Real-time EEG-based User's Valence Monitoring

Zirui Lan †, Yisi Liu †, Olga Sourina †, Lipo Wang ‡
† Fruanhofer IDM@NTU, Nanyang Technological University, Singapore
‡ School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore
(LanZ0001|LiuYS|EOSourina|ELPWang)@ntu.edu.sg

***Abstract*—An integration of real-time EEG-based human emotion recognition algorithms in brain-computer interfaces can make the user's experience more complete, more engaging, less emotionally stressful or more stressful depending on the target of the application. Valence component of emotion, level of pleasantness, is one of the most important criteria of online assessment of social processes from brain signals. Currently, EEG-based emotion recognition algorithms usually allow recognition of two to three levels of valence. In this paper, we propose a novel real-time subject-dependent algorithm that allows recognizing four levels of valence having the short sessions of calibration. The algorithm uses fractal dimension thresholds and adopts weighted average voting strategy. The proposed algorithm has a great potential to be used to monitor emotions during human-computer interaction.**

***Keywords*—EEG; emotion recognition; valence recognition; affective BCI; fractal dimension**

I. Introduction

Affective Brain-Computer Interfaces (BCI) can be adapted to the user's internal feelings and can be driven by the user's emotions. The recognized emotions of the user can help make the user's experience more complete, more engaging, and less emotionally stressful or more stressful depending on the target of the application. It is useful to implement affective interfaces in many applications such as 1) social networks where emotional companion can be created to cheer up the user if the negative emotion is detected and/or the level of the user's "pleasantness" can be monitored towards different events, 2) games where the flow can be changed according to the recognized emotions, 3) medical applications to monitor emotions of the patient who cannot express emotions, 4) neuro-marketing to adapt advertisement by evoking the targeted emotions on the audience in real-time, etc.

Various methods have been proposed to model human emotions [1-4]. Among them, the Valence-Arousal-Dominance (VAD) dimensional model was the most commonly used one. The three dimensional model proposed to break down an emotion into three dimensions: valence, arousal and dominance, each of which measures a characteristic nature of the emotion. The valence reveals the pleasantness-unpleasantness nature of the emotion. The arousal reveals the autonomic activation of the emotion, from deactivated to activated. The dominance reveals the controlling-submissive trait of the emotion. In [5], it was demonstrated that valence is the first principal component that accounts for the most variance in ratings of emotional experience. It can be said that valence determines the keynote of an emotion: positive or negative.

Attempting to differentiate different valence levels from EEG (Electroencephalogram) signals, Schaaff [6] employed absolute values of STFT (Short Time Fourier Transform) amplitude derived from 16 channels as feature and SVM as classifier to classify three valence levels. The reported accuracy was 62.07%. In [7], Schaaff reduced the number of channels to 4, but the accuracy also dropped to 47.11% for recognizing three valence levels. In [8], Brown et al. used alpha power ratio between F3 and F4 as feature and KNN as classifier. The accuracies were 85% and 64% for two valence level and three valence level recognition respectively. In [9], Chanel et al. adopted mutual information and power features derived from 64 channels and SVM classifier to discriminate emotions of three valence levels. They reported the best accuracy as 63%. In [10], Sohaib et al. extracted statistical features from 6 channels and adopted SVM as classifier to classify three valence levels. The reported accuracy was 56.10%. In [11], Liu et al. proposed to use fractal dimension value from 28 channels and differentiate four valence levels by thresholding. The accuracy was 51.49%. However, one must take note to compare these results, as they were obtained under different experiment settings (e.g., different subjects, preprocessing, feature, channels, classifiers etc.).

The asymmetry pattern of the brain has been associated with the valence level one is experiencing. In [12, 13], Trainor and Schmidt demonstrated that the asymmetry pattern of frontal activities were associated with valence perception. Positive emotions (joy and happiness) triggered greater left frontal alpha activities, while negative emotions (fear and sadness) provoked greater right alpha activities. This asymmetry pattern was also steadily reported in [14-18].

