Analysing Brain Responses to Affective Pictures from Electroencephalogram (EEG)

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Abstract

This project investigates the relationship between emotion and scalp brain activity. The aim is to verify claims on affective correlates by previous neurological studies. The study involves eliciting the emotions of subjects when they view affective pictures from the International Affective Picture System (IAPS) database, known to reliably alter emotional state. They are asked to rate how they feel based on valence (positive/approach versus negative/withdrawal) and arousal (calm versus excited) states of emotion. Scalp brain signals or electroencephalogram (EEG) are measured and recorded. Analysis and evaluation of the EEG data collected showed that an increase in midline theta (4-8 Hz) power, as well as frontal alpha (9-12 Hz) asymmetry and low theta (4-6 Hz) asymmetry is closely correlated with increase in valence. In addition, the result also showed that an increase in beta (12-35 Hz) to alpha (9-12 Hz) ratio from the frontal lobe is correlated with increase in arousal. These results agree with neuroscience studies in the literature and shows prospect of developing brain-computer interfaces to detect consumer preference that can respond to human emotions.

1 Introduction

Emotions are important in human creativity and intelligence and human rational thinking, decision making, curiosity, and human interaction (Picard, 1997). As such, research on emotion assessment is quickly gaining popularity, especially in the development of human-computer interfaces (Chanel et al, 2006). Being able to utilise affective information enables applications to respond more aptly to the user e.g. offer help when user is experiencing frustration or stress (Reuderink et al, 2013). This would enable machines to better satisfy human needs apart from productivity, especially those relating to interaction and emotion.

Darwinian Theory proposes that people share basic universal emotions such as happiness, sadness, fear, anger, which evolved from natural selection (Oude, 2006). Since emotions are not discrete but continuous, a suitable representation is to map emotions in an n-dimensional space, allowing for both categorical and numerical data to be used for analysis. In Lang's two-dimensional scale of emotion, emotions are mapped according to their valence (positive/approach versus negative/withdrawal), and arousal (calm versus excited) (Lang, 1995). For instance, fear is categorised under low valence and high arousal while content is under low valence and low arousal. Some studies include a third dimension, dominance, but this study will only focus on two dimensions for simplicity. See Figure 2.4.

While humans can recognise facial expressions at 70-98% accuracy, computers can do so at an impressive 80-90% (Takahashi, 2004). However, expressions can be concealed or forged relatively easily, thus it is important to note the distinction between the displayed behavioural expression (affect) and the conscious experience of emotion (feeling) (Oude, 2006). An alternative source of affective information less reliant on overt expression is physiological responses, such as cardiovascular responses, electrodermal activity and muscle activity. Another type of physiological response is neural activity. Cognitive theories suggest that affective reactions mainly originate from the brain as it is the central processor of stimuli, memories and thoughts, then processing eventually leads to affective response (Sander et al, 2005). Moreover, the brain responds to emotional stimulation within tens of milliseconds (Aftanas et al, 2002), making detection of neuronal activity a direct and rapid method for emotion recognition. Brain responses to affective pictures have been investigated using a variety of measures. Brain waves are categorized into frequency bands – delta (0.5-4 Hz), theta (4-8 Hz), alpha (9-12 Hz), beta (12-35 Hz) and gamma bands (40-70 Hz). This study will focus only on analysis of theta, alpha and beta bands. Alpha waves are typical for an alert, but relaxed mental state (Oude, 2006) and have been linked to brain inactivation (Pfurtscheller et al, 2009). Beta activity is related to an active state of mind, prominent during intense focused mental activity (Oude, 2006). Theta is dominant during sleep and in deep meditation. Dominance of certain power bands or certain features at certain cortical regions can be observed during different states of valence and arousal.

This experiment aims to verify correlations between brain activity and states of valence and arousal found in the past studies as seen in Table 1.1 and Table 1.2. Therefore, pictures are selected, and a program is designed to displays selected pictures of varying arousal and valence in random order to the subject while collecting EEG data simultaneously. The program will also use Self-Assessment Manikins to ask for the subject's input on how the he feels after viewing the picture. Thereafter, features of the EEG recording are analysed and correlated with the subjects' responses.

