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EMOTION ANALYSIS FROM PHYSIOLOGICAL SIGNAL USING EEG

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ABSTRACT

In modern world, hearing a song or seeing a video has become an imperative entertainment to people. Music Video Content (MVC) must be retrieved based on emotional information on human presence of mind. Many researches focus the study of relationship between videos and users' induced physiological and psychological responses. The existing system performs the emotion analysis by using single-trial classification with arousal, valence and liking using features extracted from the electroencephalogram (EEG) and peripheral physiological signals and MCA (Multimedia Content Analysis) modalities. It uses semi-automatic stimuli selection method using affective tags, which was validated by an analysis of the ratings given by the participants. But, it has limitations while considering the signal noise, physiological differences among individuals, and limited quality of self-assessments. To overcome these limitations, it is necessary to develop a new technique for effective MVC model. In the proposed work, a new framework for personalized MV affective analysis, visualization, and retrieval is used. By stimulating the human affective response mechanism, affective video content analysis extracts the affective information contained in videos, and, with the affective information, natural, user-friendly, and effective MVC access strategies could be developed. Based on the values retrieved by Independent Components Analysis (ICA), the music video is retrieved from the large-scale MV databases. The proposed approach may provide an efficient mechanism for searching results with a high degree of precision with minimal error. Thus it will be helpful for overcoming the current limitations and improve the final performance of affective computation.

I. INTRODUCTION

A Human Brain is the organ that gives the person the capacity for art, language, rational thoughts and moral judgments. It is also responsible for each individual's personality, movements, memories, and his perception about the world. It is one of the body's biggest organs, consisting of some 100 billion nerve cells that not only put together and highly coordinated physical actions but regulate our conscious body processes, such as digestion and breathing. Emotions play a significant and powerful role in everyday life of human beings. Impulsive emotions express an indication of psychosomatic disorders. These disorders are reflected as the changes in the electrical activities and chemical activities in the brain. The changes can be observed by capturing the brain signals and images. Psychiatrists nowadays, have to deal with the patients with either of two prominent psychological disorders Anxiety and Depression. Moreover, the patients are not ready to accept that the symptoms they are suffering from are indicative of some psychological disorder. It becomes a difficult job for the Psychiatrist, relatives of the patients and people around him to convince that he needs to be treated.

The proposed research is expected to quantify the psychological health of the patient from his EEG, as far as the two problems mentioned above, i.e. Anxiety and Depression is considered. Certain brainwave patterns are associated with normal states of consciousness. Others are associated with disease states (tumors) or mental health issues. To maintain good health, humans need to

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move in and out of various brainwave patterns during the course of each day. Electroencephalography, or EEGs, has been used to study brainwave patterns and states of consciousness in humans since Hans Berger invented the technology. As technology advanced and Cognitive Neuroscience developed, the EEG also gained a new role in this evolving field, as it assisted in demonstrating shifts from sympathetic (aroused) to parasympathetic (relaxed) states within the body. Neurons biofeedback has been shown to assist with performance enhancement, mood, and attainment of enhanced alpha states.

This study integrated information regarding the physiological responses to relaxation related to pulse, respiration, temperature and skin conductivity with self reported ranking of anxiety and pain. Additionally, changes in dominant brainwave patterns related to relaxation associated with respiration, skin temperature, blood pressure Group participants were recorded and analyzed by using EEG (Electroencyplography).

II. PROPOSED ALGORITHM

In the previous systems, the emotions of a user while watching music video clips will help the recommender system to first understand the user's taste and then to recommend a music clip which matches the user's current emotion. The database presented explores the possibility of classifying emotion dimensions induced by showing music videos to different users. To the best of our knowledge, the responses to this stimulus (music video clips) have never been explored before, and the research in this field was mainly focused on images, music, or non-musical video segments. In an adaptive music video recommender, an emotion recognizer trained by physiological responses to content of a similar nature, music videos are better able to find the rating of the videos.

In this proposed system we are recording the brain wave patterns of the human being by making them to watch the emotional videos. This brain wave patterns were recorded using the EEG (Electroencephalogram). Then we are using the ICA algorithm to analyses the brain activity and classify them into different patterns at different levels. The waves from the different parts of the brain were found and they were subjected to classification of alpha, beta, gamma waves according to arousal and valence. Then using this arousal and valence we are extracting emotions like heart rate (HR), skin temperature (ST) and blood pressure (BP).

We present a multimodal data set for the analysis of human affective states. The electroencephalogram (EEG) and peripheral physiological signals of 32 participants were recorded as each watched 40 one-minute long excerpts of music videos. Participants rated each video in terms of the levels of arousal, valence, like/dislike, dominance, and familiarity. For 22 of the 32 participants, frontal face video was also recorded. A novel method for stimuli selection is proposed using retrieval by affective tags from the video highlight detection, and an online assessment tool. An extensive analysis of the participants' ratings during the experiment is presented. Correlates between the EEG signal frequencies and the participants' ratings are investigated. Methods and results are presented for single-trial classification of arousal, valence, and like/dislike ratings using the modalities of EEG, peripheral physiological signals, and multimedia content analysis. Finally, decision fusion of the classification results from different modalities is performed. The data set is made publicly available and we encourage other researchers to use it for testing their own affective state estimation methods. Using this database we were analysed the Blood pressure, Skin temperature, Heart rate from the brain waves using the ICA algorithm.

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Implementation is the stage of the project when the theoretical design is turned out in to a working system. This it can be considered to be the most critical stage in achieving a successful new system and in giving the user, confidence that the new system will work and be effective. Implementation involves careful planning, investigation of the existing system and its constraints on implementation, designing of methods to achieve change over and evaluation of change over methods.

