Real Time Emotion Detection using EEG

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Abstract

Emotion is an important aspect in the interaction between humans. It is fundamental to human experience and rational decision-making. There is a great interest for detecting emotions automatically. A number of techniques have been employed for this purpose using channels such as voice and facial expressions. However, these channels are not very accurate and can be faked. In this thesis, we are trying to use EEG signals as a new channel for emotion detection. The first part of the thesis is to infer four different emotions, happiness, fear, disgust and neutral, from EEG signals. This will require using sophisticated feature selection techniques which will generate large set of features. The generation of large number of features will require using feature reduction techniques. We will then employ different machine learning classifiers to reach the best accuracy out of these classifiers. In the second part of the thesis, we will explore the accuracy of detecting four different emotions against the number of channels.

Introduction

An emotion is a mental and physiological state associated with a wide variety of feelings, thoughts, and behavior. An emotion is a subjective experience which makes studying emotions one of the most confused and still open fields of research in psychology [1]. There are more than 90 definitions of "emotion" and there is little consensus on the meaning of the term. The reason why studying emotions is important is the fact that emotion is an important aspect in the interaction between humans. Emotion is fundamental to human experience, influencing cognition, perception, and everyday tasks such as learning, communication, and even rational decision-making.

There are two models for theoretical emotion representation. The first model that is proposed by Darwin [2] and followed after that by Plutchik [1] and Ekman [3], uses the idea that all emotions can be composed of some basic emotions exactly like the white color can be composed of primary colors. Plutchik [1] claims that there are eight basic emotions which all other emotions can be derived from. These eight emotions are anger, fear, sadness, disgust, surprise, curiosity, acceptance and joy. Ekman [3] has chosen other emotions to be the basic emotions. He considered anger, fear, sadness, happiness, disgust and surprise as the basic emotions.

The second model as shown in Fig. 1 [4] used to represent emotion is the dimensional view model [5]. It describes each emotion on a multidimensional scale. The first dimension is emotional valence, with positive emotions on one side and negative emotions on the other side. The second dimension represents the arousal. Sometimes, there is a third dimension which represents dominance. However, it is rarely used. The second model is used in most of the studies because of its simplicity and universality and there is little controversy about the two dimensions of the model.

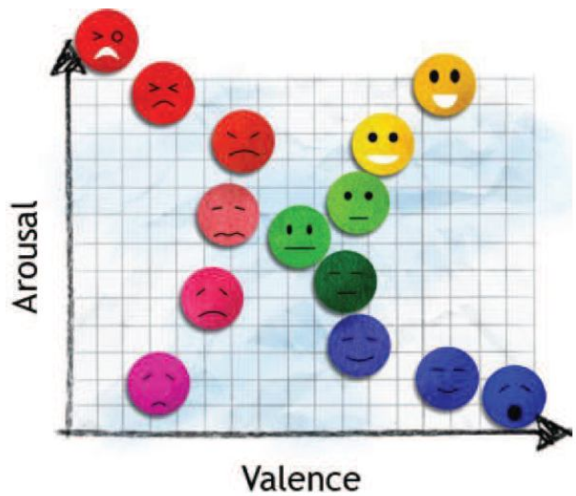

Figure 1: Two dimensional view of emotion.

There are a lot of studies to capture emotions automatically. Developing systems and devices that can capture and process human emotions and making use of them is the purpose of affective computing. Affective computing is related to, arise from or influence emotion or other affective phenomena [6]. It is an interdisciplinary field that requires knowledge in psychology, computer science and cognitive sciences.

Affective computing and emotion assessment are now growing fields because they have many potential applications. For instance, emotion assessment can be integrated in human-computer interaction systems that will lead to improve these systems by making them get close to human-human interaction. This will enhance the usability of the systems and improve the quality of life of disabled people who find difficulty in using the interfaces provided to healthy people.