Table 1.1 Valence Correlates in Past Studies

Feature/Region	Low valence or Withdrawal	High valence or Approach
Frontal activation (Reuderink et al, 2013, Harmon-Jones et al, 1998)	Right frontal cortex activation	Left frontal cortex activation
Left frontal region	Higher alpha and higher theta	Lower alpha and lower theta
Right frontal region	Lower alpha and lower theta	Higher alpha and lower theta
Frontal alpha asymmetry index, and theta asymmetry index (Aftanas et al, 2001)	More negative	More positive
Fronto-medial theta power (Sammler et al, 2008, Aftanas et al, 2001)	Lower frontal medial theta power for negative music stimuli	Higher frontal medial theta power for positive music stimuli
Medial theta power (Krause et al, 2000)	Lower midline theta power	Higher midline theta power for anger (an approach-related response)

Table 1.2 Arousal Correlates in Past Studies

Feature/Region	Low arousal state or calm	High arousal state or excited
Frontal lobe	Lower activation	Higher activation
Frontal beta power (Oude, 2006)	Lower beta	Higher beta
Global alpha power (Barry et al, 2009)	Lower alpha	Higher alpha
Frontal beta-alpha ratio	Lower beta-alpha ratio	Higher beta-alpha ratio
Posterior region (Aftanas et al, 2002)	Higher theta	Higher theta
Right posterior region (Sarlo et al, 2005)	Low beta	High beta

2 Materials and Method

2.1 Software development

A program was designed and developed to display pictures to the subjects. See Figure 2.1. The program also communicates with the EEG Neuroscan NuAmps Amplifier and software to send commands e.g. when to start and stop recording EEG. The experiment was conducted in trials whereby subjects view and rate one picture in one trial. The experimental protocol for one trial can be seen in Figure 2.2.

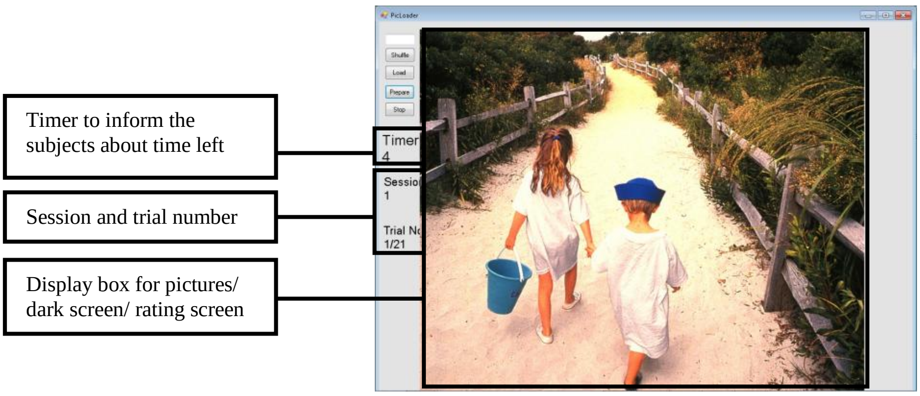
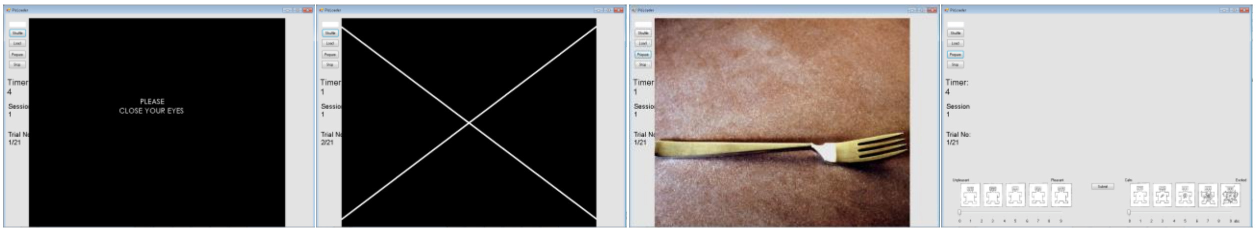