A. ALGORITHM USED

ICA

Severe contamination of EEG activity by eye movements, blinks, muscle, heart and line noise is a serious problem for EEG interpretation and analysis. Many methods have been proposed to remove eye movement and blink artifacts from EEG recordings:

- Simply rejecting contaminated EEG epochs results in a considerable loss of collected information.
- Often regression in the time or frequency domain is performed on simultaneous EEG and electrooculographic (EOG) recordings to derive parameters characterizing the appearance and spread of EOG artifacts in the EEG channels. However, EOG records also contain brain signals, so regressing out EOG activity inevitably involves subtracting a portion of the relevant EEG signal from each recording as well.
- Since many noise sources, include muscle noise, electrode noise and line noise, have no clear reference channels, regression methods cannot be used to removed them.

A new and often preferable alternative is to apply ICA to multichannel EEG recordings and remove a wide variety of artifacts from EEG records by eliminating the contributions of art factual sources onto the scalp sensors. This results show that ICA can effectively detect, separate and remove activity in EEG records from a wide variety of art factual sources, with results comparing favorably to those obtained using regression or PCA based methods.

***ICA* Assumptions**

ICA-based artifact correction can separate and remove a wide variety of artifacts from EEG data by linear decomposition. The ICA method is based on the assumptions that the time series recorded on the scalp:

- are spatially stable mixtures of the activities of temporally independent cerebral and art factual sources, that
- the summation of potentials arising from different parts of the brain, scalp, and body is linear at the electrodes, and that
- propagation delays from the sources to the electrodes are negligible.

Assumptions two and three above are quite reasonable for EEG (or MEG) data. Given enough input data, the first assumption is reasonable as well. The method uses spatial filters derived by the ICA algorithm, and does not require a reference channel for each artifact source. Once the independent time courses of different brain and artifact sources are extracted from the data, artifact-corrected EEG signals can be derived by eliminating the contributions of the art factual sources.

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B. METHODS

In EEG analysis, the rows of the input matrix, X, are EEG signals recorded at different electrodes and the columns are measurements recorded at different time points (left). ICA finds an `immixing' matrix, W, which decomposes or linearly unfixes the multi-channel scalp data into a sum of temporally independent and spatially fixed components. The rows of the output data matrix, U = WX, are time courses of activation of the ICA components.

The columns of the inverse matrix, inv(W), give the relative projection strengths of the respective components at each of the scalp sensors (right). These scalp weights give the scalp topography of each component, and provide evidence for the components' physiological origins.

SOME USEFUL HEURISTICS

- Eye movements should project mainly to frontal sites with a low pass time course.
- Eye blinks should project to frontal sites and have large punctuate activations.
- Temporal muscle activity should project to temporal sites with a spectral peak above 20 Hz.

COMPONENT PROJECTIONS

Calling the activations the matrix of unmixed component time courses,

W=weights*sphere;
activations = W * data;

And the inverse weight matrix (i.e., the mixing matrix),

Winv = inv(W);

(or Winv = pinv(W); if the number of components is les than the number of channels), then the projection of the i'th independent component onto the original data channels is given by

aqProjection = Win (: I) * activations (I, :);

The projection of the i'th component is the outer product of i'th row of the component activation (i.e., the component time course), activations (I, :), with the I'th column of the inverse matrix (i.e., the component scalp map), Win (:, I). The projected component data has the same size as the original data, has the same basis (i.e. each row is a single electrode, as in the original data), and is scaled in the original data units (e.g., uV). Scaling information and polarity are distributed between the activation waveforms and the maps.

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This means the true size (and polarity) of a component is given by the size (and polarity) of its projection. For the data shown above, all scalp maps were interpolated from 31 EEG channels and referred to the original right-mastoid reference. For each component, the amplitudes of scalp maps (given by the individually scaled color bars of the right panel) give the size of the component projections at the time point marked by the vertical blue line.
Above, artifact-free event-related brain signals were obtained by projecting the sum of selected non-art factual ICA components back onto the scalp,

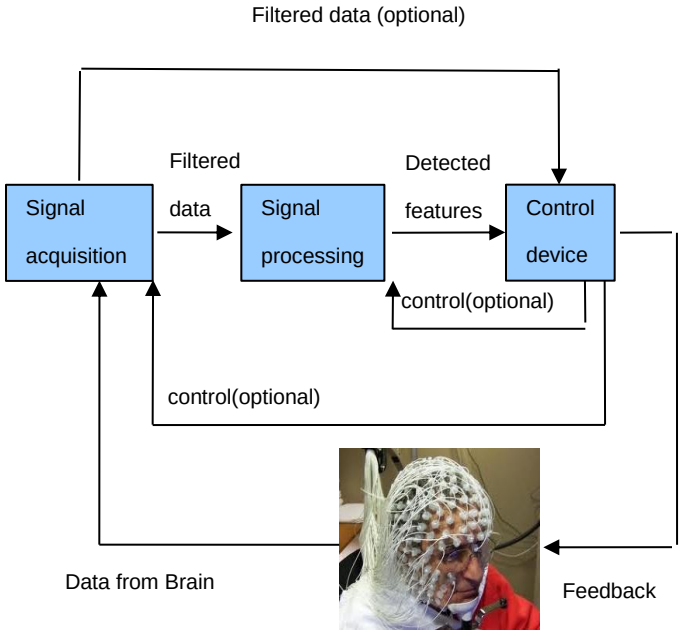
Clean data = Win(:,a) * activations(a,:);

where [a] was a vector of the selected non-art factual component numbers. The toolbox contains a function, icaproj (), that computes projections in a single line of code.

Clean data = icaproj(data,W,a);

In practice, the trick is to decide which components, [a], are art factual in the below Figure. 1.

Fig. 1. Proposed Diagram



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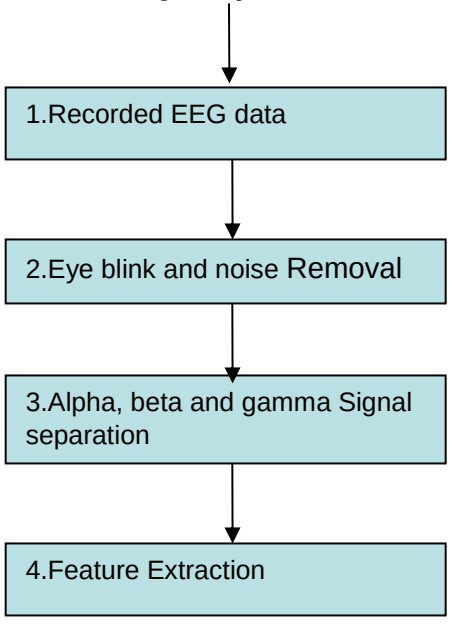
III. MODULES

In this section, the proposed method is described. It consists of three main blocks: image segmentation, segmentation matching, and in painting. The block diagram of our algorithm is shown in Fig. 1. In the following, each block is discussed in detail.