In this paper, based on the asymmetry pattern we propose a valence levels recognition algorithm that can be used to personalize in real-time different applications according to the user's current emotions. The algorithm combines use of fractal threshold proposed in [11] and adopts different voting strategies. The algorithm requires less training data: only two EEG trials are needed for training (to find thresholds), comparing to traditional machine learning algorithms using classifiers where the number of training trials must be equal to the number of valence levels to be differentiated. The performance of the new algorithm to recognize four valence levels is compared with the algorithm using SVM classifier on the benchmark DEAP database [19].

II. METHODS

A. Experimental EEG Database: DEAP Database

The DEAP database (Database for Emotion Analysis using Physiological signals) [19] is a publicly available affective database developed by Koelstra et al. This database contains multimodal physiological data collected from 32 subjects during their emotional moments, whose emotions were induced by watching 40 one-minute long music videos. The collected physiological data include 32-channel EEG, 4-channel EOG (Electrooculogram), 4-channel EMG (Electromyogram), respiration, plethysmograph, temperature and facial expression videos. After the presentation of affective stimuli, subjects were required to rate the valence, arousal, dominance level etc. based on the VAD emotion model. Such ratings would be used to assess the true emotions that subjects were experiencing during exposure to affective stimuli

In our experiment, we investigate the EEG data from DEAP database. Considering that the emotion model consists of three dimensions, when we examine the valence dimension only, the other two dimensions should be kept invariant. However, due to the limited amount of data in DEAP database, it is impracticable to find EEG trials that vary in valence levels but share absolutely the same arousal and dominance levels. Therefore, relaxation has been placed to the control of arousal and dominance levels. We consider arousal ratings greater than 5 as high arousal, smaller than 5 as low arousal, and dominance ratings greater than 5 as high dominance and smaller than 5 as low dominance. Thus, the arousal and dominance are under high/low control, and there are four combinations: high arousal high dominance (HAHD), high arousal low dominance (HALD), low arousal high dominance (LAHD) and low arousal low dominance (LALD). We looked in DEAP database for EEG trials that vary in valence levels while controlling the arousal and dominance level to be one of these four combinations (HAHD/HALD/LAHD/LALD). Additionally, we only consider EEG trials with at least four different valence levels under controlled arousal and dominance level. Four valence levels are partitioned as follows: if the rounded valence rating falls in 1 and 2, it is considered as the valence level 1; 3 and 4 are considered as the valence level 2; 5 and 6 are considered as the valence level 3; 7, 8 and 9 are considered as the valence level 4. The valence levels and their adjective interpretation are presented in Table I.

Following the abovementioned selection criteria, 22 subjects were screened out, leaving only 10 subjects with enough EEG trails suitable for our experiment. For each selected subject, one EEG trial is chosen from each of the four valence levels. In the case when there were more than one trials falling in the same valence level available, we randomly selected one trial from all available trials.

TABLE I. PARTITIONS OF VALENCE LEVELS.

Valence Level	Ratings	Interpretation
Level 1	1, 2	Very unpleasant
Level 2	3, 4	Unpleasant
Level 3	5, 6	Pleasant
Level 4	7, 8, 9	Very pleasant

B. EEG Data Preprocessing

The developers of DEAP database have preprocessed the EEG data for better usability. The EEG signals were down-sampled to 128 Hz and truncated to be 8064 points in length (equal to 63 seconds). Additionally, we applied a 2-42 Hz band-pass filter on the EEG data to remove artifacts (e.g. noise introduced by neck movement, ocular movement etc.), since it is reported that major EEG components lie within this bandwidth [20].

C. Feature Extraction

It is shown in literature that valence level is associated with the asymmetry pattern of the brain [12-18]. The asymmetry pattern refers to the observation that left hemisphere of the brain is more activated during exposure to positive affective stimuli, whereas right hemisphere of the brain is more dominant in processing negative affective stimuli. When certain part of the brain is more active, the EEG it generates is expected to be more complex. Fractal dimension (FD) is the feature that measures the complexity of signals. In order to measure the difference of activity level between left and right hemisphere, Liu et al. proposed to use difference of FD (ΔFD) as feature [11]. The superiority of FD feature over other features such as statistical feature and power feature has also been justified in [11].