Another type of emerging applications that make use of capturing users' emotions is quantifying customers' experience. These types of applications require an automated system to deduct customers' emotions without having them state it explicitly. Quantifying customers' experience using machine-aided techniques is becoming of great interest to many companies. These companies often conduct market research to build market share, competitive advantage and to predict how people would like their product. The problem with predicting customer's experience is that the current evaluation methods such as relying on customers' self reports are very subjective. People are not always feeling comfortable revealing their true emotions. They may inflate their degree of happiness or satisfaction in self reports. Participants report higher well-being in face-to-face interviews than they do in mail surveys or self-administered questionnaires [7]. This is because participants are unwilling to reveal their true emotions to strangers. In case of interviews, this interviewer effect disappears when the interviewer is severely handicapped [8]. Participants would like to give positive feelings to others but would rather not exaggerate when faced with another's unfortunate situation. This can show that self reports are very subjective and affected by external factors. Due to the inaccuracy of self reports, market researchers are trying to find new channels by which they can capture the users' affective states without asking them for their direct opinion.

Another type of important applications is helping people who suffer from psychological problems to interact and communicate easily with computers and humans by capturing the person's emotion and make the system self adapt based on the user's current emotion. For instance, people who are suffering from autism have difficulty in interacting with others in social environment. An affective computing system can provide solution to those people. One of these systems proposed in [9] captures the emotions of people interacting with the person suffering from Asperger Syndrome, autistic spectrum. It then gives an advice to the autistic patient of a good response.

Affective computing helps people to better interact with machines and computers and have a wide variety of applications. The success of an affective computing or an emotion assessment system is mainly based on the accuracy of detecting emotions from expressive human channels. These expressive channels include facial expressions, voice and electroencephalography (EEG). Affective computing, coupled with new wearable computers, will also provide the ability to gather new data necessary for advances in emotion and cognition theory [6].

Emotion Detection Channels

There is much work done in the field of emotion and cognitive state detection by analyzing facial expressions or/and speech. Some of these systems showed a lot of success such as those discussed in [10] [11]. The system proposed in [10] uses an automated inference of cognitive mental states from observed facial expressions and head gestures in video. The system is based on a multilevel dynamic Bayesian network classifier which models cognitive mental states as a number of interacting facial and head displays. The system proposed in [11] makes use of multimodal fusion of different timescale features of the speech. They also, make use of the meaning of the words to infer both the angry and neutral emotions.

Although facial expressions are considered to be a very powerful means for humans to communicate their emotions [2], the main drawback of using facial expressions or speech is the fact that they are not reliable indicators of emotion because they can either be faked by the user or may not be produced as a result of the emotion. The other alternative for emotion and cognitive state detection is analyzing physiological signals because they are not experiencing the same drawback of video and speech.

These types of signals cannot be faked due to the fact that they are produced from some involuntary secretion glands as a result of specific stimulus. Some of the systems that rely on detecting physiological signals make use of the signals generated from the peripheral nervous system such as skin temperature variation, heart rate, blood pressure and skin conductance. One of the systems that was able to classify four different emotions, anger, sadness, stress and surprise, is proposed by Kim et al. [12]. In this system, Kim et al. [12] made use of ECG and body temperature to recognize the four emotions. They tested their hypothesis on large dataset generated from 50 subjects and were able to reach an accuracy of 78.4% and 61.8% for three and four emotion categories respectively.

Based on the cognitive theory of emotion, the brain is the center of every human action [13]. Consequently, emotions and cognitive states can be detected through analyzing physiological signals that are generated from the central nervous system such as EEG signals. However, there is little work done in this area of research. Thanks to the success of brain computer interface systems, a few new studies have been done to find the correlation between different emotions and EEG signals. Most of these studies combine both EEG signals with other physiological signals generated from the peripheral nervous system [14] [15]. However, in this research, we will focus on inferring emotion from EEG signals.

EEG Primer [16]

Electroencephalography (EEG) is a method used in measuring the electrical activity of the brain from the cerebral cortex. This activity is generated by billions of nerve cells, called neurons. Each neuron is connected to thousands of other neurons. When this sum exceeds a certain potential level, the neuron ¯res nerve impulse. The electrical activity of a single neuron cannot be measured with scalp EEG. However, EEG can measure the combined electrical activity of millions of neurons [16].

There are two approaches for capturing EEG signals which differ in the brain layer where the electrodes are placed to capture the signals. The first approach is the invasive approach. In which very small electrodes are implanted directly over the cortex during neurosurgery as shown in the Fig. 2. The advantage of this approach is that it gives a very high quality EEG signals. However, it requires surgical operation.