Figure 2.1 Picture-displaying program



Phase 1 6s | Phase 2 2s | Phase 3 12s | Phase 4 20s

Figure 2.2 Four phases of picture-displaying program

In phase 1, a dark screen is displayed for 12s. The subject will be instructed to close their eyes. This is for the subject to rest and to return their mental state to normal. (Khosrowabadi et al, 2014). The program plays a 'beep' sound to alert the subject to open his eyes. Simultaneously, phase 2 begins and a white cross is drawn on the centre of the screen for 2s to avoid accustoming and to attract the subject's attention (Chanel et al, 2006, Huster et al, 2009). In phase 3, affective images are then displayed for 6s (Cuthbert et al, 2009, McManis et al, 2001, Keil et al, 2002). During this period, subjects are instructed to refrain from moving in order to avoid recording of motor-related processes from the EEG. In phase 4, the subject evaluates his feelings using SAM for a maximum time of 20s. The timeline for one trial is presented in Figure 2.3.

Stimuli Set

The program will flash a total of 126 pictures. Images are used for emotion elicitation because the time-course and peak of emotional response is clear. It is less likely to cause excessive variations in affective response (Huster et al, 2009) and it is proven to elicit emotional reactions (Keil et al, 2002). Pictures from the IAPS database (Lang et al, 2008) were used because they are established and reliable elicitor of emotional experience (Huster et al, 2009). They were grouped into nine categories, based on three levels of arousal and valence. The categories were divided based on ratings provided in the IAPS manual (Lang et al, 2008) into low rating (<4), middle rating (4-6), and high rating (>6). See Figure 2.4. Gruesome and sexually explicit pictures were excluded to prevent discomfort or stress. Fourteen pictures are randomly selected for each subject from each of the nine categories, giving a total of 126 pictures. The interface shuffles the pictures and flashes them in random order.

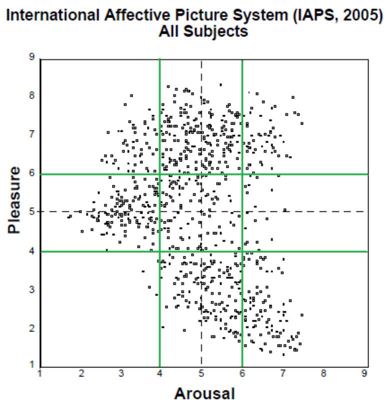


Figure 2.3 IAPS Pictures in nine categories

Self-Assessment Manikins (SAM)

As feelings induced by an image on a particular subject can be very different likely due to differences in experience and personality, the SAM pictorial assessment technique (Lang, 1980) is used to collect subject ratings (1-9) in Phase 4. See Figure 2.5.

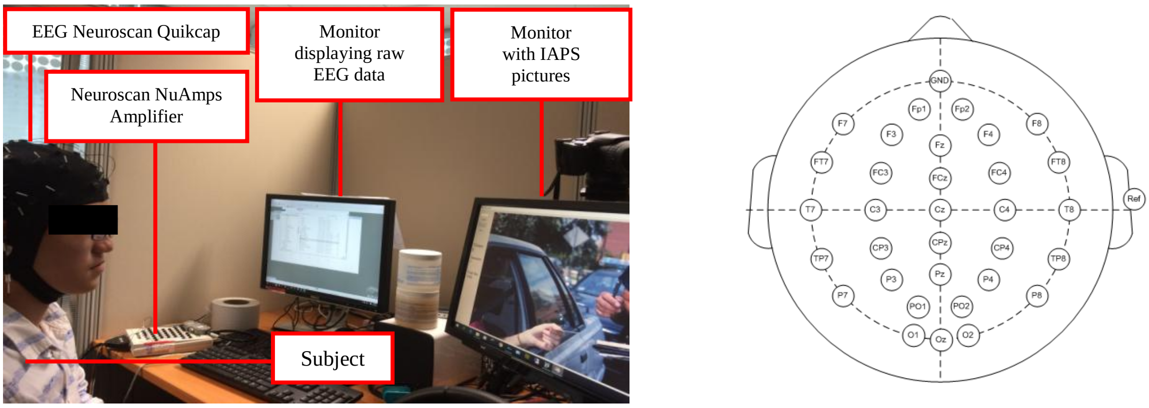
Figure 2.4 Self-assessment manikins for rating valence (left) and arousal (right)

