Analysing Brain Responses to Affective Pictures from Electroencephalogram (EEG)

Tiffany Chong

1 Background and Purpose of Research

Research on emotion assessment is gaining popularity, especially in the development of human-computer interfaces (Chanel et al, 2006). Being able to use affective information enables applications to respond more aptly to the user e.g. offer help when user is experiencing stress (Reuderink et al, 2013). This would enable machines to better satisfy human needs. Darwinian Theory proposes that people share basic universal emotions such as happiness, sadness, fear, etc. 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. 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. See Figure 1 in Appendices. Computers can already recognise facial expressions so at 80-90% (Takahashi, 2004). However, expressions can be concealed or forged easily. An alternative source of affective information less reliant on overt expression is physiological responses, an example of which 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 (Sander et al, 2005). Moreover, the brain responds to emotional stimulation within milliseconds (Aftanas et al, 2002), making detection of neuronal activity a direct and rapid method for emotion recognition. 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.

2 Hypothesis

This experiment aims to verify correlations between brain activity and states of valence and arousal found in the past studies as seen in Table 2.1 and Table 2.2. The hypothesis is that the following correlates will be found upon analysis of data.

Table 2.1 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 2.2 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

3 Method and Materials

3.1 Software development

A program was designed and developed to display pictures to the subjects. See Figure 3.1. 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 is divided into phases and can be seen in Figure 3.2.

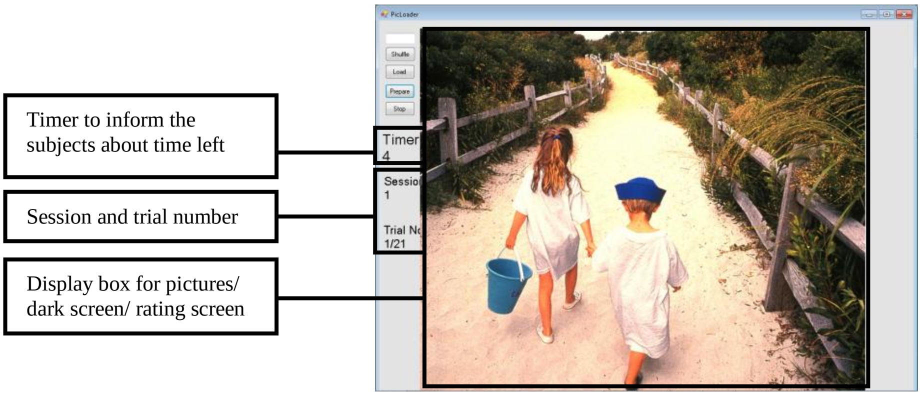
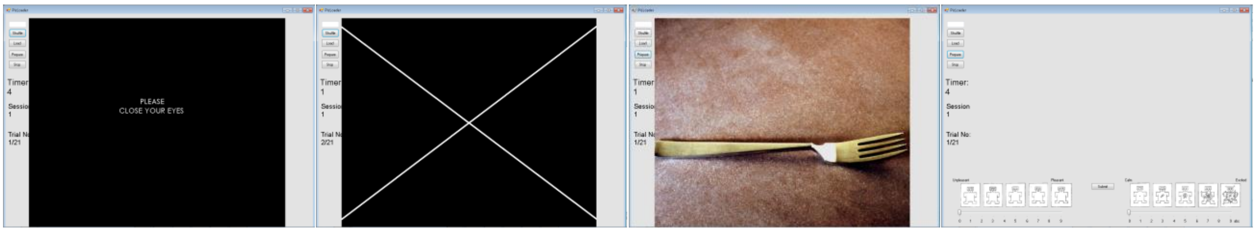


Figure 3.1 Picture-displaying program

In phase 1, a dark screen is displayed for 12s. Subjects are instructed to close their eyes to rest and to return their mental state to normal. (Khosrowabadi et al, 2014). The program plays a ‘beep’ sound to alert subjects to open their eyes. Phase 2 begins and a white cross is drawn on the centre of the screen for 2s to avoid accustoming (Chanel et al, 2006, Huster et al, 2009). In phase 3, affective images are displayed for 6s (Cuthbert et al, 2009, McManis et al, 2001, Keil et al, 2002). Subjects are instructed to refrain from moving in order to avoid recording of motor-related processes from the EEG. In phase 4, subjects evaluate their feelings using SAM for a maximum time of 20s.