The DEAP database provides EEG data recorded from 32 channels, 14 of which were from Left Hemisphere (LH = {FP1, AF3, F3, F7, FC5, FC1, C3, T7, CP5, CP1, P3, P7, PO3, O1}), 14 from Right Hemisphere (RH = {FP2, AF4, F4, F8, FC6, FC2, C4, T8, CP6, CP2, P4, P8, PO4, O2}), and 4 from MidLine (ML = {Oz, Pz, Fz, Cz}).

In order to compute ΔFD, firstly the Higuchi FD values [21] FD_{left} from 14 left-hemispheric channels and FD_{right} from 14 right-hemispheric channels are computed with a sliding window of size 512 and step size 1 (move forward 1 sample point at each step).

Secondly, subtract FD_{right} from FD_{left} for all left-hemispheric channels and right-hemispheric channels:

$$\Delta FD = FD_{left} - FD_{right}, \forall left \in LH, \forall right \in RH. \quad (1)$$

Thirdly, apply simple moving average (SMA) function with window size 128 and step size 128 on (1).

D. Linear Correlation between Valence Levels and ΔFD

In order to justify the use of thresholds to discriminate different valence levels, the correlation between feature parameters and valence levels has been investigated. The Pearson's correlation coefficient was adopted to quantify the linear correlation between feature parameters ΔFD and valence level.

E. Threshold-based Valence Recognition Algorithm

The algorithm takes the maximal and minimal ΔFD values, and equally divides the range between max ΔFD and min ΔFD to determine the thresholds. Therefore, the algorithm requires only two EEG trials for training: the EEG trials from valence level 1 and valence level 4. To allow for individual difference in asymmetry pattern, max ΔFD and min ΔFD could either be taken from level 1's trial and level 4's trial respectively, if proportionality holds, or be taken from level 4's trial and level 1's trial respectively, if inverse proportionality holds. When new and unseen EEG data come, the algorithm computes the ΔFD (as introduced in Section II.C) from new EEG data and compares the ΔFD value with predefined thresholds to determine the valence level associated with the testing data.

F. Fusion of Recognized Valence Levels

It has to be pointed out that there are 14 channels from left hemisphere and 14 channels from right hemisphere in the DEAP EEG database, therefore when computing the ΔFD between left and right hemisphere according to (1), totally 196 ΔFDs would be obtained, from 196 different channel pairs (e.g. $\Delta FD_{FP1\text{-}FP2}$, $\Delta FD_{FP1\text{-}AF4}$, …, $\Delta FD_{O1\text{-}O2}$). However, the algorithm proposed in [11] did not specify which channel pair to use for the calculation of ΔFD . Therefore, here we propose a novel algorithm with fixed channels employing two fusion strategies so that the new algorithm can be more feasible towards real-time use.

Studies have revealed that the emotion perception in human brain requires coordination between different brain regions. The main lobes involved in emotion perception include frontal lobes [22, 23], temporal lobes [24] and parietal lobes [23, 25]. It is reasonable that channels over these lobes are expected to contain more information relevant to emotion processing. Therefore, channels over these brain regions shall be involved in our algorithm. The selected channels are $LH' = \{AF3, F3, F7, T7, P3, P7\}$ from left hemisphere, and $RH' = \{AF4, F4, F8, T8, P4, P8\}$ from right hemisphere, resulting in 36 channel pairs leading to 36 ΔFDs : $\Delta FD_{AF3\text{-}AF4}$, $\Delta FD_{AF3\text{-}F4}$, …, $\Delta FD_{FP1\text{-}FP2}$, $\Delta FD_{P7\text{-}P8}$. Since each of these ΔFDs can give a recognized valence level, in order to fuse the recognized results from 36 ΔFDs , we propose to adopt two voting strategies: (1) max vote, and (2) weighted average vote. By max vote strategy, the recognized valence level is determined by the class that has the most votes from 36 voters, whereas the weighted average vote strategy assigns to the recognized valence level the arithmetic mean of classes weighted by their votes.