2.2 Experimental session

EEG is a rapid and non-invasive technique that reads electrical activity generated by brain structures (Teplan, 2002) and has been used in other studies (e.g. Cuthbert et al, 2009, Khosrowabadi et al, 2014). For each experimental recording, the EEG Neuroscan Quikcap is placed on the subject's head. The EEG data is then recorded using The Neuroscan NuAmps amplifier. The subject sits in front of a monitor which displays the picture interface. The ssubject rates all 126 pictures in six successive sessions with break times in between to rest.

2.3 Subjects and Data Acquisition

Five subjects (1-5) participated in the experiment, three male (1, 3, 4) and two female subjects (2, 5). Subject 3 is left-handed. All had normal or corrected-to-normal vision, and had given informed consent to participate in the study. See Figure 2.6. EEG was recorded at a sample rate of 250Hz. The 32 Ag/AgCl electrodes are placed on the subject's scalp using the 10/20 system of electrode placement shown in Figure 2.7.



(a) (b)

Figure 2.5 Experimental set-up (a) subject viewing IAPS pictures (b) 10-20 System of electrode placement

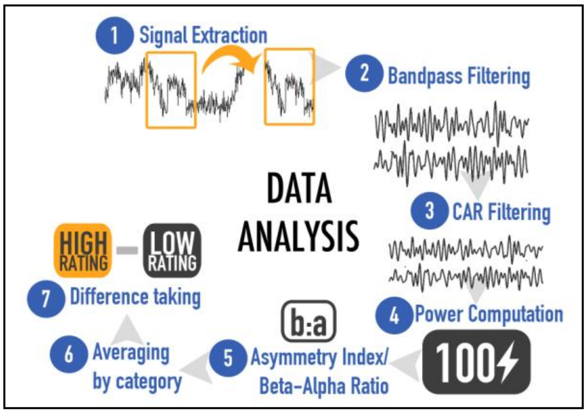


Figure 2.6 Data Analysis Procedure

2.4 Data Analysis

Signals for channels during the 5 experiments were collected then processed using the method seen in Figure 2.8.

2.4.1 Signal Extraction and Bandpass Filtering

For each trial, the EEG time segment during the 6 seconds of picture viewing was extracted from the EEG recording for further analysis. Bandpass filtering removes specific frequencies and so it only the frequencies of interest.

2.4.2 CAR Filtering

Spatial common average reference (CAR) filtering is applied by subtracting the mean amplitude of the signals of the entire electrode montage from the signal of interest. (McFarland et al, 1997)

$$V_i^{CAR} = V_i^{ER} - 1/n \sum_{j=1}^{n} V_j^{ER}$$

where V_i^{CAR} is the voltage amplitude of the signal of the *i*th channel after CAR filtering, V_i^{ER} is the potential between the *i*th channel and the reference, and *n* is the number of electrodes used.

2.4.3 Power of a Frequency Band

Power value for each frequency band was then computed using the following power formula for signals. Power represents the average energy of the entire 6-second signal for one EEG channel.

$$P_i = \frac{1}{T} \sum_{t=1}^{T} X_i(t)^2$$

where P_i represents the power of the channel, T is the total number of time samples (6s x 250Hz) and $X_i(t)$ is the voltage amplitude recorded for one time sample in the channel

2.4.4 Asymmetry Indices

Asymmetrical activity is used to measure relative band powers across homologous electrodes. Asymmetry index is calculated for each pair by taking the log-power of the bands for each channel, then subtracting the band power of electrodes on the left hemisphere from corresponding electrodes on the right hemisphere (Allen et al, 2004).

$$A_{(R,\,L)} = \log(P_R) - \log(P_L)$$

where $A_{(R, L)}$ represents the alpha asymmetry between electrodes R and L, and P_R and P_L represent band powers at the R and L electrodes respectively.

