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## Review Article

# EEG-BASED RECOGNITION OF POSITIVE AND NEGATIVE EMOTIONS USING FOR PLEASANT VS. UNPLEASANT IMAGES

***Chew Lin Hou, James Mountstephens and Jason Teo**

Faculty of Computing and Informatics of Universiti Malaysia Sabah, Kota Kinabalu, Malaysia

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**ABSTRACT**

Emotions play an important role in our daily life. AntonioDamasiofamously stated: "We are not thinking machines that feel; rather we are feeling machines that think". Human emotions can be recognized through facial expression, speech and gesture. The use of electroencephalograms (EEGs) to understand and recognize human emotion has been widely studied, where those recognition techniques greatly benefit in human-computer interaction (HCI). In this investigation, we study the use of EEGs to recognize emotions. Pleasant and unpleasant images are used as stimuli to elicit human pleasant and unpleasant emotions.The brainwaves are recorded using a 9-electrode medical grade wireless EEG headset from Advance Brain Monitoring (ABM), the B-alert X10. The features comprising alpha, beta, gamma, theta, and delta bands are then extracted from the recorded brainwaves using time-frequency analysis. Different channels and rhythms are used in support vector machine (SVM) and K-nearest neighbors (KNN) classifiers to train and classify pleasant vs. unpleasant mind states. The best accuracy obtained was 70.43% using SVM with alpha and beta rhythmsfromchannel F3 and Fz, and also with gamma rhythms from channel POz.

## INTRODUCTION

It is widely known that emotions play a crucial part in our daily life. Emotionsare believed to play key roles in human intelligence, creativity, decision making and rational human thinking (Picard, 2000). Several famous researchers have developed their own definitionsfor emotions, some of which the better known onesincludeJames (1884), Arnold (1960), Lazarus (1991), and Pultchik (1991). Since human emotion is one of the key factorsthat rule our everyday life, the ability to recognize human emotions automatically using machines would be highly beneficialin enhancing the human's experience with machines, in particular computers. Many studies have been conducted to understand human emotion through imaging technologies (e.g. functional magnetic resonance imaging (FMRI), electroencephalogram (EEG), and magnetoencephalography (MEG)) (Murugappan *et al*., 2009; Rached and Perkusich, 2013; Singh *et al*, 2013; Luangrat *et al.* 2012), and conventional measurements of physiological parameters (e.g. blood pressure, heart rate, body core temperature and respiration rate) (Nasoz *et al*., 2003; Kim*et al*., 2004). EEG is a technique of reading electrical activity from the human scalp that are generated by neural activity in the brain, whereby this technique is both mature and relatively cost effective. The obtained EEG signals are required to undergo several processes such as artefact removal, bandpass filter and feature extraction to obtain useful signals from brainwaves. To evoke emotion, stimuli are required either in the form of images, soundtracks or videos. Several studies have previously been conducted to recognize human emotions such as happy vs. sad (Li and Lu, 2009; Luangrat *et al*., 2012), positive, negative vs. neutral (Brown *et al*., 2011), sad vs. disgust (Singh *et al*., 2012), and sad, joy, relaxedvs. Fear(Wang *et al*., 2011). Several studies have shown that the frontal lobe is believed to process emotion (Li and Lu, 2009; Luangrat *et al*., 2012; Brown *et al*., 2011; Wang *et al*., 2011; Liu *et al*., 2010).

****Corresponding author: Chew Lin Hou,***
*Faculty of Computing and Informatics of Universiti Malaysia Sabah, Kota Kinabalu, Malaysia.*

In this study, the stimuli used are selected to form pleasant and unpleasant datasets respectively. Users are allowed to rate the images individually based on their own feelings. A medical grade wireless EEG device, the B-alert X10, with 9 channels is used to obtain and capture the users' brainwaves. Then, time frequency analysis is used to extract features from the acquired brain signals. The features of interestare alpha, beta, gamma, theta and delta rhythms. We focus on using different combinations of channels and rhythms. Machine learning algorithms in the form of support vector machines (SVM) and K-nearest neighbor classifiers (KNN) are used to classify and detect the twoemotional states, which are pleasant vs. Unpleasant, based on the features obtained through time-frequency analysis. Fig. 1 shows the process flow of this study.