The following are the modules used in our proposed system below Figure. 2.

Fig. 2. Proposed Module



RECORDING EEG DATA

Electroencephalography (EEG) is the recording of electrical activity along the scalp. EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20–40 minutes, as recorded from multiple electrodes placed on the scalp. Diagnostic applications generally focus on the spectral content of EEG, that is, the type of neural oscillations that can be observed in EEG signals. In neurology, the main diagnostic application of EEG is in the case of epilepsy, as epileptic activity can create clear abnormalities on a standard EEG study. A secondary clinical use of EEG is in the diagnosis of coma, encephalopathy's, and brain death. A third clinical use of EEG is for studies of sleep and sleep disorders where recordings are typically done for one full night, sometimes more. EEG used to be a first-line method for the diagnosis of tumors, stroke and other focal brain disorders, but this use

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has decreased with the advent of anatomical imaging techniques with high (<1 mm) spatial resolution such as MRI and CT. Despite limited spatial resolution, EEG continues to be a valuable tool for research and diagnosis, especially when millisecond-range temporal resolution (not possible with CT or MRI) is required.

SOURCE OF EEG

The brain's electrical charge is maintained by billions of neurons. Neurons are electrically charged (or "polarized") by membrane transport proteins that pump ions across their membranes. Neurons are constantly exchanging ions with the extracellular milieu, for example to maintain resting potential and to propagate action potentials. Ions of similar charge repel each other, and when many ions are pushed out of many neurons at the same time, they can push their neighbors, who push their neighbors, and so on, in a wave. This process is known as volume conduction. When the wave of ions reaches the electrodes on the scalp, they can push or pull electrons on the metal on the electrodes. Since metal conducts the push and pull of electrons easily, the difference in push or pull voltages between any two electrodes can be measured by a voltmeter. Recording these voltages over time gives us the EEG.

The electric potential generated by single neuron is far too small to be picked up by EEG or MEG. EEG activity therefore always reflects the summation of the synchronous activity of thousands or millions of neurons that have similar spatial orientation. If the cells do not have similar spatial orientation, their ions do not line up and create waves to be detected. Pyramidal neurons of the cortex are thought to produce the most EEG signal because they are well-aligned and fire together. Because voltage fields fall off with the square of distance, activity from deep sources is more difficult to detect than currents near the skull.

Scalp EEG activity shows oscillations at a variety of frequencies. Several of these oscillations have characteristic frequency ranges, spatial distributions and are associated with different states of brain functioning (e.g., waking and the various sleep stages). These oscillations represent synchronized activity over a network of neurons. The neuronal networks underlying some of these oscillations are understood (e.g., the thalamocortical resonance underlying sleep spindles), while many others are not (e.g., the system that generates the posterior basic rhythm). Research that measures both EEG and neuron spiking finds the relationship between the two is complex with the power of surface EEG in only two bands (gamma and delta) relating to neuron spike activity.

THE 10-20 EEG SCALP

To make replicable setups figure. 3, there are standardized sets of locations for electrodes on the skull. One of these sets of electrode positions or montages is the 10/20 system. To make the results of this experiment reproducible, this system is taken as a vantage point for determining a suitable electrode placement. The name of the system is derived from its method for finding the exact electrode positions. Head size is a variable measure. Therefore this system uses instances in percentages from a couple of fixed points on the head. The starting points are the nasion, the dent at the top of the nose, and the inions which is the boney bump at the back of the skull. There is an imaginary vertical line from the nasion to the in ion and a horizontal line from the left ear lobe to the right. From 10% above the nasion and anion, along the vertical line, a theoretical circle is drawn around the head, hence the10 in the name. The other electrodes are positioned maintaining a 20% inter-electrode distance, as is indicated by the 20. 20% up from the circle from the nasion is Fz, and another 20% further along is the top of head labeled Cz. Pz is positioned on the vertical line in a similar manner. C3, T3, C4 and T4 are positioned in the same way along the horizontal mark. The electrodes on the imaginary circle are also at a 20% distance from each other, while keeping T3 and T4 on the horizontal line. The remaining electrodes are placed equidistant between de vertical line and the circle, filling the horizontal lines of the frontal and parietal electrodes.

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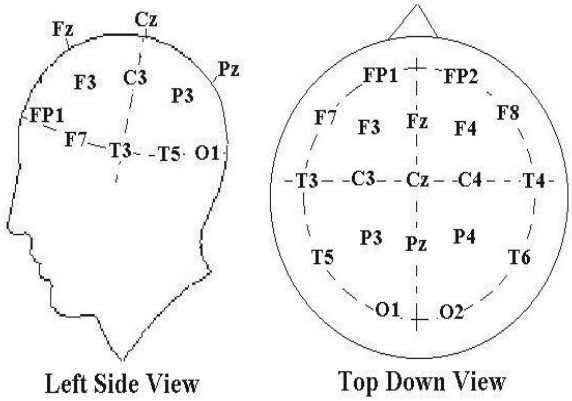
Fig. 3. EEG Scalp



To make this textual explanation a little less abstract for a visual representation is mentioned above. This is not a normal top view of the head, in which the positions on the circle would be shown on the outer border and the temporal lobe would not be visible. The positions are stretched along the nasion-inions outer circle. A general indication of the cortical areas is also shown: the top half is the frontal lobe, parietal just below the frontal lobe, the temporal areas to the sides, and the occipital cortex at the bottom.