The other approach is the non invasive approach in which electrodes are placed on the surface of the scalp as shown in the Fig. 3. The problem with non invasive EEG recording is the poor quality of the signals because the skull dampens the signals, dispersing and blurring the electromagnetic waves created by the neurons. Another problem of the non invasive approach is that it has a low spatial resolution. It is very difficult to determine the area of the brain that created them or the actions of individual neurons. Almost all today's EEG recordings are done non-invasively.

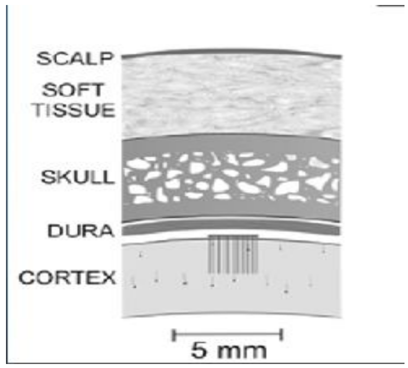

Figure 2: Invasive BCI. The electrode is implanted directly over the cortex.

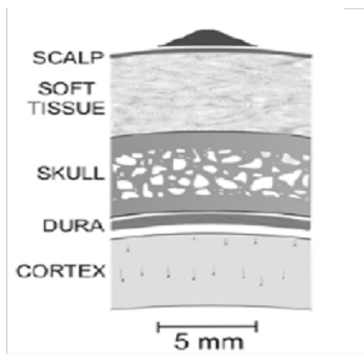

Figure 3: Noninvasive BCI. The electrodes capture the signals from the surface of the scalp.

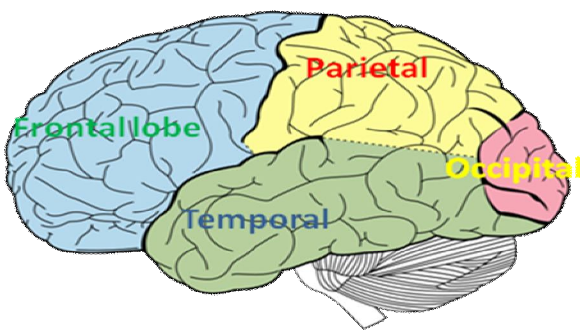

Figure 4: Different parts of the human brain.

The semantic of the EEG signal depends mainly on the places where the signals are captured. Each part of the brain has its own function. The brain has four main areas as shown in the Fig. 4. The frontal lobe is responsible for body limb movements and facial muscle movements. The parietal region is responsible for sensory information such as taste, pressure, sound and temperature. The occiptal region is the center of visual processing. Finally, the temporal region is the center of auditory processing.

In order to allow EEGs performed in one laboratory be interpreted in another, the 10-20 system, an international system of electrode placement, was introduced during the 1950s. This system utilizes several distinctive landmarks to help researchers capture EEG related to the tasks of interest. A top view is shown in the Fig 5.

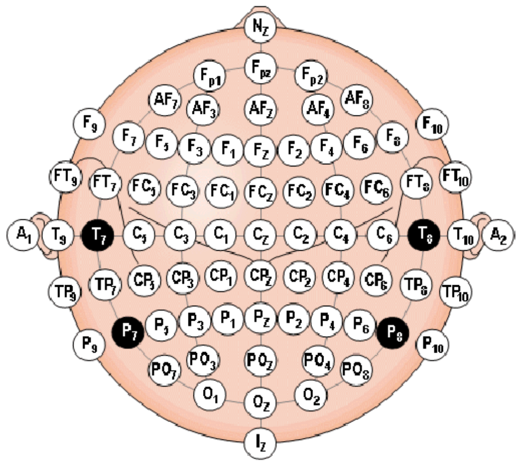

Figure 5: A top view of the brain that shows the locations for EEG recording according to the 10-20 system.

Rhythmic Activity

Rhythm	**Frequency Range**	**Location**	**Reason**
Delta	(0-4) Hz	Frontal lobe	Deep sleep
Theta	(4-7) Hz	Midline, temporal	Drowsiness and meditation
Alpha	(8-13) Hz	Frontal, Occipital	Relaxing, closed eyes
Mu	(8-12) Hz	Central	Contralateral Motor acts
Beta	(13-30) Hz	Frontal, central	Concentration and thinking

Gamma	(30- 100+) Hz		Cognitive functions

Table 1: Different EEG Rhythms

Rhythmic Activity

EEG can be described in terms of the signal rhythmic activity. This rhythmic activity can be divided into number of bands that differ in the range of the frequency they cover. Table 1 gives an overview on the different rhythmic bands, their frequency range, the brain location where they are most obvious and the reason why these signals are generated.