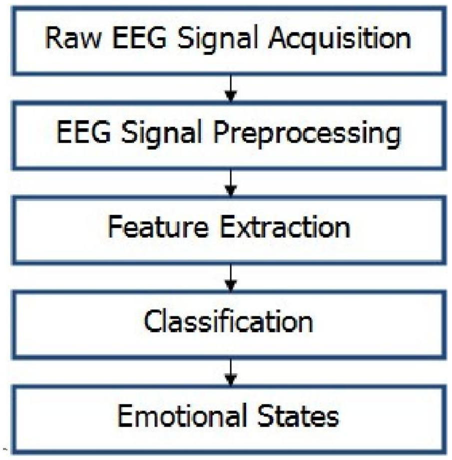


**Fig. 1. The flow structure of the study**

## Data Acquisition

The flow of data acquisition is as shown in Fig. 2.

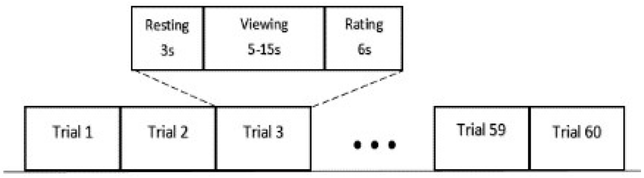


**Fig. 2. The flow structure of the data acquisition process**

At the beginning of the data acquisition process, a blank screen of 3s is displayed as a resting state in order to avoid any brain activities related to the previous trial. This is followed by 5 to 15s of stimuli viewing with the minimum and maximum time of 5s and 15s respectively. After the minimum time, the subject is able to proceed to the rating state based on their free will while at the maximum time, the system will automatically proceed to the rating state. The purpose of enabling the subject to decide on their viewing time for the stimuli is to avoid the subject from becoming bored and fatigued during the data acquisition process. Asking the user to view repetitively at fixed intervals and rate the stimuli could lead to boredom (Craig *et al*., 2012), which may then further cause fatigue (Shackleton, 1981). Hence, allowing the user the option to move to the next stimuli could save time and avoid fatigue since the subject no longer needs to wait until the maximum time in order to conduct the rating and moving on to the next stimuli. At the end of the shape viewing process, a rating with a 5 point scale ranging from positive to negative (1: like very much, 2: like, 3: undecided, 4: do not like, 5: do not like at all) is displayed to the subject. Rating for 1 and 2 were considered as pleasant judgements while rating for 4 and 5 were considered as unpleasant judgements.

## Stimuli

The images are selected from internet where the resolution of the images are above 1366 x 768, which are then resized to 1366 x 768 to fit the screen. Most online image databases have much lower resolutions to reduce the size of large image databases. Resolution is important as it contains information, thus any reduction in resolution could decrease the information in an image. Therefore in this study, we have maintained a lower bound on the resolution when selecting the images to be presented to the users as stimuli.A total of 40 images were obtained online comprising 20 pleasant and 20 unpleasant images. Pleasant images include cute animals, flowers and natural scenes, while unpleasant images include human body parts, corpses, scenes of war, slaughterhouses, scenes of accidents, animal cruelty and bedridden patients. The further description of the images are in Table 1 and Table 2 for pleasant images and unpleasant images respectively.

**Table 1. Description for pleasant image set**

| Image No. | description |
|---|---|
| 1c | Mule deer in maple forest. |
| 2 | House above the sea. |
| 3 | Hot air balloon on the sky. |
| 4 | Dolphins jump out from the sea with sea and sky as background. |
| 5 | A chick in flower's bush. |
| 6 | Town snow scene. |
| 7 | A rabbit with a group of chicks. |
| 8 | Dandelion field with sky as background. |
| 9 | 2 Fishes in the sea with sky and cloud as background. |
| 10 | Purple flowers with sky as background. |
| 11 | Panda mother and panda cub play on a field. |
| 12 | Eiffel tower with sunset as background. |
| 13 | Purple flowers bush. |
| 14 | Polar cub plays on snow. |
| 15 | A rabbit and a hamster playing in house. |
| 16 | A sunset scene from a lake. |
| 17 | Houses above the sea with sunset. |
| 18 | A baby leopard is kissing another leopard. |
| 19 | A red house near the lake with sky as background. |
| 20 | A sunset scene from higher ground. |