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

Figure 3.2 Four phases of picture-displaying program

Stimuli Set

Images are used for emotion elicitation it is less likely to cause excessive variations in affective response (Huster et al, 2009). 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 ratings provided by the IAPS manual (Lang et al, 2008) into low rating (<4), middle rating (4-6), and high rating (>6). Annex. 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 program shuffles the pictures and flashes them in random order.

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 in Appendices.

3.2 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 program. The ssubject rates all 126 pictures in six successive sessions with break times in between to rest.

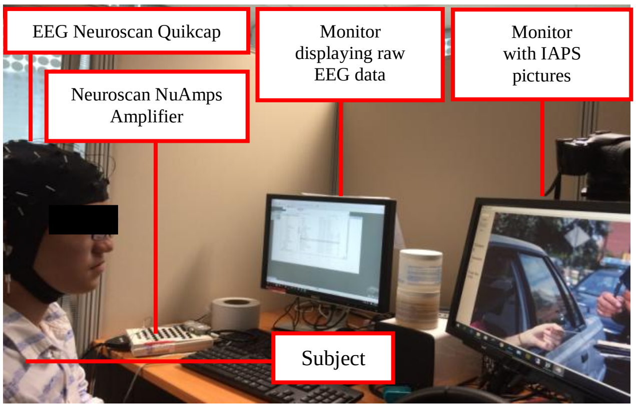


Figure 3.3 Experimental set-up - subject viewing IAPS pictures

3.3 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. 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. Refer to Figure 3 in Appendices. See set-up in Fig 3.3.

3.4 Data Analysis

Signals for channels during the 5 experiments were collected then processed using the method below. A summary of the method can be seen in Figure 4 of Appendices.

3.4.1 Signal Extraction and Bandpass Filtering

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

3.4.2 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 ith channel after CAR filtering, V_i^{ER} is the potential between the ith channel and the reference, and n is the number of electrodes used.

3.4.3 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 6s 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

3.4.4 Asymmetry Indices

Asymmetrical indices are used to measure relative band powers across homologous electrodes. It is calculated by subtracting the log-power of band power of electrodes on the left hemisphere from the log-power of the 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. Thus, asymmetry indices should increase with increasing valence (Refer to Table 2.1).

3.4.5 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.

3.4.6 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.

3.4.7 Difference taking

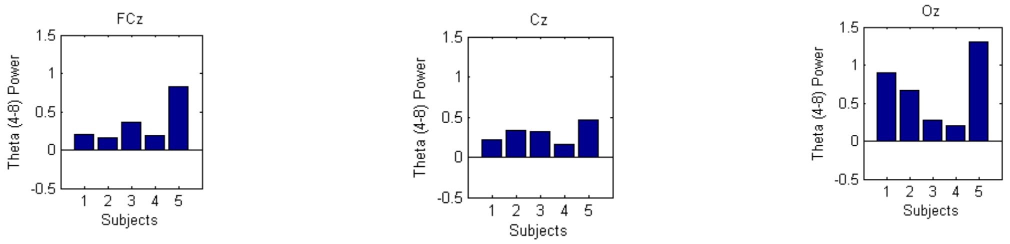
After categorising and averaging, the differences between the extreme categories were computed by subtracting average of the lowest-rating category from the average value of the highest-rating category. A positive value would indicate an increasing trend while a negative value indicates a decreasing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

4 Results and Discussion

This section describes the findings and results of the experiment.

4.1 Midline Theta Power

The difference between average theta power of high (8-9) and low (1-2) self-reported valence ratings was plotted in Figure 4.1 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.

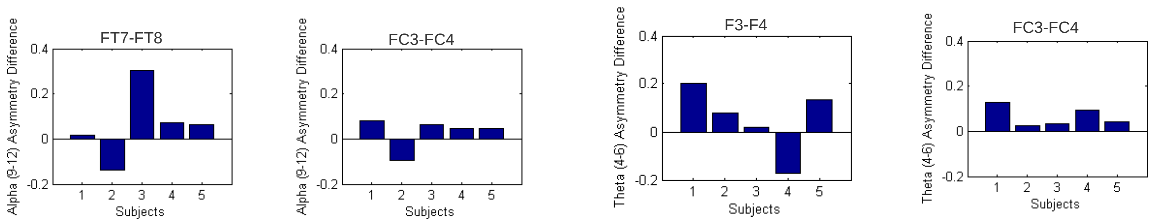


(a) (b) (c)

Figure 4.1 Difference between average theta power of high rating and low rating category

4.2 Frontal Alpha and Theta Asymmetry

The difference between average alpha asymmetry of high (8-9) and low (1-2) self-reported valence ratings was plotted in Figure 4.2(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 4.2(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.