Emotion and Rhythmic Activity

There has been number of approaches to infer emotions from EEG rhythmic activity. Most emotions are found in the alpha band with different peak frequencies where the right hemisphere shows negative emotions such as fear, disgust and stress whereas the left hemisphere shows positive emotions such as happiness. Shemyakina et al. [17] show that significant differences in the local EEG power and spatial synchronization can be observed with different emotions. Musha et al. [18] showed that cerebral blood Flow (CBF) increases during sadness and decreases during happiness. The region that shows the difference between sadness and happiness is the frontal pole with left CBF being higher during sadness and lower during happiness.

Kostyunina et al. [19] showed that emotions such as joy, aggression and intention results in an increase in the alpha power whereas, emotions such as sorrow and anxiety results in a decrease in the alpha power. As for the valence and the arousal of emotions, Musha el al. [18] showed that valence of emotion is associated with asymmetries in the frontal lobe whereas, arousal is associated with generalized activation of both the right and the left frontal lobes

Related Works

Detecting users' cognitive states and emotions are very useful in many different fields. One of these areas is usability engineering. They can provide information about the efficacy of the system interface and can provide information for system adaptation for better usability. Cognitive states, emotions and working memory load are also, important to show how hard the user is working to use an interface. This can be an important indicator of potential user's errors and a predictive way to know how well a user gets acquainted with the system. Another important field which cognitive state and emotion detection have a great effect on is monitoring the alertness state of the subject. This can help in monitoring people while working on safety critical systems such as air traffic control and nuclear power plants.

Cognitive State Detection using EEG

Cognitive state detection has been around for quite some time. There are some interesting conclusions that were made by neuroscientists in this area. Kilmesch et al [20] found that the decrease in the theta rhythm and the increase in the beta rhythm indicate the presence of higher memory load. The problem is that these indicators are only valid when averaged over large amount of time and over data captured from different number of users. This can be considered a problem especially for real time applications. They also, use 32 electrodes for experimentation which hinders integrating their approaches in real time system. Grimes et al [21] tried to devise a technique for reliable measurement of working memory load to be used in real time adaptable systems. They managed to reduce the number of channels to only 8 channels, have their system trained on smaller datasets and experiment with smaller window sizes so that their approach can be used in real time systems.

They managed to reach an accuracy of 99% in classifying between two levels of working memory load and 88% in classifying between four levels of working memory loads which differ in the mental effort the user has to exert in order to use the application. In order to produce different memory workloads, Grimes et al [21] used the N-back task technique. In their experiments, a sequence of images or letters will be viewed to the participant. The participant will be given a letter or an image and asked whether this letter or image appeared in the sequence N letters before. The variation in the value of N will result in higher memory load.

For the signal processing, the authors down sampled the captured signals to only 256 Hz using a low pass filter. They divided the signal into overlapping widows and then converted it into the frequency domain using power spectral density estimation (PSD). As for feature generation, they divided the signal into three power bands. They collected the values of signal power ranging from 4 Hz to 13 Hz in 1 Hz intervals. They also, collected the values of signal power ranging from 14 Hz to 31 Hz in 2 Hz intervals. Finally, they collected the values of signal power ranging from 32 Hz to 50 Hz in 4 Hz interval. The reason why they made such choices is to have higher resolution estimates and more distinct features in these smaller power bands. Feature selection and dimensionality reduction is done by selecting the most predictive and robust features using relative information gain criteria. This is done by discretizing each feature into 15 equally spaced bins and calculating mutual information based on Nave Bayes density model.

As for the classification, Grimes et al [21] propose using 24-fold cross validation. They made sure that the selected training sets are drawn from blocks that are different from those used for testing. The reason why they made such choice is to make sure that the training data are not found close to the testing data which will overestimate their accuracy of the system and will not be suitable for a real time HCI system. Grimes et al [21] experimented with different number of EEG channels that range from only 1 channel to 32 channels. They showed that 8 channels provide a good tradeoff between accuracy and speed. They also, experimented with different window sizes that range from 2 seconds to 120 seconds and showed the tradeoff between the accuracy and the choice of the window size which is considered to be a major factor on applying the approach in real time systems.

