EEG based Emotion Recognition of Image Stimuli

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Introduction

Emotion is playing a great role in our daily lives. The necessity and importance of an automatic Emotion recognition system is getting increased. Traditional approaches of emotion recognition are based on facial images, measurements of heart rates, blood pressure, temperatures, tones of voice/speech, etc. However, these features can potentially be changed to fake features. Thus, to detect hidden and real features that is not controlled by the person are data measured from brain signals. There are various ways of measuring brain waves: EEG, MEG, FMRI, etc. On the bases of cost effectiveness and performance tradeoffs, EEG is chosen for emotion recognition in this study.

The main aim of this study is to detect emotion based on EEG signal analysis recorded from brain in response to visual stimuli. The approaches used were the selected visual stimuli were presented to 11 healthy target subjects and EEG signal were recorded in controlled situation to minimize artefacts (muscle or/and eye movements). The signals were filtered and type of frequency band was computed and detected.

Brain computer interface(BCI) based Emotion recognition are used in a variety of applications include advertisement, patient treatment, depression management, music player, human computer interaction, detecting children learning disabilities, assist disabilities with communication, game playing, automatic addition of emotional pictures during conversation, emotion enabled avatar, neuromarketing, etc.[1].

To introduce few facts of the human brain, our brain is one of the largest and complex organs of human body. It is the center of consciousness which enables the human to think, innovate, learn and create that makes human different from other animals. It is quite challenging to understand how the brain functioning as it is made from million of million neuron cells (around 100 billion nerves) which in turn communicate trillions of connections (called synapses).

This research focus on the outermost layer of human brain which is the cerebral cortex (cerebrum). The cerebrum is broadly divided in to left and right hemispheres, which are symmetrically nearly equal. Each hemisphere is in turn divided into four lobes including Frontal lobe, Parietal lobe, Temporal lobe and Occipital lobes. These lobes get their names from the bones of the skull that overlie them.

Human uses peripheral device such as mouse, keyboards, monitor, etc to interact with the computer whereas brain computer interface (BCI) is a device that allows the computer to read the human brain neuro-physiological activity and processes to perform a particular task without using traditional peripheral devices. The typical components of a BCI includes: signal acquisition, pre-processing, feature extraction and pattern recognitions. Signal acquisition, where the brain activity is recorded, pre-processing, where filtering, dimensionality reduction and feature extraction is carried out, pattern recognition where the selected features are used for detecting the target concept in the application. Finally, Post processing could be performed to instruct a particular device/system. The user might receive feedback from the device/system. For example, human can instruct the computer to write what he wants based on just sending thought signals from the brain to the computer.

In this research, we use EEG as it is more cost effective with reasonable quality trade-off than other types of neuroimaging approaches. The other reason is that EEG has capability to handle high temporal resolution and can directly measure the brain activity (non-invasive) with simple and portable device [2].

The brainwave activity is broadly divided into five frequency bands. The boundary between the frequency bands is not strict but not varying much. The frequency bands include delta(0.5-4Hz), theta(5-8Hz), alpha(9-12Hz), beta(13-30Hz) and gamma(above 30Hz) [3]. For this study, EEG data is collected using Emotiv EPOC device with 14 electrodes located at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. The electrodes are placed according to a 10-20 placement system with sampling rate of 128Hz [4].

Problems: According to the literature, even though it is possible to measure emotion from EEG signals recorded from

stimulated brain in practice, the outputs of BCI related research works are quite different with same stimuli and with brain response of same or different subjects [5]. The other problem is that parts of the brain that responds to emotion is not clearly identified or mixed up research results. For example, emotion is responded either or both on Frontal lobe or temporal lobe. Besides this, the brain wave contains emotion is not clearly known in that whether Alpha frequency band or gamma frequency band. These are some of the problems to motivates us to work on it.

Research questions: This study attempts to find out answers for the following research questions: (1) What regions of the brain are associated with visual emotion? (2) Which frequency bands of the brain waves are used for emotion recognition? (3) How accurately the chosen features were recognizing emotions using machine learning approaches? Due to space limitation on this report, we tried to present methods and results for answering some of this research questions.

Methods

Data Sets Preparation. We collected and prepared three image data sets for stimuli presentation and classification. These image data sets include: 90 sample images of Geneva Affective Picture Database (GAPED), 8 Colour images and 36 Indian company logo images. As classification algorithms require labeled data sets for building models via in supervised training, we merged class label information for each EEG records of each image stimulus in the data sets.

Hardware and Software Tools: EMOTIV EPOC head sets, Emotiv EPOC TestBench Control panel software and EventIDE are used for EEG brain activity recording. Emotiv headset is relatively simple to setup, it can uniformly capture brain signal from almost all regions of cerebral cortex and it is cost effective. Saline was applied to properly hydrate electrodes and fully contact with the scull.

EventIDE was used to record the Power Spectrum Density (PSD) of all 14 channels along with five frequency bands including: theta, alpha, *low_beta*, *High_beta* and gamma frequency bands. Therefore, the total of 70 channels are recorded for a total of 11 subjects for each of the three image data sets. These bands are filtered and finally, saved in .csv file format for further processing. The proposed approach in this study has consists of six stages: image stimulus presentation, subjects, EEG Signal recordings, Signal Filtering, feature extraction and classification. For pre-processing and building machine learning models, Weka is used.

Results and Discussion: To answer research question 1 and 2, the top ranked features for each subject are extracted using Relief algorithm in [6]. The brain frequency bands where it has top ranked features are counted for each subject. On the basis of this result, 37.5% of the subjects are responded to emotional images with alpha brain waves. The brain frequency bands and the channel numbers are counted in each of the three experiments on the three data sets. For this study, we build supervised machine learning models implemented in Weka. These includes Bayesian Network, J48(decision tree), Adaboost(meta learner) and Random forest. After fine tuning the selected machine learning models, it predicts an emotion type (positive/negative) in response to the presented stimuli. Finally, the performance of these models are tested on test sets. The average accuracy of machine learning algorithms (i.e. J48, Bayes Net, Adaboost and Random Forest) are 78.86, 74.76, 77.82 and 82.46 respectively. In conclusion, we tried to address three key issues. First, we empirically identified the brain regions which more responsible for emotion. On the basis of feature evaluation result, frontal lobe is more emotionally informative than other regions of the brain. Second, alpha and theta frequency bands are more discriminative than other brain frequency waves for emotion recognition. Third, random forest outperformed the other three algorithms (bayes Net, J48 and adaboost) in detecting the customers' emotion of image stimuli regardless of domain of application and gender. For real world applications, we have also demonstrated EEG developed machine learning models in the context of neuro-marketing. The results provides intelligence actions to detect the favourite colour preference of customers in response to the logo colour of an organization or Service.

Conclusion: This project is an EEG based Emotion recognition of image stimuli where there are a number of challenges including the variability of emotion recognition system that in turn caused by lack of quality in the recording of EEG data due to the variability among level of attention of subjects, the variability arise in multiple session, the variability caused by muscle movement, the variability due to machine noise, differing physiology of subjects, differing cognitive patterns and differing behaviour of subjects [5]. Thus, we tried handle our bests to regulate the causes of variability in EEG data recordings. For example, besides precautions during recordings, we applied filters for removing artifacts. Thus, we recommended interested

researchers to work on EEG based researches in the areas of neuro-marketing, TV ads evaluation, product branding, product preferences, disability treatment, stress management, just to name a few.

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