Define $C(x)$ the function that counts the votes for each valence level, where argument $x \in \{1,2,3,4\}$ is the valence level, $C(x)$ gives the vote counts of valence level x and $\sum_{x=1}^{4} C(x) = 36$. Mathematically, the max vote strategy can be formulated as:

$$L = \arg\max_{x} C(x). \tag{2}$$

where L is the recognized valence level.

The weighted average strategy can be formulated as:

$$L = \frac{\sum_{x=1}^{4} xC(x)}{\sum_{x=1}^{4} C(x)}. \tag{3}$$

For (3), fraction number may be obtained. In such cases, rounded L value can be used.

III. RESULT AND DISCUSSION

The linear correlation coefficients between ΔFD and valence levels for selected subjects are listed in Table II. The reported coefficients were the highest one for each subject. Also shown in Table II are the p values that indicate the significance level. The asterisk mark (*) under column "p values" indicates p<0.05, suggesting significant linear relationship.

As can be seen in Table II, linear correlations do exist between valence levels and feature ΔFD for these subjects, and the p values suggest that significant linearity be assured. The linear correlation justifies the use of threshold to discriminate different valence levels. It can be seen that for some subjects (e.g. subject 1, 13, 19 etc.), ΔFD is proportional to valence levels, while for other subjects (e.g. subject 5, 10, 14 etc.) inverse proportionality holds. If proportionality holds, that is to say ΔFD will increase when valence level increases. Since ΔFD is the difference between FD values from left and right hemisphere, an increasing ΔFD value indicates the activity difference between left and right hemisphere is increasing: left hemisphere is more activated than right hemisphere. This result is in consistence with the findings in [12-18]. The inverse proportionality between ΔFD and valence levels leads to an opposite conclusion: right hemisphere is more dominating than left hemisphere. This is not disproving the asymmetry pattern, as it was reported in [26, 27], while for most of the subjects left hemisphere was the dominating hemisphere in perceiving positive emotions, individual difference existed and for some other subjects, right hemisphere was observed to be more stimulated in perceiving positive emotions.

TABLE II. PEARSON'S CORRELATION COEFFICIENTS BETWEEN ΔFD AND VALENCE LEVELS.

Subject ID	Controlled Arousal Dominance Condition	*r* value	*p* values
1	HAHD	0.6168	1.30*e*-23*
5	HAHD	-0.5010	7.12*e*-15*
	LALD	-0.4892	3.73*e*-14*
7	HALD	0.5497	3.91*e*-18*
	LALD	-0.4493	6.24*e*-12*
10	HAHD	-0.6027	2.36*e*-22*
13	HALD	0.5320	6.84*e*-17*
14	HAHD	-0.5826	1.16*e*-20*
16	HALD	-0.6784	6.19*e*-30*
19	HAHD	0.4999	8.37*e*-15*
	LALD	0.6582	1.06*e*-27*
20	HAHD	-0.5928	1.66*e*-21*
	HALD	-0.3957	2.34*e*-09*
22	HAHD	-0.3492	1.79*e*-07*
	LAHD	0.3980	1.85*e*-09*

The best accuracies recognizing four valence levels obtained by threshold-based algorithm are listed in Table III under "accuracy" column, which shows the best accuracies achievable from one of the 196 channel pairs (since there are 14 channels over left hemisphere and 14 channels over right hemisphere in DEAP EEG database, producing 196 left-right channel pairs in a pairwise fashion). The "channel pair" column lists the channel pair that scored the best accuracy for each subject. In Table IV, the accuracies recognizing four valence levels by employing different fusion strategies are contrasted against those obtained by SVM. For the SVM classifier, polynomial kernel was chosen and the *g*, *d*, *r*, *c* parameters were set to 1, 5, 1 and 1 respectively, given by a grid search approach. Five-fold cross validation (4 folds for training, 1 fold for testing) was applied to four valence EEG trials to examine the accuracies, and the average accuracy across 5 runs for each subject is reported.