Cognitive State Detection using EEG

Another approach for mental task classification was proposed by Lee and Tan [22]. The main purpose of their approach is to prove that they can detect mental states with a low cost EEG data acquisition and amplifiers and with only 2 electrodes. The authors were able to classify between three main mental tasks which are rest, mathematical calculation and geometric rotation. The participants are asked to stay still and to perform all the actions while their eyes are closed. These instructions were gives to the subjects in order to minimize the motion and eye movement artifact. The participants are given the instructions aurally and they are asked to perform the action within a given time period.

For the signal processing, Lee and Tan [22] suggests transforming the signal into the frequency domain. They do that by slicing the EEG signal into small overlapping windows and then take the Fourier Transform of the resulted signal. For each window, the authors compute the signal power in each of the six frequency bands for each channel, the phase coherence in each band across the channels and each band power difference between the two channels. In addition to these features, they compute the mean spectral power, peak frequency, peak frequency magnitude, mean phase angle, mean sample value, zero crossing rate, number of samples above zero and the mean spectral power difference. After that they compute the product and division of each pair of features. The reason why they do that is the fact that non linear manipulation of features is a common machine learning technique used to compensate for potential lack of expressiveness in the statistical model used for classification. After feature extraction, the authors apply Weka's VfsSubsetEval operator for dimensionality reduction. This operator reduces the number of features to only 51 features. They then applied a more computationally expensive feature selection process that builds a classifier with an empty set. The algorithm stars to add or remove features based on their effect on the overall accuracy. Finally, they used a Bayesian network classifier to identify the three different tasks. The used 10 fold cross validation as in [21] and reached an average accuracy of 84%. The major drawback of this approach is that it is not suitable for real time application where there will be lots of motion and eye blinks.

Another type of cognitive tasks is alertness. An approach for measuring users' alertness is proposed by Jung et al [23]. In order to collect EEG data, the participants are seated in front of a computer. The participants receive ten different visual and auditory stimuli per minute. For each stimulus, the user has to press a button to show whether the stimulus was visual or auditory. The time required by the user to press the button in response to the stimulus defines how alert the user is.

After recording the signal, Jung et al [23] suggest using a heuristic based approach for artifact removal. They suggest removing parts of the signals that are below or above 50 uV because they are produced due to eye blinks and muscle movement. After that a median filtering using a moving a 5-sec window was used to further minimize the presence of artifacts. After artifact removal, the signal is converted to a logarithmic scale. Due to the variability of EEG signals from one subject to another, Jung et al [23] suggests using artificial neural networks due to its flexibility and strong discriminative power. Principal Component Analysis (PCA) was applied to the full EEG log spectral data on the subspace formed by the eigenvectors corresponding to the largest eigen values. The authors found that using only 4 principal components will result in accuracy of 89%.

The area of cognitive detection using EEG has captured the attention of researchers working in the US market. One of the US application patents that describe a technique of task classification and recognizing activity is proposed by Microsoft Corporation [24].

The main goal of this patent is to make use of users' cognitive state to provide a better user interface for better usability. Tan and Lee [24] propose a method for classifying brain states using EEG signals. The captured data will be divided into a number of overlapping windows. Each window will be transformed to the frequency domain and then features are generated from the data in the EEG power spectrum. More features will be generated using the EEG base features and then they propose applying a feature selection algorithm for dimensionality reduction. The authors are suggesting similar techniques to that described in [22]. There are number of mental states that are of great importance such as cognitive workload, task engagement, communication mediation, interpreting and predicting system response, surprise, satisfaction, and frustration. The goal of this patent is to distinguish between at least two of these cognitive states and to determine the transition between the different mental states.

Emotion Detection using EEG

One of the earliest attempts to prove that EEG signals can be used for emotion detection is proposed by Chanel et al [14]. Chanel et al [14] were trying to distinguish among excitement, neutral and calm signals. They compared the results of three emotion detection classifiers. The first one was trained on EEG signals, the second classifier was trained on peripheral signals such as body temperature, blood pressure and heart beats. The third classifier was trained on both

EEG and peripheral signals. In order to use EEG signals, they used a band pass filter to remove both technical and physiological artifacts. In order to stimulate the emotion of interest, the user is seated in front of a computer and is viewed an image to inform him/her which type of emotion s/he has to think of. They then captured the signals from 64 different channels that cover the whole scalp. The reason why they used 64 channels is to capture signals in all the rhythmic activity of the brain neurons. As for feature extraction, they simply transformed the signal into the frequency domain and use the power spectral as the EEG features. Finally, they used a Naive Bayes Classifier which resulted in an average accuracy of 54% compared to only 50% for a classifier trained on physiological signals. The accuracy of combining both types of signals resulted in a boost of accuracy that reached up to 72%.