**Table 2. Description for unpleasant image set**

| Image No. | Description |
|---|---|
| 1 | Women and kids running for their life during war. |
| 2 | A father cries over his son death body during war. |
| 3 | A father hugging his son with blood all over his body. |
| 4 | A under nutrition bedridden patient. |
| 5 | A suffering bedridden patient. |
| 6 | Several human corpses putted side by side. |
| 7 | A human corpse whom was shot in head. |
| 8 | Accident scene with death body around. |
| 9 | Women killed in accident with disfigured face. |
| 10 | Two human heads chopped off human body. |
| 11 | A male corpse in a forest. |
| 12 | A under nutrition beggar on the roadside. |
| 13 | Corpse of cow with blood all over the ground. |
| 14 | An elephant seal with bloody scar all over its body. |
| 15 | Men chopping off head of goat. |
| 16 | An injured goat and exposed bone. |
| 17 | Rabbits are hanged and cutting on throat. |
| 18 | A pig been cut on throat and left to bleed to death. |
| 19 | Death rabbits hanged and waiting to get its fur removed. |
| 20 | War scene with protesting, smoke and fire around. |

## Subjects

A total of 4 subjects (3 females and 1 male) with an average age of 22were selected to participate in this study. All subjects had no history of psychiatric illnesses and had normal or corrected-to-normal vision. All subjects are informed of the aim, estimated time and design of the study before performing the experiment. Subjects are advised to minimize their movements, to sit at their most comfortable position and not to touch or put their hands on their faces during the experiment to reduce artefacts on the EEG signals being acquired.

**Data Acquisition Device**

A medical grade wireless EEG device from Advanced Brain Monitoring (ABM), the B-alert X10 headset as shown in Fig. 3(a), wasused in this study to acquire the EEG signals from the subjects. The B-alert X10 consists of 9 electrode channels (i.e. F3, Fz, F4, C3, Cz, C4, P3, POz and P4) with electrode placements on the subjects' scalp based on the international 10-20 electrode placement system as shown in Fig. 3(b) with reference electrodes placed on left and right mastoids. The sampling frequency of the device is 256 Hz with a resolution of 16 bits. Fig 3. (a) The ABM b-alert X10 headset. (b) Electrode positions of ABM b-alert X10 according to international 10-20 electrode placement system.

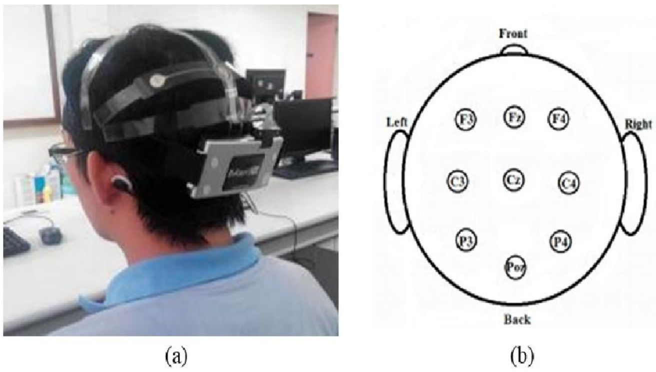


**Fig. 3. (a) The ABM b-alert X10 headset. (b) Electrode positions of ABM b-alert X10 according to international 10-20 electrode placement system**

**Signal Processing and Feature Extraction**

The acquired EEG signals were decontaminated internally using the software development kit (SDK) provided by ABM in Matlab from 5 types of artefacts, namely EMG (electromyography), eye blinks, excursions, saturations and spikes, which are conducted automatically. Artefacts such as excursions, saturations and spikes in the signals are replaced with zero values by the ABM SDK. The nearest neighbor interpolation (NNI) (Gracia, 2010) is then applied to replace zero values in the signals. The features of interest in this experiment are the 5 frequency bands comprising alpha (8-13 Hz), beta (13-30 Hz), gamma (30-49 Hz), theta (4-8 Hz), and delta (1-4 Hz). This experiment adopts Hadjidimitriou and Hadjileontiadis (2012; 2013) methods in feature extraction where the feature estimation is based on the event-related synchronization/desynchronization (ERDS/ ERD) theory. Feature F was computed as shown in (2).