IV. EXPERIMENTAL SETUP

During this laboratory session you will record four channels of EEG. Two channels will be recorded from the frontal region and two channels will be recorded from the occipital region. You should view the setup included with the experimental setup for this laboratory session figure. 4.

Fig. 4. Electrode scalp implementation

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- If possible, the subject for this laboratory should be a person with shorter hair. The subject also should have their scalp free of any types of hair gel. You will need seven gold cup electrodes for this laboratory. Gold cup electrodes will be placed at locations O1, O2, Fp1, and Fp2 to measure EEG, on each mastoid as references, and at Fp3 (middle of the forehead) for the ground. The mastoid processes (A1 and A2) are the bony structures that you can feel behind the ears. Before applying electrodes to the subject it is first important to properly prepare and clean the electrode sites.
- Now the gold cup electrodes can be attached. Generously fill a gold cup electrode with the provided conductive gel allowing some gel to fill over the top of the cup. Squeeze some of the conductive gel onto a gauze pad as well. Push the electrode into the gel on the gauze pad and then gently push aside the hair and place the electrode on the back of the subject's head at position O1. Repeat for the other gold cup electrode at different locations.
- Connect gold cup leads and jumpers to channel inputs 1, 2, 3, 4, and the ground using the picture below as a reference [1] . The left side view of the head is symmetrical to the right side view as seen in the top down view Figure. 5.

Fig. 5. EEG Experimental setup

PROCEDURE AND DATA COLLECTION

- Click on the EEG data Tab and then on the green "Start" button.
- You should begin to see four channels of EEG scrolling across the screen. Set the time scale to show a 2 second window of data. Click on "Screen Capture" to capture a picture of this to your report. This may not look like EEG yet because you are not filtering out high frequency noise that may be contaminating the signal such as 60Hz noise.
- Now click on the Spectral Analysis Tab. Click on the time plot tab and set the time scale on the time domain plot to be 1 second. Set the channel to process to channel 1.
- Instruct the subject to look at the screen. Under filter parameters, set the switch to filtered data, filter type to band pass, the high pass cutoff to 1Hz and the low pass filter to 20Hz and set the filter order to 4.

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- Instruct the subject to begin blinking rapidly and note what happens to the EEG signal. Capture a screen shot of this. Also, save approximately 10 seconds of this data to a file named "blink". About half the time should be blinking and half the time not blinking.
- Instruct the subject to begin to chew and note what happens to the EEG signal. Capture a screen shot of this. Also save approximately 10 seconds of this data to a file named "chew". About half the time should be chewing and half the time not chewing.
- Set the channel to process to be channel 1. After a few seconds instruct the subject to close their eyes and relax. You are attempting to record alpha waves from the subject (8- 13Hz waves). You should see these waves show up when the subject closes their eyes and relaxes. You should use a 4th order band-pass filter between 1 and 20 Hz.
- Repeat step 10 with the "channel to process" set to 2, 3, and 4. Find the channel that gives the best alpha waves. You should already have some idea what this should be from the text. Once you find the best channel, report a screen shot of the EEG signal when the subject's eyes are open and when they are closed.
- Do not change the parameters, but now click on the frequency domain plot tab. Examine what the estimated peak frequency is when the subject's eyes are open and when they are closed. When they are open, the estimated peak frequency should be fairly random; however, when they are closed, this frequency should remain within a certain range. Record this range, as you will need it for the next step.
- Save approximately 30 seconds of data to file while the subject's eyes are opened. Name the data file "eyes open".
- Save approximately 30 seconds of data to file while the subject's eyes are closed and they are relaxed. Name the data file "eyes closed".

1. EMOTIONS IN THE BRAIN

Stimuli enter the brain at the brain stem. The limbic system which is like a cortical ring around the brain stem is responsible for initial emotional interpretation of these signals from the autonomic nervous system. This part of the brain has also been found important for motivation and memory functions. Although motivation and memory also have their influence on the reaction to emotional stimuli, the rest of the text will focus on the limbic structures that are specifically relevant for emotional reactions.

The hypothalamus is responsible for processing the incoming signals and triggering the corresponding visceral physiological effects, like a raised heart rate or galvanic skin response. From the hypothalamus the stimuli information is passed on to the amygdale, which is important for learning to connect stimuli to emotional reactions (reward / fear) and for evaluating new stimuli by comparing them to past experience.

The amygdale is considered vital for emotion processing. However, since it is an underlying structure like the rest of the limbic system, it cannot be detected directly in recordings from the scalp. The amygdale is connected to the temporal and prefrontal cortices, which is thought to be the way visceral sensations are interpreted cognitively, resulting in a consciously experienced feeling of an emotion .The temporal lobe (the side areas covering T3–T6) is essential for hearing, language and emotion, and also plays an important role in memory.

The prefrontal lobe (directly behind the forehead) is involved in the so-called highest level of functioning. It is responsible for genitive, emotional and motivational processes. The prefrontal lose is part of the frontal cortex (top half), which is said to be the

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emotional control center and to even determine personality. It is involved in, among others, judgment and social behavior. These functions are very much based on the experience of emotions.

2. EYE BLINK AND NOISE REMOVAL

REMOVING ARTIFACTS FROM EEG

Severe contamination of EEG activity by eye movements, blinks, muscle, heart, and line noise is a serious problem for EEG interpretation and analysis. Many methods have been proposed to remove eye movement and blink artifacts from EEG recordings: Simply rejecting contaminated EEG epochs results in a considerable loss of collected information. Often regression in the time or frequency domain is performed on simultaneous EEG and electroculographic (EOG) recordings to derive parameters characterizing the appearance and spread of EOG artifacts in the EEG channels.

However, EOG records also contain brain signals, so regressing out EOG activity inevitably involves subtracting a portion of the relevant EEG signal from each recording as well. Since many noise sources, include muscle noise, electrode noise and line noise, have no clear reference channels, regression methods cannot be used to removed them. A new and often preferable alternative is to apply ICA to multichannel EEG recordings and remove a wide variety of artifacts from EEG records by eliminating the contributions of artifactual sources onto the scalp sensors. Our published results show that ICA can effectively detect, separate and remove activity in EEG records from a wide variety of artifactual sources, with results comparing favorably to those obtained using regression- or PCA-based methods.