The problem with the research done by Chanel et al [14] is the idea of using 64 channels which results in large processing time which hinders the fact of using this system in real time. They also, used simple feature extraction and classification algorithms which resulted in the low 54% accuracy. Ansari et al [15] improved the work done by Chanel et al [14]. They proposed using Synchronization Likelihood (SL) method as a multichannel measurement which allowed them along with anatomical knowledge to reduce the number of channels from 64 to only 5 with a slight decrease in accuracy and huge improvement in performance. The goal is to distinguish between three emotions which are exciting-positive, exciting-negative and calm. For signal acquisition, they acquired the signal from (AFz, F4, F3, CP5, CP6). For feature extraction, they used sophisticated techniques such as Hjorth Parameters and Fractal Dimensions and they then applied Linear Discriminant Analysis (LDA) as their classification technique. The results showed an average accuracy of 60% in case of using 5 channels compared to 65% in case of using 32 channels.

Another approach was adopted by Kostyunina et al [19]. They used 10 different electrodes located at F3, F4, C3, C4, T3, T4, P3, P4, O1, O2 in order to detect four emotions which are joy, anger, fear and sorrow. Kostyunina et al [19] applied a low pass filter to reject all frequencies higher than 30 Hz. They applied FFT and focused on getting the features from the range of [0-30] with resolution of 0.2 Hz. The interesting thing about this research is that the authors used event related desynchronization in which the subjects are asked to imagine a situation that will result in changing their emotion to one of the four emotions of interest. Kostyunina et al [19] reached the conclusion that joy and anger emotions result in an increase in the peak frequencies of the alpha band whereas the case of fear and sorrow emotions result in a decrease in the peak frequencies of the alpha band.

A different technique was taken by Musha et al [18]. They used 10 electrodes (FP1, FP2, F3, F4, T3, T4, P3, P4, O1, and 02) in order to detect of four emotions which are anger, sadness, joy and relaxation. They rejected frequencies lower than 5 Hz because they are affected by artifacts and frequencies above 20 Hz because they claim that the contributions of these frequencies to detect emotions is small. They then collected their features from the theta, alpha and beta ranges. They performed cross correlation on each channel pairs. The output of this cross correlation is a set of 135 variables that is linearly transformed to a vector of 1x4 using a transition matrix. Each value indicates the magnitude of the presence of one of the four emotions. This means that any testing sample will be a linear combination of the four emotions. After that they apply certain threshold to infer the emotion of interest. Creating the transition matrix is done by collecting data from 9 different subjects who were trained to make 4 emotions. The training data are divided into two sets and the matrix was generated on one set and tested on another.

Other researches imply a multimodal technique for emotion detection. One of these studies was done by Savran et al [25]. They propose using EEG, functional near-infrared imaging (fNIRS) and video processing. fNIRS represents a low-cost, user-friendly, practical device for monitoring the cognitive and emotional states of the brain. fNIRS detects the light that travels through the cortex tissues and is used to monitor the hemodynamic changes during cognitive and/or emotional activity. Savran et al [25] combined EEG with fNIRS along with some physiological signals in one system and fNIRS with video processing in another system. They decided not to try video processing with EEG because facial expressions result in much in noise in the EEG signals. Also, when they recorded both EEG and fNIRS, they excluded the signals captured from the frontal lobe because of the noise produced by the fNIRS recordings. For experimentation, they showed the participant images that will induce the emotion of interest and then recorded fNIRS, EEG and video after showing these images. The most difficult part of this research is making an accurate synchronization mechanism for making the different recordings at the same time especially because every device was made to be used alone so they managed to run each system on a different computer and send a trigger to all computers at the time of showing the stimulus. The fusion among the different modalities is done on the decision level and not on the feature level.