As can be seen in Table III, the threshold-based algorithm can achieve the best average accuracy 56.72%, which is better than all average accuracies reported in Table IV. However, it can also be seen from the third column in Table III that for different subjects, the best accuracy is obtained from different channel pairs. Therefore, it is impossible to single out one channel pair from which the valence level can be recognized while maintaining the best accuracy. Furthermore, in order to find out the channel pair that scores the best accuracy, four EEG trials from four valence levels are required, but only two EEG trails are available for training. That is to say, given only two EEG trials' training data, it is impracticable to determine which channel pair shall be used for the best accuracy performance. This is the main reason why we propose to fix the channel pairs with fusion method. Take a further look at the channel pairs, it can be found that channels from our selected channel sets LH' and RH' frequently appear in the channel pairs that score the best accuracies (e.g., P3, P7, P8, AF3, AF4, F4, F7, T7, T8 etc.). This justifies our choice of the channel sets, and again demonstrates that main lobes involved in emotion perception include frontal lobes, temporal lobes and parietal lobes, consistent with findings in [22-25].

The performance of the threshold-based valence recognition algorithms employing different fusion strategies proposed in this paper is given in Table IV. In order to examine the effect of the proposed channel selection, the accuracies obtained from selected channels are contrasted against those obtained from all channels. From selected channels, the threshold-based algorithm employing weighted average voting strategy performs the best: achieving 79.31% max accuracy and 49.40% average accuracy. From all channels, the SVM-based algorithm outperforms the other two: achieving 78.33% max accuracy and 55.38% mean accuracy. However, to train the SVM classifier, the number of classes contained in the training data should be equal to the number of classes to be recognized. That is, we must provide four EEG trials of four different valence levels as training data. It has to be pointed out that for valence level recognition, it is important to reduce training data, as the acquisition of training data can be challenging. It is easier to induce different emotions (e.g., happy, frightened, angry, sad etc.), but it is difficult to induce different valence intensity (e.g., pleasant, a little pleasant, very pleasant etc.) in the subject. Considering that threshold-based algorithm requires only two EEG trials of max and min valence levels, SVM in this sense is inferior to the threshold-based algorithm.

It can also be seen from Table IV that, for the SVM-based algorithm and the threshold-based algorithm employing max vote, the accuracies can be improved when all channels are utilized, whereas for threshold-based algorithm employing weighted average vote, the accuracy slightly drops. This suggests that the proposed channel sets LH' and RH' could be used with confidence on the weighted average vote strategy. The proposed threshold-based valence level recognition algorithm with voting strategy is superior to SVM-based algorithm for its simplicity, less demands for training data, smaller feature dimensionality and better efficiency. At the same time, this algorithm avoids the two problems that achieving the best accuracy would face: the channel pair that scores the best accuracy varies from person to person, and the best channel pair is not knowable beforehand given only two EEG trials as training data. The valence level recognition algorithm with weighted average vote strategy is an acceptable compromise between accuracy, real-time feasibility, simplicity, feature dimensionality, and demands for training data.

IV. CONCLUSION

The proposed algorithm in this paper can recognize four valence levels. We used difference of FD values between left and right hemispheres to measure the asymmetry pattern of the

TABLE III. ACCURACIES OF THRESHOLD-BASED VALENCE RECOGNITION ALGORITHM

Subject ID	Accuracy	Channel pair
1	51.72	P7-T8
5	59.49	CP1-C4,O1-P8
7	59.92	O1-AF4,AF3-AF4
10	59.48	T7-T8
13	53.45	C3-F4
14	53.45	C3-FC2
16	68.10	PO3-AF4
19	55.60	PO3-CP2,O1-T8,O1-C4
20	49.14	O1-FC2,FC5-FP2,CP5-FP2
22	56.90	P3-CP6,F7-CP6
Average	56.72	N/A