ICA ASSUMPTIONS

ICA-based artifact correction can separate and remove a wide variety of artifacts from EEG data by linear decomposition. The ICA method is based on the assumptions that the time series recorded on the scalp: are spatially stable mixtures of the activities of temporally independent cerebral and artifactual sources, that the summation of potentials arising from different parts of the brain, scalp, and body is linear at the electrodes, and that propagation delays from the sources to the electrodes are negligible.

Assumptions two and three above are quite reasonable for EEG (or MEG) data. Given enough input data, the first assumption is reasonable as well. The method uses spatial filters derived by the ICA algorithm, and does not require a reference channel for each artifact source. Once the independent time courses of different brain and artifact sources are extracted from the data, artifact-corrected EEG signals can be derived by eliminating the contributions of the artifactual sources.

METHODS

In EEG analysis, the rows of the input matrix, X, are EEG signals recorded at different electrodes and the columns are measurements recorded at different time points (left). ICA finds a `un mixing' matrix, W, which decomposes or linearly unmixed the multi-channel scalp data into a sum of temporally independent and spatially fixed components. The rows of the output data matrix, U = WX, are time courses of activation of the ICA components.

The columns of the inverse matrix, inv (W), give the relative projection strengths of the respective components at each of the scalp sensors (right). These scalp weights give the scalp topography of each component, and provide evidence for the components' physiological origins.

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COMPONENT PROJECTIONS

Calling the activations the matrix of unmixed component time courses,

W=weights*sphere;

activations = W * data;

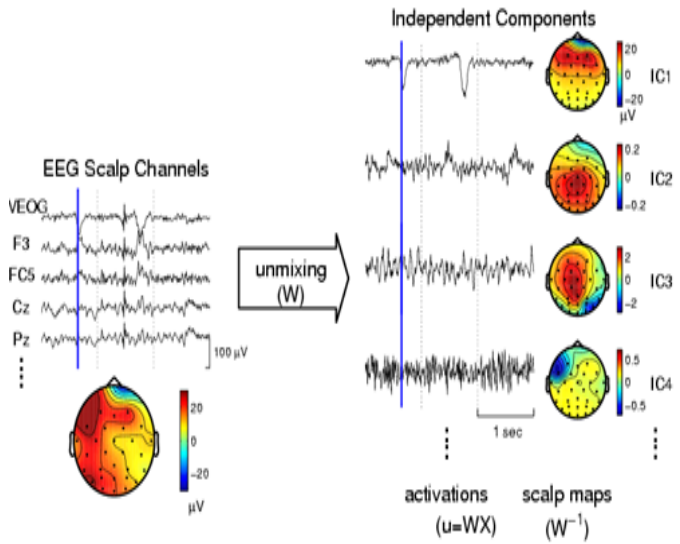
And the inverse weight matrix (i.e., the mixing matrix),

Win = inv (W);

If the number of components is less than the number of channels, then the projection of the I'th independent component onto the original data channels is given by figure. 6.

Projection = Win (I) * activations (I);

Fig. 6. ICA decomposition



The projection of the i'th component is the outer product of i'th row of the component activation (i.e., the component time course), activations, with the i'th column of the inverse matrix (i.e., the component scalp map), Winv(:,i). The projected component data has the same size as the original data, has the same basis (i.e. each row is a single electrode, as in the original data), and is scaled in the original data units (e.g., uV). Scaling information and polarity are distributed between the activation waveforms and the maps.

This means the true size (and polarity) of a component is given by the size (and polarity) of its projection.

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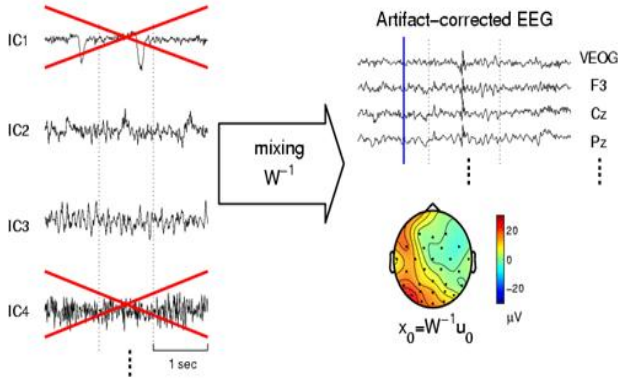
Fig. 7 Summed Projection of Selected Components



For the data shown above Figure. 7, all scalp maps were interpolated from 31 EEG channels and referred to the original right-mastoid reference. For each component, the amplitudes of scalp maps (given by the individually scaled color bars of the right panel) give the size of the component projections at the time point marked by the vertical blue line.
Above, artifact-free event-related brain signals were obtained by projecting the sum of selected non-artifactual ICA components back onto the scalp,

Clean data = Win (a) * activations (a);

Where [a] was a vector of the selected non-artifactual component numbers. The toolbox contains a function, icaproj (), that computes projections in a single line of code.

Clean data = icaproj (data, W, a);

In practice, the trick is to decide which components, [a], are artifactual. Above, we list some heuristics we have found useful.

REMOVING BLINK AND MUSCLE ARTIFACTS

The figure below shows a 3-sec portion of the recorded EEG time series and its ICA component activations, the scalp topographies of four selected components, and the artifact-corrected EEG signals obtained by removing four selected EEG and muscle noise components from the data. The eye movement artifact at 1.8 sec in the EEG data (left) is isolated to ICA components 1 and 2 (left middle). The scalp maps (right middle) indicate that these two components account for the spread of EEG activity to frontal sites.

Eliminating the four artifact components whose scalp maps are shown above, and projecting the remaining components back onto the scalp channels produced artifact-corrected EEG data (right) free of these artifacts.