$$F = \frac{A-R}{R} \qquad \ldots\ldots \text{(2)}$$

where A represents the estimated quantity during stimulus viewing (SV) and R represents the estimated quantity during reference state (RS).

Additionally, A is computed for each trial j and channel i as the average of the TF values in all five EEG frequency bands (fb) as in (3).

$$A^{fb}(i,j) = \frac{1}{N}\sum_t \left(\frac{1}{N_{fb}}\sum_f \ TF_{i,j}^{SV}[t,f]\right) \ldots\ldots \text{(3)}$$

where [t, f] represents the discrete (time, frequency) point in the TF plane.

The short-time Fourier transform (STFT) was used in this experiment in which it is a built-in Matlab function called *spectrogram*.

The number of features (F) for pleasant and unpleasant for the training and testing sets are shown in Table 3. In the training set, the number of features for pleasant and unpleasant are 45 and 59 respectively. In the testing set, the number of features for pleasant and unpleasant are 18 and 26 respectively.

**Table 3. Training and Testing Feature for Each Subject**

| | Training Set | | | Testing Set | | |
|---|---|---|---|---|---|---|
| | pleasant F | unpleasant F | Total F | pleasant F | unpleasant F | Total F |
| Total | 45 | 59 | 104 | 18 | 26 | 44 |

**Classification**

The classifiers used are the Gaussian kernel support vector machines (SVM)(Gunn, 1998)and K-nearest neighbor (KNN) classifier (Song *et al*., 2007) with the nearest neighbor parameter set to 4. The features were grouped into 2 classes, namely pleasantvs. unpleasant. In the pleasant class, it is corresponding to the trials which were rated by the subjects at "4: like" and "5: like very much" while in the unpleasant class, the feature vectors were corresponding to the trials which were rated by the subject as "1: do not like at all" and "2: do not like". The neutral class which is corresponding to the rating "3: undecided" is not included. The ratio of training to testing cases of the data is 7:3.

## RESULTS AND DISCUSSION

Different electrode channels and rhythms are selected to identify the suitable rhythms and channels in attempting to recognize pleasant vs. unpleasant emotions. Different combinations of channels are tested, which includes each of the channels, midline channels, symmetry point of left and right channels, combinations of frontal lobe channels, and also all of the channels.The results of the classification for SVM and KNN are as shown in Table 4 and Table 5 respectively, where $\alpha$ represents alpha, $\beta$ represents beta, $\theta$ represents theta, $\gamma$ represents gamma, and $\delta$ represents delta rhythm bands respectively. The accuracy using SVM ranged from 38.64% to 70.45% with a mean average accuracy of 56.35%, while the accuracy of KNN ranged from 36.36% to 70.45% with a mean average accuracy of 55.45%. This shows the performance of SVM is slightly better than KNN. For both SVM and KNN, the mean accuracy of theta rhythms is the lowest, 49.33% and 51.87% respectively. The theta rhythm can be observed during a certain state of sleep, quiet focus, memory encoding and retrieval (Baars and Gage, 2010). This suggests that theta might not be suitable to use as a feature in emotion recognition. Meanwhile, the mean accuracy of gamma is highest between alpha, beta, theta and delta with a mean average accuracy of 59.90% and 57.35% for SVM and KNN respectively.