There are a number of products that are currently available in the US market and are based on detecting emotions using EEG. One of these products is Emotiv Systems headset. The researchers at Emotiv developed a methodology for detecting and classifying mental states [26]. They developed a headset with up to 16 channels shown in Fig. 6. This headset covers the four main regions of the brain. After capturing the signal, a signal preparation is performed. This includes noise filtering and artifact removal using techniques such as Independent Component

Analysis (ICA). After that they start buffering the captured EEG signals and then they transform the buffered data to the frequency domain and extract features based on the different power bands. Due to the large number of extracted features, they apply some techniques for feature refinement and then they apply a method for detecting and classifying mental states which include emotions such as instantaneous excitement, long term excitement and boredom/engagement. The authors claim that different mental states and emotions result in the change and the increase of the signal power of one or more than one bio-signal representations [26].

Figure 6: Emotiv headset with 16 channels to cover the different parts of the brain.

In order to make sure that Emotiv system works for new users, Emotiv system allows the new user to train the system on his/her signals so that the classification accuracy increases. This is done by a method of calibrating the signature for use in the method of detecting and classifying the mental state [26].

The Problem of Emotion Detection using EEG

As we have seen from the related works, the area of emotion detection using EEG is relatively new. There is much of work that can be done to enhance the current state of the art. The available systems have two main drawbacks. The first is that some of the previously mentioned systems [14,18,19,25] are using large number of electrodes to acquire EEG signals that range from 10 to 32 electrodes which hinder the possibility of making these systems run in real time. Another problem with large number of electrodes is that it will require sophisticated headset which will make it difficult in mobile applications. The only system that uses only 5 electrodes [15] can differentiate between three emotions, positive, negative and calm, with a low accuracy of 60%.

Another problem with all the previously mentioned researches is that they are using expensive data acquisition devices that cannot be used for market purposes. The alternative to this expensive hardware is provided by Emotiv Systems which provides data acquisition hardware with only 300$. However, they are using 16 electrodes and they are differentiating between excitement and calm emotions. Also, Emotiv is providing this headset as a platform for gaming applications. Due to commercial and proprietary interests, there is no available documentation or any reports about the accuracy of detecting such emotions.

Research hypothesis

Given these problems, the goal of this research is to help answer the following questions

1. Can we detect four different emotions, happiness, sadness, disgust and neutral, using a relatively inexpensive hardware?

2. What is the minimum number of electrodes that can be used to detect the four emotions with a reasonable accuracy?

Our first goal is to collect EEG signals that represent the four different emotions.

EEG Montage

The first step in our research is deciding on the locations where we are going to capture the EEG signals. As shown in Fig. 7, we will be using 8 electrodes that will be spread on the four main regions of the brain (frontal, central, parietal and occipital)

The reason is that we are going to use visual stimulus which will result in having the signals in the occipital region more obvious. Parietal region is the region where we can capture theta band. And the beta band can be captured from both the central and frontal regions. Finally, the alpha band which is the most discriminative band in emotion detection can be captured from both the frontal and occipital regions.

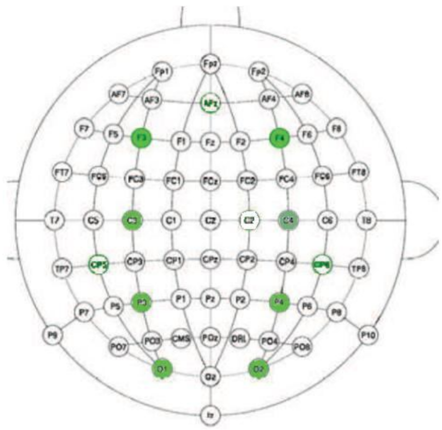

Figure 7: The positions where we are going to capture EEG according to the 10-20 system.

Test Protocol

The second step in our research methodology is deciding on the test protocol shown in Fig 8. The subjects will be asked to sit in front of a computer with minimal movements.

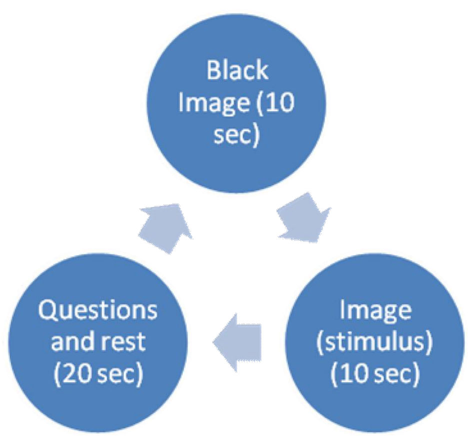

Figure 8: Test protocol

A black image will appear on the screen for ten seconds. This will be used to capture the user's attention. After that a stimulus will appear for ten seconds. This image will represent either a disgusting image to stimulate the user's disgust or an image that will stimulate the user's state of happiness or a blank image that will not stimulate any emotion. The user will rest for twenty seconds and within those twenty seconds the user has to mention whether the image made him happy or sad or feel disgusted or did not have any effect.