Higher $A_{(R, L)}$ score indicates more right alpha activity and thus represent a left hemispheric activation, which is present during approach-related emotions. Hence the asymmetry indices should increase with increasing valence. (Refer to table 1.1)

2.4.5 Beta-Alpha Ratio

Since beta waves are present during an alert state of mind, whereas alpha waves are more prevalent in a relaxed brain, beta/alpha ratio could be used indication of brain activation or state of arousal. It is calculated by dividing beta power of one channel by the alpha power in the same channel (Oude, 2006). Beta-alpha ratio should increase with arousal.

2.4.6 Averaging

The trials were divided into three categories, respectively based on arousal or valence, based on the average IAPS rating or based on the subject's SAM rating. The average power ratios, asymmetry indices, and beta-alpha ratios were then taken for all trials in that category.

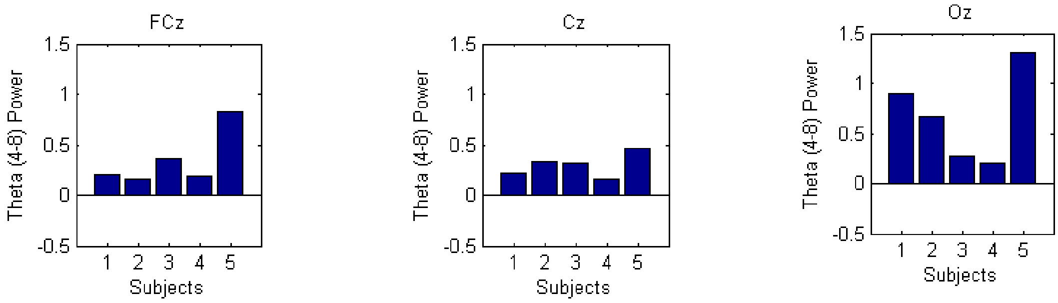
2.4.7 Difference taking

After categorising and averaging, the differences between the extreme categories were computed by subtracting average of the lowest-rating category from the average value of the highest-rating category. A positive value would indicate an increasing trend while a negative value indicates a decreasing trend.

3 Results & Discussion

This section describes the findings and results of the experiment.

3.1 Midline Theta Power

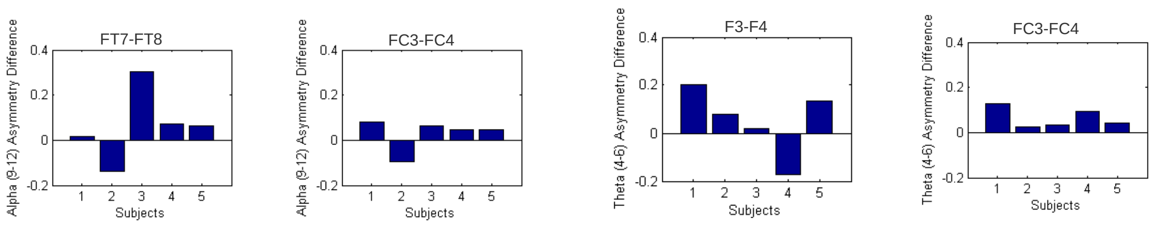


(a) (b) (c)

Figure 3.1 Difference between average theta power of high rating and low rating category

The difference between average theta power of high (8-9) and low (1-2) self-reported valence ratings was plotted in Figure 3.1 for EEG channels FCz, Cz, and Oz along the midline. The result shows a consistent increase in theta power across all subjects along the midline electrodes as the subjects viewed pictures of increasing valence. Thus the result showed an increased midline theta power is correlated with increasing valence. This trend was only found at the midline and not found for electrodes at the left and right hemispheres.