TABLE IV. COMPARISON OF ACCURACIES BY DIFFERENT VOTING STRATEGIES AND SVM-BASED ALGORITHMS

Subject ID	From Selected Channels			From All Channels		
	Thresholding			*Thresholding*		
	Max Vote	*Weighted Average Vote*	*SVM*	*Max Vote*	*Weighted Average Vote*	*SVM*
1	28.45	47.41	48.33	35.34	50.00	59.17
5	29.74	48.28	50.83	30.60	43.53	57.92
7	37.07	41.38	42.50	44.40	47.41	54.59
10	25.86	74.14	51.67	34.48	73.28	74.17
13	33.62	46.55	32.50	38.79	44.83	34.17
14	25.86	39.66	34.17	27.59	44.83	56.67
16	45.69	79.31	32.50	53.45	77.59	45.00
19	21.98	47.42	72.08	27.16	40.95	78.33
20	23.28	29.75	48.33	28.02	31.90	58.75
22	27.16	40.09	29.17	29.74	37.93	35.00
Average	29.87	49.40	44.21	34.96	49.22	55.38

brain, which has been associated with the valence level one is experiencing. The linear correlation between ΔFD and different valence levels was established on the benchmark DEAP EEG database. We proposed to use two voting strategies from fixed channel pairs to fuse the recognized valence levels. By employing weighted average voting strategy on 12 selected channels constituting 36 channel pairs, we obtained max accuracy 79.31% and mean accuracy 49.40% for four valence levels recognition. The threshold-based valence level recognition algorithm has the following advantages. Firstly, the number of training trials required to train the algorithm (in the sense of finding thresholds) is fixed: only two trials are needed, one highest valence level and the other lowest. Whereas for the classifier-based algorithm, the number of training trials should be equal to the number of different valence levels we need to differentiate. Secondly, the number of valence levels to be recognized between max-min valence levels can theoretically be an arbitrary number for the threshold-based algorithm. Thirdly, the threshold-based algorithm runs much faster than a classifier-based algorithm, both in training an in testing. The proposed threshold-based valence level recognition algorithm with voting strategy is an acceptable compromise between accuracy, simplicity, feature dimensionality, demands for training data, and real-time feasibility. The proposed algorithm has a great potential in many applications, such as a social networks application where the level of the user "pleasantness" can be monitored towards different stimuli and/or an emotional companion can be created to cheer up the user if the user's negative emotion is detected.

ACKNOWLEDGMENT

The work is supported by Fraunhofer IDM@NTU, which is funded by the National Research Foundation (NRF) and managed through the multi-agency Interactive & Digital Media Programme Office (IDMPO).

REFERNECE

[1] R. Plutchik, Emotions and life : perspectives from psychology, biology, and evolution, 1st ed. Washington, DC: American Psychological Association, 2003.

[2] J. A. Russell, "A circumplex model of affect," Journal of Personality and Social Psychology, vol. 39, pp. 1161-1178, 1980.

[3] A. Mehrabian, "Framework for a comprehensive description and measurement of emotional states," Genetic, social, and general psychology monographs, vol. 121, pp. 339-361, 1995.

[4] A. Mehrabian, "Pleasure-Arousal-Dominance: A general framework for describing and measuring individual differences in temperament," Current Psychology, vol. 14, pp. 261-292, 1996.

[5] I. Daly, A. Malik, F. Hwang, E. Roesch, J. Weaver, A. Kirke, et al., "Neural correlates of emotional responses to music: an EEG study," Neuroscience letters, vol. 573, pp. 52-57, 2014.

[6] K. Schaaff, "EEG-based Emotion Recognition," Diplomarbeit am Institut fur Algorithmen und Kognitive Systeme, Universitat Karlsruhe (TH), 2008.

[7] K. Schaaff and T. Schultz, "Towards an EEG-based emotion recognizer for humanoid robots," in Proceedings - IEEE International Workshop on Robot and Human Interactive Communication, 2009, pp. 792-796.

