**0.17**	**0.16**	**0.22**	0.11
	BETA1	**0.15**	0.09	0.1	0.11	**0.48**	0.05	**0.33**	**0.18**	**0.21**	**0.4**	**0.24**	**0.2**	**0.3**	**0.2**
	BETA2	0.05	0.03	0.03	0.06	**0.27**	0.02	0.08	0.06	0.07	**0.18**	0.1	0.07	0.11	0.06
	THETA1	**0.26**	0.12	0.07	0.06	0.07	0.04	**0.17**	0.13	**0.16**	**0.16**	**0.2**	**0.27**	**0.3**	**0.35**
	THETA2	0.1	0.05	0.04	0.03	0.04	0.02	0.09	0.09	0.1	0.11	0.1	0.13	**0.17**	**0.19**
	ALPHA1	0.08	0.05	0.04	0.03	0.04	0.03	0.08	0.09	0.11	0.12	0.11	0.12	**0.15**	0.14
SAD	**ALPHA2**	0.05	0.03	0.04	0.02	0.03	0.02	0.05	0.07	0.08	0.11	0.09	0.1	0.1	0.09
	ALPHA3	0.11	0.06	0.07	0.04	0.07	0.03	0.09	**0.15**	**0.16**	**0.2**	**0.15**	**0.17**	**0.18**	**0.17**
	BETA1	**0.21**	0.12	0.1	0.08	0.2	0.09	0.13	**0.16**	**0.21**	**0.33**	**0.22**	**0.2**	**0.26**	**0.28**
	BETA2	0.1	0.04	0.02	0.03	0.1	0.04	0.04	0.04	0.06	0.11	0.07	0.06	0.08	0.09

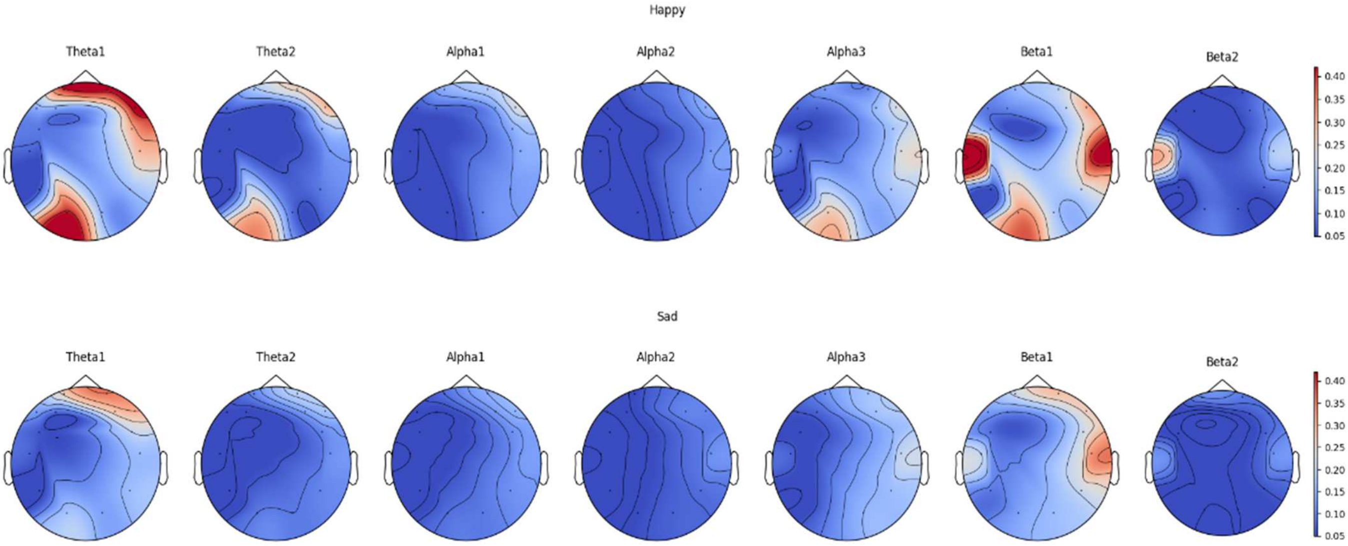

Fig. 6. Topographical head heat maps showing the distribution of PSD values for different emotion states.

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