3.2 Frontal Alpha and Theta Asymmetry



(a) (b) (c) (d)

Figure 3.2 Difference between (a)-(b) average alpha asymmetry and (c)-(d) average theta asymmetry of high rating and low rating category

The difference between average alpha asymmetry of high (8-9) and low (1-2) self-reported valence ratings was plotted in Figure 3.2(a)-(b) for frontal EEG channels pairs FT7-FT8 and FC3-FC4. The difference between average low theta asymmetry of high (8-9) and low (1-2) IAPS valence ratings was also plotted in Figure 3.2(c)-(d) for frontal EEG channels pairs F3-F4 and FC3-FC4. The result shows an increase in alpha asymmetry power across 4 out of 5 subjects at channel pairs FT7-FT8 and FC3-FC4 as the subjects viewed pictures of increasing valence. The result also shows an increase in low theta asymmetry power across all subjects for channel pairs FC3-FC4 and across 4 out of 5 subjects at channel pairs F3-F4 as the subjects viewed pictures of increasing valence. No discernable differences were found in other frontal electrode pairs.

3.3 Frontal Activation (Beta-Alpha Ratio)

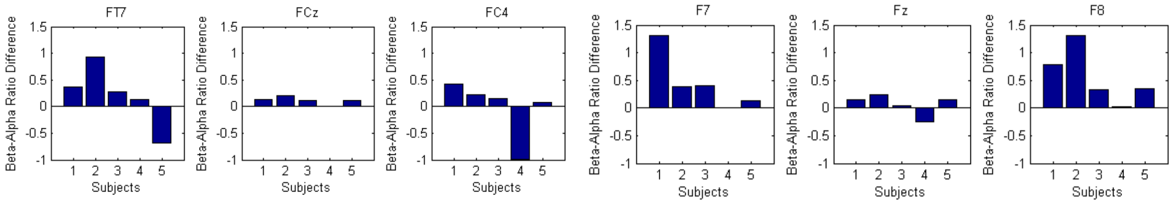


Figure 3.3 Difference between average beta-alpha ratio of high rating and low rating category in frontal electrodes

The difference between average beta-alpha ratio of high (8-9) and low (1-2) self-reported arousal ratings was plotted in Figure 3.3 for frontal EEG channels F7, Fz, F8, FT7, FCz, and FC4. The result shows an increase in beta-alpha ratio as the subjects viewed pictures of increasing arousal.

4 Conclusion

The experiment involved subjects viewing IAPS pictures on a screen while their EEG data is being recorded. The analysis of the EEG data collected in this study affirmed the results observed in other neurological studies in the literature. The increase in midline theta observed was similar to the results found in neuroscience studies (Krause et al, 2000 , Aftanas et al, 2001) where it was observed that midline theta power increased with increasing valence. The result also agrees with neuroscience studies (Reuderink et al, 2013, Harmon-Jones et al, 1998, Aftanas et al, 2001) that observed increased activation in the left frontal hemisphere and right frontal hemisphere for positive and negative valence respectively. Finally, the results also agree with neursocience study (Oude, 2006) that reported increased frontal beta-alpha ratio with increasing arousal. The limitation of this study is the low number of subjects' EEG data collected. The study could be improved further by collecting more data for a comprehensive study. The experimental conditions can also be improved by performing the experiment in a more isolated condition such as a dark room, leaving the subject alone, in order to remove possible distractions. Pictures may also be shown along with music and duration of display can also be lengthened in order to elicit a stronger emotion. Finally, the EEG filtering process can also be improved by removing EEG artifacts. The significance of the findings from this study is that emotions can be detected by placing electrodes only in specific regions of the brain and using certain algorithm to process the EEG data (e.g. to compute alpha asymmetry) to determine whether a subject likes the picture or not. Hence, people's preferences and emotions can be analysed using such a brain-computer interface system to design more visually appealing products or enhance the interaction between humans and computers.