[8] L. Brown, B. Grundlehner, and J. Penders, "Towards wireless emotional valence detection from EEG," in Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE, 2011, pp. 2188-2191.

[9] G. Chanel, J. J. M. Kierkels, M. Soleymani, and T. Pun, "Short-term emotion assessment in a recall paradigm," International Journal of Human Computer Studies, vol. 67, pp. 607-627, 2009.

[10] A. T. Sohaib, S. Qureshi, J. Hagelbäck, O. Hilborn, and P. Jerčić, "Evaluating Classifiers for Emotion Recognition Using EEG," in Foundations of Augmented Cognition, ed: Springer, 2013, pp. 492-501.

[11] Y. Liu and O. Sourina, "Real-Time Fractal-Based Valence Level Recognition from EEG," Transactions on Computational Science XVIII, vol. 7848, pp. 101-120, 2013/01/01 2013.

[12] L. J. Trainor and L. A. Schmidt, "Processing emotions induced by music," The cognitive neuroscience of music, pp. 310-324, 2003.

[13] L. A. Schmidt and L. J. Trainor, "Frontal brain electrical activity (EEG) distinguishes valence and intensity of musical emotions," Cognition & Emotion, vol. 15, pp. 487-500, 2001.

[14] N. A. Jones and N. A. Fox, "Electroencephalogram asymmetry during emotionally evocative films and its relation to positive and negative affectivity," Brain and Cognition, vol. 20, pp. 280-299, 1992.

[15] K. Trochidis and E. Bigand, "EEG-based emotion perception during music listening."

[16] R. J. Davidson, "Cerebral asymmetry and emotion: Conceptual and methodological conundrums," Cognition & Emotion, vol. 7, pp. 115-138, 1993.

[17] E. Harmon-Jones, "Contributions from research on anger and cognitive dissonance to understanding the motivational functions of asymmetrical frontal brain activity," Biological psychology, vol. 67, pp. 51-76, 2004.

[18] C. P. Niemic, "Studies of Emotion: A Theoretical and Empirical Review of Psychophysiological Studies of Emotion.," Journal of Undergraduate Research, vol. 1, pp. 15-18, 2004.

[19] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, et al., "DEAP: A Database for Emotion Analysis ;Using Physiological Signals," IEEE Transactions on Affective Computing, vol. 3, pp. 18-31, 2012.

[20] S. Sanei and J. Chambers, EEG signal processing. Chichester, England ; Hoboken, NJ: John Wiley & Sons, 2007.

[21] T. Higuchi, "Approach to an irregular time series on the basis of the fractal theory," Physica D: Nonlinear Phenomena, vol. 31, pp. 277-283, 1988.

[22] D. T. Stuss and R. T. Knight, Principles of frontal lobe function: Oxford University Press, 2013.

[23] Y. P. Lin, C. H. Wang, T. P. Jung, T. L. Wu, S. K. Jeng, J. R. Duann, et al., "EEG-based emotion recognition in music listening," IEEE Transactions on Biomedical Engineering, vol. 57, pp. 1798-1806, 2010.

[24] F. Dolcos, K. S. LaBar, and R. Cabeza, "Remembering one year later: role of the amygdala and the medial temporal lobe memory system in retrieving emotional memories," Proceedings of the National Academy of Sciences of the United States of America, vol. 102, pp. 2626-2631, 2005.

[25] P. Sarkheil, R. Goebel, F. Schneider, and K. Mathiak, "Emotion unfolded by motion: a role for parietal lobe in decoding dynamic facial expressions," Social cognitive and affective neuroscience, vol. 8, pp. 950-957, 2013.

[26] S. Hamann and T. Canli, "Individual differences in emotion processing," Current Opinion in Neurobiology, vol. 14, pp. 233-238, 2004.

[27] Y. Liu, O. Sourina, and M. K. Nguyen, "Real-Time EEG-Based Emotion Recognition and Its Applications," Transactions on Computational Science XII, Lecture Notes in Computer Science, vol. 6670, pp. 256-277, 2011.