**Table 4. The accuracy of different channels with different rhythms using SVM**

| | α | β | θ | γ | Δ | αβθ | βθ | αβ | αβθγδ | αβθγ |
|---|---|---|---|---|---|---|---|---|---|---|
| POz | 61.36% | 59.09% | 56.82% | 59.09% | 52.27% | 59.09% | 59.09% | 59.09% | 47.73% | 50.00% |
| Fz | 59.09% | 59.09% | 45.45% | 59.09% | 61.36% | 59.09% | 59.09% | 59.09% | 65.91% | 63.64% |
| Cz | 56.82% | 59.09% | 50.00% | 59.09% | 52.27% | 54.55% | 59.09% | 54.55% | 54.55% | 50.00% |
| C3 | 59.09% | 59.09% | 52.27% | 59.09% | 56.82% | 59.09% | 59.09% | 59.09% | 54.55% | 54.55% |
| C4 | 52.27% | 59.09% | 47.73% | 59.09% | 56.82% | 43.18% | 59.09% | 43.18% | 54.55% | 56.82% |
| F3 | 61.36% | 59.09% | 40.91% | 59.09% | 52.27% | 63.64% | 59.09% | 65.91% | 54.55% | 52.27% |
| F4 | 59.09% | 59.09% | 50.00% | 59.09% | 50.00% | 56.82% | 59.09% | 56.82% | 65.91% | 54.55% |
| P3 | 56.82% | 59.09% | 38.64% | 59.09% | 45.45% | 52.27% | 59.09% | 52.27% | 50.00% | 47.73% |
| P4 | 59.09% | 59.09% | 56.82% | 59.09% | 54.55% | 56.82% | 59.09% | 56.82% | 45.45% | 52.27% |
| POz,Cz,Fz | 52.27% | 59.09% | 52.27% | 59.09% | 63.64% | 56.82% | 59.09% | 56.82% | 59.09% | 59.09% |
| C3, C4 | 45.45% | 59.09% | 52.27% | 59.09% | 56.82% | 40.91% | 59.09% | 40.91% | 56.82% | 61.36% |
| F3, F4 | 54.55% | 61.36% | 43.18% | 59.09% | 47.73% | 59.09% | 61.36% | 56.82% | 56.82% | 52.27% |
| P3, P4 | 59.09% | 59.09% | 43.18% | 59.09% | 52.27% | 54.55% | 59.09% | 54.55% | 47.73% | 52.27% |
| Fz, F3 | 59.09% | 59.09% | 45.45% | 59.09% | 50.00% | 68.18% | 59.09% | 70.45% | 61.36% | 56.82% |
| Fz, F4 | 59.09% | 59.09% | 52.27% | 59.09% | 54.55% | 63.64% | 59.09% | 61.36% | 63.64% | 54.55% |
| Fz, F3, F4 | 63.64% | 63.64% | 47.73% | 59.09% | 47.73% | 63.64% | 61.36% | 63.64% | 59.09% | 56.82% |
| ALL | 52.27% | 52.27% | 63.64% | 59.09% | 63.64% | 61.36% | 59.09% | 59.09% | 59.09% | 59.09% |
| Mean | 57.09% | 59.09% | 49.33% | 59.09% | 54.01% | 57.22% | 59.36% | 57.09% | 56.28% | 54.95% |