5 Acknowledgements

I would like to thank my mentor, Dr. Ang Kai Keng, for taking me in as his student, helping me with the literature review, and the guiding me in the writing of the report. I would also like to thank my mentor, Mr. Chin Zheng Yang for being very patient as he taught me programming and concepts about data analysis, and for diligently guiding me throughout the course of the project. I would also like to thank my teacher advisor, Mr. Ong Kim Lin for the support he gave me for this project.

References

Aftanas, L., Varlamov, A., Pavlov, S., Makhnev, V., & Reva, N. (2001). Event-Related Synchronization and Desynchronization During Affective Processing: Emergence of Valence-Related Time-Dependent Hemispheric Asymmetries in Theta and Upper Alpha Band. *International Journal of Neuroscience, 110*(3-4), 197-219. doi: 10.3109/00207450108986547

Aftanas, L. I., Varlamov, A. A., Pavlov, S. V., Makhnev, V. P., & Reva, N. V. (2002). Time-dependent cortical asymmetries induced by emotional arousal: EEG analysis of event-related synchronization and desynchronization in individually defined frequency bands. *International Journal of Psychophysiology, 44*(1), 67-82. doi: http://dx.doi.org/10.1016/S0167-8760(01)00194-5

Allen, J. J. B., Coan, J. A., & Nazarian, M. (2004). Issues and assumptions on the road from raw signals to metrics of frontal EEG asymmetry in emotion. *Biological Psychology, 67*(1–2), 183-218. doi: http://dx.doi.org/10.1016/j.biopsycho.2004.03.007

Barry, R. J., Clarke, A. R., Johnstone, S. J., & Brown, C. R. (2009). EEG differences in children between eyes-closed and eyes-open resting conditions. *Clin Neurophysiol, 120*(10), 1806-1811. doi: 10.1016/j.clinph.2009.08.006

Chanel, G., Kronegg, J., Grandjean, D., & Pun, T. (2006). Emotion Assessment: Arousal Evaluation Using EEG's and Peripheral Physiological Signals. In B. Gunsel, A. Jain, A. M. Tekalp & B. Sankur (Eds.), *Multimedia Content Representation, Classification and Security* (Vol. 4105, pp. 530-537): Springer Berlin Heidelberg.

Cuthbert, B. N., Schupp, H. T., Bradley, M. M., Birbaumer, N., & Lang, P. J. (2000). Brain potentials in affective picture processing: covariation with autonomic arousal and affective report. *Biological Psychology, 52*(2), 95-111. doi: http://dx.doi.org/10.1016/S0301-0511(99)00044-7

Harmon-Jones, E., & Allen, J. J. (1998). Anger and frontal brain activity: EEG asymmetry consistent with approach motivation despite negative affective valence. *J Pers Soc Psychol, 74*(5), 1310-1316.

Huster, R. J., Stevens, S., Gerlach, A. L., & Rist, F. (2009). A spectralanalytic approach to emotional responses evoked through picture presentation. *International Journal of Psychophysiology, 72*(2), 212-216. doi: http://dx.doi.org/10.1016/j.ijpsycho.2008.12.009

Kabuto, M., Kageyama, T., & Nitta, H. (1993). EEG power spectrum changes due to listening to pleasant music and their relation to relaxation effects. *Nihon Eiseigaku Zasshi, 48*(4), 807-818.

Keil, A., Bradley, M. M., Hauk, O., Rockstroh, B., Elbert, T., & Lang, P. J. (2002). Large-scale neural correlates of affective picture processing. *Psychophysiology, 39*(5), 641-649. doi: 10.1111/1469-8986.3950641

Khosrowabadi, R., Chai, Q., Kai Keng, A., & Wahab, A. (2014). ERNN: A Biologically Inspired Feedforward Neural Network to Discriminate Emotion From EEG Signal. *Neural Networks and Learning Systems, IEEE Transactions on, 25*(3), 609-620. doi: 10.1109/TNNLS.2013.2280271

Krause, C. M., Viemero, V., Rosenqvist, A., Sillanmaki, L., & Astrom, T. (2000). Relative electroencephalographic desynchronization and synchronization in humans to emotional film content: an analysis of the 4-6, 6-8, 8-10 and 10-12 Hz frequency bands. *Neurosci Lett, 286*(1), 9-12.