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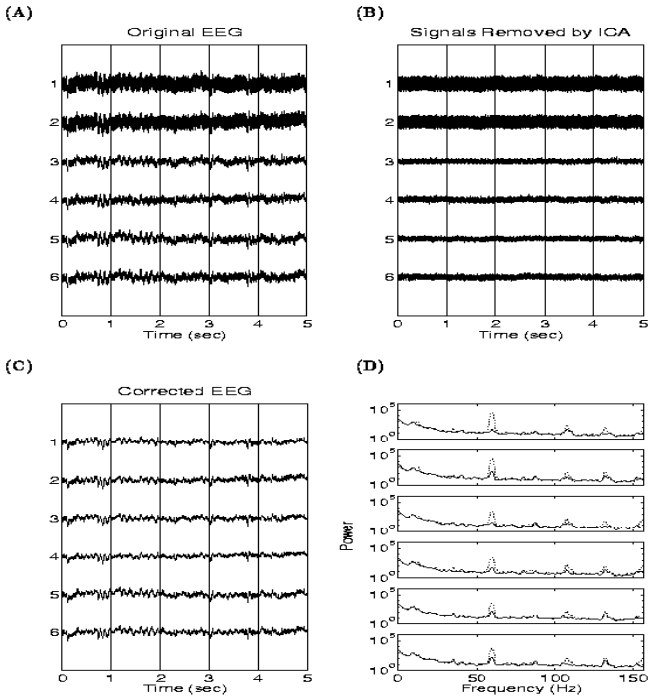
Note that removing the eye blink activity from frontal channels (Fp1, Fp2 left panel) clearly reveals frontal alpha activity occuring during the blink that is obscure in the original data.

Note also the regular right fronto-temporal muscle spike component #13 (middle panel) which, though difficult to see in the original data (e.g., in channel: T4), was nevertheless cleanly separated from other activity by ICA.

A five-second portion of a corrupted EEG time series resulting from a poor data-acquisition setting; (B) noise components extracted by ICA (right panel). (C) The same EEG signals corrected for artifacts by ICA by removing the six selected components, and, (D) spectral analysis of the original and artifact-corrected EEG recordings. Figure. 6, note that EEG activity is more visible than in (A), particularly in channels 1 and 2, and the line noise (60 Hz) and aliased line noise frequencies (near 12 Hz, 105 Hz, 135 Hz) are reduced.

Fig. 8. Some heavily contaminated EEG data.



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3. ALPHA, BETA AND GAMMA SIGNAL SEPARATION

SIGNAL SEPARATION

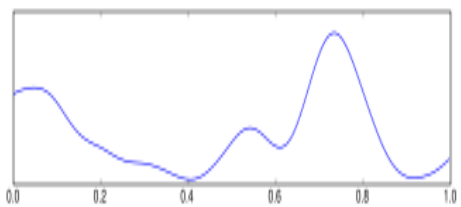
The separation of different frequency classes (0.1 – 4 Hz) delta, (4 -8 Hz) theta, (8 - 13 Hz) alpha and (13-30 Hz) beta for EEG signals are performed here. For this, use the FIR digital band pass filters. Now, compute the power spectrum of each to analyze the different frequency bands. The low frequency and high amplitude EEG signals are generated at the time of sleep or in relaxed state of healthy person, while the high frequency and lower amplitude EEG signals are generated in awake and working state of person. In this study, the EEG data of visual attention task of one subject (80 trials) (32-channel).

Electrodes are placed according to the 10-20 system and total time of recording is 119 sec, signals are sampled at frequency of 256 Hz. Above specified data after processing gives following results shows in Figure.7 and Table 1. From Figure.8, it can be observed that the maximum signal power is up to 30 dB. Normally, freq range from 0.1-4(Delta) and 4-8(theta) are generated in sleep and relaxed condition. Our EEG signals contains some of these components and shows maximum power in range of 0-5 Hz but same power levels also reaches in frequency bands of 15-25 Hz and rest of frequencies have low power levels. From the following observations are found.

DELTA

- 0.1-4 (delta) - in this range, the maximum power is 25-30 dB corresponding to 0-0.5 Hz (Figure. 9).

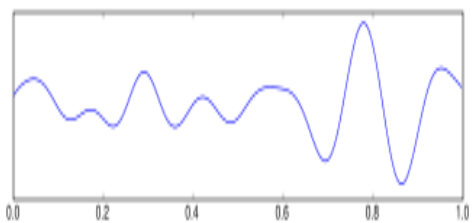
Fig. 9. Delta wave



THETA

- 4-8(theta) - in this range, the maximum power is 8-9 dB corresponding to 4.5-5 Hz (Figure. 10).

Fig. 10. Theta waves



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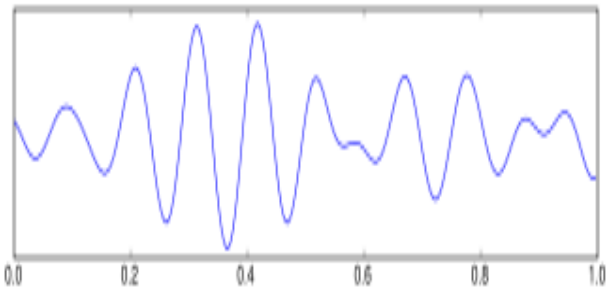
ALPHA

- 8-13(alpha) - in this range, the maximum power is 6-7 dB corresponding to 8.5-9 Hz (Figure. 11).

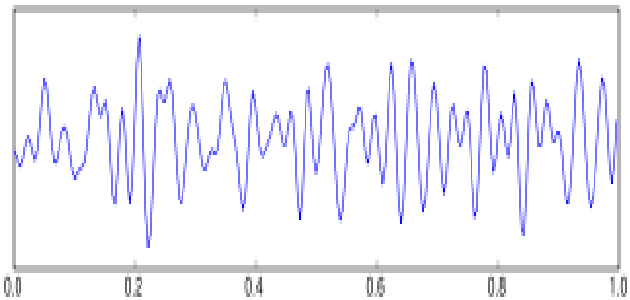
Fig. 11. Alpha wave



BETA

- 13-30(beta) - in this range, the maximum power is 10-12 dB corresponding to 18-22 Hz (Figure. 12).