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

Figure 4.2 Difference between (a)-(b) average alpha asymmetry and (c)-(d) average theta asymmetry of high rating and low rating category

4.3 Frontal Activation (Beta-Alpha Ratio)

The difference between average beta-alpha ratio of high (8-9) and low (1-2) self-reported arousal ratings was plotted in Figure 4.3 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.

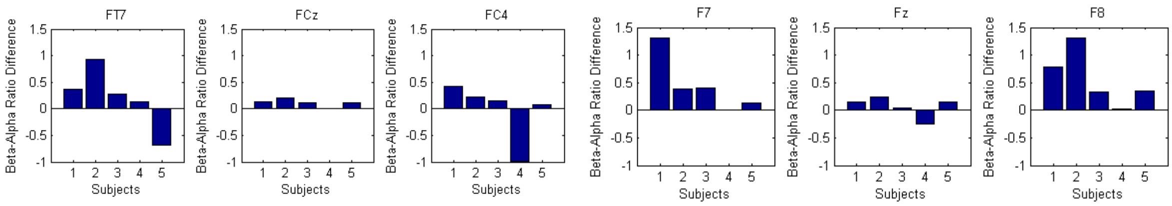


Figure 4.3 Difference between average beta-alpha ratio of high rating and low rating category in frontal electrodes

5 Conclusion and Recommendation for Future Work

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.

6 References

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7 Appendices

Figure

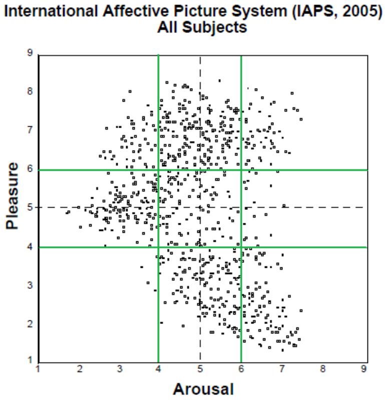

Figure 1 IAPS pictures in nine categories

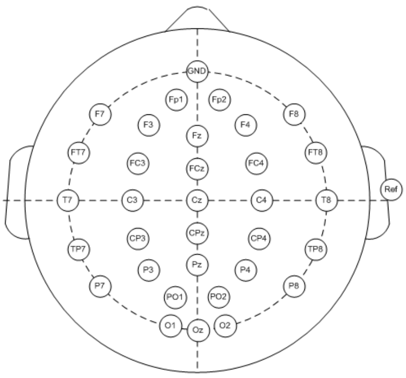

Figure 3 10-20 System of Electrode placement

Figure 2 Self-assessment manikins for rating valence (left) and arousal (right)

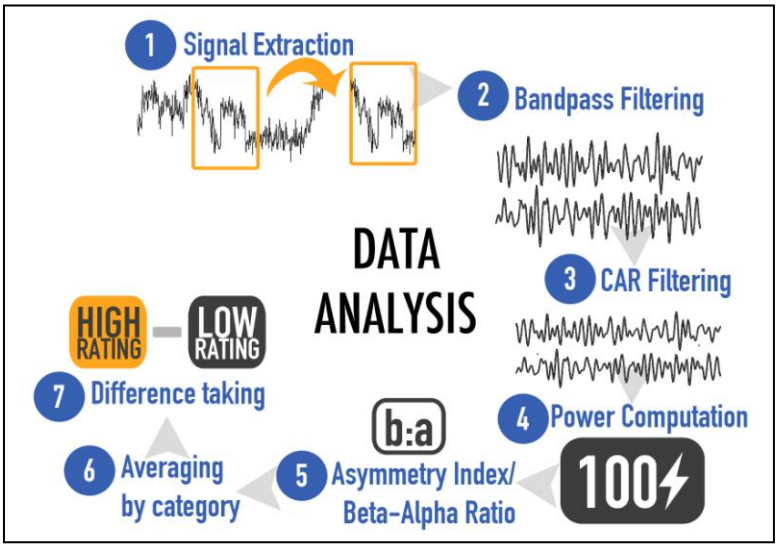

Figure 4 Data Analysis Procedure