Lang, P., Bradley, M., & Cuthbert, B. N. (2008). International affective picture system (IAPS): Affective ratings of pictures and instruction manual.

Lang, P. J. (1980). Behavioral treatment and bio-behavioral assessment: Computer applications. In J. Sidowski, J. Johnson & T. Williams (Eds.), *Technology in Mental Health Care Delivery Systems* (pp. 119-137). Norwood, NJ: Ablex Pub. Corp.

Lang, P. J. (1995). The emotion probe: Studies of motivation and attention. *American Psychologist, 50*(5), 372-385. doi: 10.1037//0003-066X.50.5.372

Lotte, F. (2014). A Tutorial on EEG Signal-processing Techniques for Mental-state Recognition in Brain–Computer Interfaces. In E. R. Miranda & J. Castet (Eds.), *Guide to Brain-Computer Music Interfacing* (pp. 133-161): Springer London.

McFarland, D. J., McCane, L. M., David, S. V., & Wolpaw, J. R. (1997). Spatial filter selection for EEG-based communication. *Electroencephalogr Clin Neurophysiol, 103*(3), 386-394.

McManis, M. H., Bradley, M. M., Berg, W. K., Cuthbert, B. N., & Lang, P. J. (2001). Emotional reactions in children: verbal, physiological, and behavioral responses to affective pictures. *Psychophysiology, 38*(2), 222-231.

Müller, M. M., Keil, A., Gruber, T., & Elbert, T. (1999). Processing of affective pictures modulates right-hemispheric gamma band EEG activity. *Clinical neurophysiology, 110*(11), 1913-1920. doi: http://dx.doi.org/10.1016/S1388-2457(99)00151-0

Murugappan, M. (2010). Classification of human emotion from EEG using discrete wavelet transform. *Journal of Biomedical Science and Engineering, 03*(04), 390-396. doi: citeulike-article-id:9468489

Oude Bos, D. (2006). *EEG-based emotion recognition - The Influence of Visual and Auditory Stimuli.* Paper presented at the Capita Selecta (MSc course).

Picard, R. W. (1997). *Affective computing*: MIT press.

Pfurtscheller, G., & Lopes da Silva, F. H. (1999). Event-related EEG/MEG synchronization and desynchronization: basic principles. *Clinical neurophysiology, 110*(11), 1842-1857. doi: citeulike-article-id:1038424

Reuderink, B., M, C., #252, hl, & Poel, M. (2013). Valence, arousal and dominance in the EEG during game play. *Int. J. Auton. Adapt. Commun. Syst.*, *6*(1), 45-62. doi: 10.1504/ijaacs.2013.050691

Sammler, D., Grigutsch, M., Fritz, T., & Koelsch, S. (2007). Music and emotion: electrophysiological correlates of the processing of pleasant and unpleasant music. *Psychophysiology*, *44*(2), 293-304. doi: 10.1111/j.1469-8986.2007.00497.x

Sander, D., Grandjean, D., & Scherer, K. R. (2005). A systems approach to appraisal mechanisms in emotion. *Neural Networks*, *18*(4), 317-352. doi: http://dx.doi.org/10.1016/j.neunet.2005.03.001

Sarlo, M., Buodo, G., Poli, S., & Palomba, D. (2005). Changes in EEG alpha power to different disgust elicitors: the specificity of mutilations. *Neuroscience Letters, 382*(3), 291-296. doi: http://dx.doi.org/10.1016/j.neulet.2005.03.037

Teplan, M. (2002). *FUNDAMENTALS OF EEG MEASUREMENT*.

Takahashi, K. (2004, 8-10 Dec. 2004). *Remarks on emotion recognition from multi-modal bio-potential signals.* Paper presented at the Industrial Technology, 2004. IEEE ICIT '04. 2004 IEEE International Conference