Fig. 12. Beta wave



4. FEATURE EXTRACTION

EEG signals were first preprocessed by band pass filtering to keep frequencies in the 4-45Hz range. Concerning peripheral signals, heart rate was estimated from the blood pressure signal by computing its continuous wavelet coefficients (CWT) at an empirically determined scale and then identifying maxima of the CWT by simple derivation. Each maximum then corresponds to a heart rate. The 5peripheral signals to analyze are therefore: GSR, blood pressure, heart rate, respiration and temperature.

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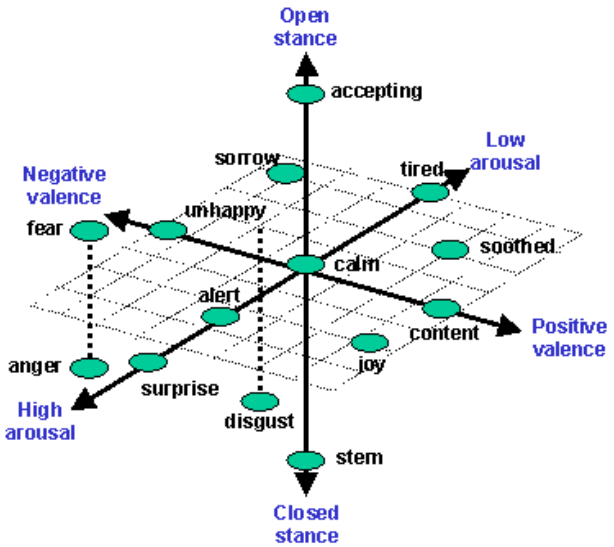
Fig. 13. 3D Representation of arousal and valence



From each of these signals were determined the following features over the 6s epoch: mean, variance, minimum and maximum, except for heart rate for which only mean and variance were used. Physiological signals such as heart rate, respiration, blood pressure, skin temperature are used to obtain individual's level of concentration in terms of tiredness, fatigue and stress. Heart rate variability (HRV), respiration sinus arrhythmia (RSA), and respiration and respiration pattern are the parameters use to measure stress. HRV and RSA can be calculated from the heart rate. Inhale and exhale cycle and breathing pattern signal above the figure. 13.

AROUSAL: BETA/ALPHA RATIO

Brain ball is a game based on brain activity in which the person that stays the most relaxed will win. How relaxed a player is, is determined by the ratio of the beta and alpha brainwaves as recorded by the EEG. The EEG is measured by three electrodes mounted on the forehead. There is no mentioning of reference leads or whether the measurements are bipolar or monopoles. However, as the application is to measure alpha and beta activity, not relative to other positions, monopole measurements can be assumed. Beta waves are connected to an alert state of mind, whereas alpha waves are more dominant in a relaxed person. Research has also shown a link between alpha activity and brain inactivation, which also leads to the same conclusion. This beta/alpha ratio could therefore be an interesting indication of the state of arousal the subject is in the arousal.

VALENCE: HEMISPHERICAL INACTIVATION

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Psycho physiological research has shown the importance of the difference in activation between the two cortical hemispheres in the reaction that test subjects show towards stimuli. Left frontal inactivation is an indicator of a withdrawal response, which is often linked to a negative emotion. On the other hand, right frontal inactivation is a sign of an approach response, or positive emotion High alpha activity (8-12Hz on the EEG frequency band) is shown to be an indication of low brain activity, and vice versa. So when mentioning cortical inactivation, in the EEG an increase in alpha activity is observed, joined with a decrease in beta waves. F3 and F4 are the most used positions for looking at this alpha activity, as they are located above the dorsolateral prefrontal cortex. As mentioned in the previous section about emotion in the brain, the prefrontal lobe plays a crucial role in emotion regulation and conscious experience.

Harmon-Jones' research suggests that the hemispherical differences are not an indication of affective valence (feeling a positive or negative emotion), but of motivational direction (approach or withdrawal behavior to the stimulus). Affective valence does seem tightly linked to motivational direction, but one example can clearly show the difference: Anger is experienced as a negative emotion, but generally results in an approach behavior with the intention to remove the stimulus. The author however does not provide a better alternative for detecting emotional valence. Therefore, this method of comparing hemispherical activation does promise the best results for valence detection.

HEART RATE VARIABILITY (HRV)

Heart is not operating in a regular, steady rhythm. Even in a resting conditions heart beats are irregular and also the signal pattern varies from person to person. Heart beats are frequently varying with the time interval. This beat time from one beat to the next beat is called the HRV variation in heart rate where each beat appears in different intervals.

HRV becomes a parameter in patient chart like other parameters such as pulse, blood pressure or temperature. HRV has been used as a diagnosis testing tool in many disease processes. Different kinds of medical and clinical Heart rate is not operating in rhythmic fashion that is the signal is non the signal pattern varies for person to person. Furthermore, heart rate signal is varies due to a range of aspects like age, physical infant, cardiac disease, neuropathy, respiration, maximum. HRV represents the activity of autonomous nervous system (ANS) therefore it is frequently used as a quantity of stress.

To obtain HRV it is required to extract a noise free inter signal from the EEG signal. Q2 complex is the major waveform in the EEG and it gives the basis to analyze heart rate variability (HRV). The intervals between adjacent Q2 computations called the normal to normal (NN) or the R to R intervals. HRV refers to the beat alternations in heart rate. The HRV measurements are captured noninvasively signal. Physiological conditions of a patient can depict from the are important indicators of cardiac disease. HRV is clinically associated to the lethal arrhythmias, hypertension, coronary artery disease, congestive heart failure, organ transplant, tachycardia, neuropathy, and diabetes derive HRV are describes in between HRV and stress.