In order to have our approach be applied in real time uncontrolled systems, the EEG will have lots of artifacts that come from different sources. This includes technical artifacts such as the static electricity or electromagnetic fields that are produced from surrounding devices. This results in contaminating the EEG signal with a signal of frequency of 50 Hz. One approach to remove such noise is to use a notch filter. The second type of noise is the physiological noise. This noise comes from eye blinks, eye movements, muscle movements, respiration, sweat, etc. These signals usually have a low frequency that is lower than 3 Hz. One approach is to use a high pass filter to remove such noise. However, this will prevent us from using the information in the delta range. So we will use a more sophisticated technique of noise rejection. We will apply blind source separation techniques that include Principal component analysis. This will decompose the signal into the original EEG signal and the signal that is resulted from the physiological artifacts.

For feature extraction, we will try to use different techniques and compare the obtained results from these different techniques. We will first divide the signal into overlapping 2-sec windows just after the stimulus. After that we will transform the signal to the frequency domain and use Fast Fourier Transform. We will extract features such as power band in the theta, alpha and beta bands. We will then select further features such as the phase angle between different electrodes. This will result in a huge feature set so we will apply a dimensionality reduction technique such as Weka's VfsSubsetEval or correlation-based filter. We will use other techniques in the spatial domain that includes wavelet transforms and Hjorth parameters and compare the results against those obtained in the frequency domain.

As for training and classification, we will use K-fold cross validation in order to select the best parameters for our classifier. We will then train the extracted features on Bayesian Networks, Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs). We will experiment with different kernels for both the SVMs and ANNs After creating our own database of EEG signals representing emotions, we will try to find an answer to our second question by applying the signal preprocessing and processing techniques on different number of channels from 2 up to 8 channels and compare the resulting accuracy.

Tools

g.MobiLAB

To acquire EEG brain signals, we will use the g.MobiLAB, biomedical amplifier and A/D converter, from g.TEC [27]. g.MobiLAB is a biomedical amplifier that captures data at a sampling rate of 256 Hz. It provides storage of up to 8 channels. Active electrodes will be used along with g.MobiLAB to capture EEG data. Active electrodes are new technology of EEG sensors that puts a unity-grain amplifier next to the electrode up on the scalp. This increases the signal to noise ratio [27].

BCI2000

BCI2000 is a flexible modular open source BCI platform written in C++. It can be used easily by BCI researchers and developers as it provides a convenient interface between hardware used and the signal processing and application modules [28]. BCI2000 is compatible with g.MobiLAB which makes it a good choice for our research. BCI2000 facilitates the implementation of different BCI systems and other psychophysiological experiments. It provides an operator module that allows it to communicate easily with any external application using UDP/IP sockets. BCI2000 also, provides an interface to connect to Matlab which allows us to make use of Matlab in the signal processing and BCI200 in the signal acquisition. Finally, BCI2000 is available with full documentation and free of charge for research or educational purposes and is currently being used in a variety of studies by many research groups.

International Affective Picture System (IAPS) [29]

In order to induce the emotion of interest, the participant will be faced by an image that acts as a stimulus to generate this emotion. We will use a subset of images from the International Affective Picture System (IAPS) [29]. IAPS is a database of emotionally-annotated images. Each image of the IAPS database has been extensively evaluated by different participants of different ages and genders. The images are coded with values of valence/arousal. Several researches have shown the usefulness of the IAPS images in eliciting emotional responses that generate discriminative patterns [14, 15, 25].

EEGLAB

EEGLab consists of a set of Matlab functions that can be used in signal preprocessing. It provides the different techniques used to reject artifacts and remove it from the signal. This includes low pass, high pass filters and blind source separation techniques such as Principal Component Analysis and Independent Component Analysis. Providing Matlab functions will help us in integrating EEGLab with BCI2000.

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