**Table 5. The accuracy of different channels with different rhythms using KNN**

| | α | β | θ | γ | δ | αβθ | βθ | αβ | αβθγδ | αβθγ |
|---|---|---|---|---|---|---|---|---|---|---|
| POz | 61.36% | 56.82% | 52.27% | 70.45% | 45.45% | 56.82% | 56.82% | 56.82% | 47.73% | 59.09% |
| Fz | 54.55% | 52.27% | 59.09% | 59.09% | 50.00% | 61.36% | 52.27% | 59.09% | 59.09% | 61.36% |
| Cz | 52.27% | 61.36% | 43.18% | 56.82% | 61.36% | 54.55% | 54.55% | 54.55% | 50.00% | 56.82% |
| C3 | 52.27% | 54.55% | 52.27% | 54.55% | 65.91% | 54.55% | 59.09% | 52.27% | 52.27% | 54.55% |
| C4 | 56.82% | 59.09% | 50.00% | 56.82% | 52.27% | 59.09% | 52.27% | 59.09% | 47.73% | 65.91% |
| F3 | 52.27% | 65.91% | 43.18% | 65.91% | 54.55% | 68.18% | 63.64% | 59.09% | 56.82% | 56.82% |
| F4 | 65.91% | 59.09% | 59.09% | 61.36% | 68.18% | 56.82% | 50.00% | 61.36% | 56.82% | 45.45% |
| P3 | 54.55% | 45.45% | 61.36% | 50.00% | 61.36% | 52.27% | 59.09% | 52.27% | 47.73% | 56.82% |
| P4 | 54.55% | 56.82% | 52.27% | 63.64% | 61.36% | 68.18% | 61.36% | 61.36% | 47.73% | 36.36% |
| POz,Cz,Fz | 61.36% | 61.36% | 45.45% | 59.09% | 56.82% | 54.55% | 52.27% | 54.55% | 50.00% | 52.27% |
| C3, C4 | 52.27% | 47.73% | 52.27% | 54.55% | 59.09% | 47.73% | 50.00% | 47.73% | 59.09% | 56.82% |
| F3, F4 | 59.09% | 50.00% | 47.73% | 54.55% | 50.00% | 47.73% | 52.27% | 50.00% | 52.27% | 52.27% |
| P3, P4 | 59.09% | 54.55% | 50.00% | 40.91% | 61.36% | 56.82% | 50.00% | 56.82% | 47.73% | 54.55% |
| Fz, F3 | 54.55% | 59.09% | 50.00% | 65.91% | 52.27% | 68.18% | 68.18% | 56.82% | 56.82% | 56.82% |
| Fz, F4 | 56.82% | 61.36% | 54.55% | 54.55% | 52.27% | 56.82% | 56.82% | 63.64% | 50.00% | 56.82% |
| Fz, F3, F4 | 47.73% | 50.00% | 52.27% | 52.27% | 52.27% | 54.55% | 61.36% | 50.00% | 54.55% | 56.82% |
| ALL | 54.55% | 47.73% | 56.82% | 54.55% | 59.09% | 54.55% | 56.82% | 56.82% | 56.82% | 59.09% |
| Mean | 55.88% | 55.48% | 51.87% | 57.35% | 56.68% | 57.22% | 56.28% | 56.02% | 52.54% | 55.21% |

This suggests that gamma might play an important role in emotion.It is interesting to note that Nie *et al*. (2011) and Li &Lu (2009) also suggest that high frequency rhythms are associated with emotion response. The SVM with the highest accuracy could was observedwhen using F3 and Fz with the alpha and beta rhythms, obtaining an accuracy of 70.45%. Wang *et al*. (2011) and Nie *et al*. (2011) using SVM to classify emotion had also suggested that alpha, beta and gammarhythms aremore important features in emotion recognition than theta and delta rhythms, which is consistent with the findings of our study when using SVM as the classifier. The KNN with the highest accuracy was observedwhen using channel POz with the gamma rhythm,also obtaining an accuracy of 70.45%. Channel POz corresponds to the primary visual cortex of the brain.Pourtois *et al*. (2004) suggested that activation of primary visual cortex could be related to the emotion of fear.

## Conclusion

The aim of this study was to investigate the different combinations of channels and rhythms that are most useful when attempting to two types of emotions, which are pleasant vs. unpleasant emotions, through the use of images to evoke emotional respond from users. A 9-channel medical grade wireless device, the ABM B-alert X10 device, was used to capture and record the brainwaves of 4 subjects. The decontaminated signals obtained through the ABM SDK then underwent interpolation followed by feature extraction using time frequency analysis to obtain the alpha, beta, gamma, theta and delta rhythms. SVM and KNN classifiers were trained with different combinations and selections of rhythms and EEG channels. The classifier was then tested with another set of data to identify the accuracy of the classifier. In general, the SVM classifiers performed more consistently in providing classification of the EEG signals compared to the KNN classifiers. The best accuracy was obtained from the SVMclassifier trained with 2 EEG channels, F3 and Fz, using the alpha and beta rhythms, and also from KNN with the POz channel using the gamma rhythms as features. The experimental results suggest that higher frequency rhythms may able be beneficial when attempting to identify human emotions. On the other hand, the theta rhythm appears to be less suitable to be used when attempting to identify human emotions.

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