SKIN TEMPERATURE

Skin temperature is one of the physiological parameters, which is used as an indicator of brain activity, state of mind, or psychological state. Skin temperature depends on three types of factors: a) environment conditions, b) individual variables, and c) cognitive or psychological state. When first two conditions are controlled then still skin temperature can vary 1 and 2 of due to psychological states. Finger temperature (FT) is one way of recording skin temperature. FT variation reflects the activities of sympathetic and

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parasympathetic nervous system of ANS. In response to stress, sympathetic nervous system activates and decreases the peripheral circulation and because of it FT also decreases.

The opposite situation occurs in response to relaxation when parasympathetic nervous system activates. Hence, psycho physiological dysfunctions or stress related dysfunctions can be diagnosed by monitoring rise and fall of figure temperature. Finger temperature is a measure of stress response since the changes of temperature are the reflection of blood flow. In a simple word the fundamental rule of these changes can be described as colder temperature reflects stress and warm finger temperature reflects relaxation. In response to stress SNS activates body's "fight or flight" system which leads heart rate and vital organs speed up and as a result blood flow is directed to the vital organs to facilitate the increased level of arousal . Therefore, changes in skin or finger temperature occur within a few minutes. The amount of temperature change depends on the stressor and also varies on how individual response to stress.

Stress diagnosis and biofeedback training are less expensive using FT than using other measures, which is an advantage usage of ST. Individual's response to stress in their own way and figure temperature is a simple and effective method to measure the stress level.

BLOOD PRESSURE

From the above analysis blood pressure may vary due to the respiratory and the skin temperature which occur for the several minutes during the experimental setup. This blood pressure may be analyzed by detecting the changes from the above two emotions.

Therefore, changes in skin or finger temperature and heart rate occur within a few minutes. The amount of blood pressure change depends on the stressor and also varies on how individual response to stress. This considered being a big emotion analysis from the EEG raw data. The HRV measurements are captured noninvasively signal.

Physiological conditions of a patient can depict from the are important indicators of cardiac disease. HRV is clinically associated to the lethal arrhythmias, hypertension, coronary artery disease, congestive heart failure, organ transplant, tachycardia, neuropathy, and diabetes derive blood pressure are describes in between heart rates and stress.

V. EXPERIMENT AND RESULT

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

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Beta	(13-30) Hz	Frontal, central	Concentration and Thinking
Gamma	(30- 100+) Hz	Cognitive	Functions

Table. 1. Range of signals

VI. CONCLUSION AND FUTURE ENHANCEMENTS

CONCLUSION

In this paper two categories of physiological signals, from the central and the peripheral nervous systems. This has been evaluated on the problem of assessing the arousal dimension of emotions. The focus was on the feature fusion in which several distinct features or parameters are integrated from the EEG including heart rate variability, blood pressure, and skin temperature.

Classification was performed for the scales of arousal, valence, and liking using features extracted from the EEG peripheral device. Using arousal and valence we were extracted the Blood pressure, Skin temperature and Heart rate of the person. The advantages of our system include the reduction of required signal monitoring time, applicability to multiple users and the use of signals that cause the minimum amount of user inconvenience. The system consists of characteristic waveform detection, and feature extraction.

FUTURE ENHANCEMENT

We were demonstrated for the normal human who have the normal mental and physical activity. And the future trends of this project may contain the following parameters. Analysising the emotions for the disabled and abnormal mental activity human and also it may be implemented for the animals also.

VII. REFERENCES

[1] Sander Koelstra, Mohammad Soleymani, Jong-seok Lee, Student Member, IEEE, Christian Muhl, ," DEAP: A Database for Emotion Analysis Using Physiological Signals", IEEE Transactions on Affective Computing, Vol. 3, No. 1, Page No 18-31,January – March 2012.

[2] Shiliang Zhang, Qingming Huang, Shuquang Jiang, , Wen Gao, Fellow, and Qi Tian, Senior Member, "Affective Visualization and Retrieval for Music Video" , IEEE Transaction on Multimedia , Vol. 12, No.6, Pages 510-522, October 2010.

[3] M. Soleymani, J. Lichtenauer, T. Pun, and M. Pantic, "A Multi-Modal Database for Affect Recognition and Implicit Tagging," IEEE Trans. Affective Computing, vol. 3, no. 1, pp. 42- 55, Jan.-Mar. 2012.

[4] S. Koelstra, A. Yazdani, M. Soleymani, C. Mu¨ hl, J.-S. Lee, A. Nijholt, T. Pun, T. Ebrahimi, and I. Patras, "Single Trial Classification of EEG and Peripheral Physiological Signals for Recognition of Emotions Induced by Music Videos," Proc. Brain Informatics, pp. 89-100, 2010.

IJESMR
International Journal of Engineering Sciences & Management Research

[5] M.K. Shan, F.F. Kuo, M.F. Chiang, and S.Y. Lee, "Emotion-Based Music Recommendation by Affinity Discovery from Film Music," Expert Systems with Applications, vol. 36, no. 4, pp. 7666-7674, May 2009.
[6] M. Tkal_ci_c, U. Burnik, and A. Ko_sir, "Using Affective Parameters in a Content-Based Recommender System for Images," User Modeling and User-Adapted Interaction, vol. 20, pp. 1-33-33, Sept. 2010.
[7] J.J.M. Kierkels, M. Soleymani, and T. Pun, "Queries and Tags in Affect-Based Multimedia Retrieval," Proc. IEEE Int'l Conf. Multimedia and Expo, pp. 1436-1439, 2009.
[8] Bergsma.A and van Petersen. K Het brain van A to Z., "Her sense tichting Sunderland Het Spectrum B.V.", 2003.BraInquiry. Pet EEG installation manual, 2005. Last visited: April 20, 2007.
[9] Chanel.G, Kronegg.J, Grandjean.D, and Pun.T, " Emotion assessment: Arousal evaluation using eegs and peripheral physiological signals.", In MRCS, pages 530–537, 2006.
[10] Choppin. "A EEG-based human interface for disabled individuals: Emotion expression with neural networks", Master's thesis, Tokyo Institute of Technology, Yokohama, Japan, 2000.
[11] Donchin.E., Spencer.K.M., and Wijesinghe.R., "The mental prosthesis: assessing the speed of a P300-based brain-computer interface," IEEE Transactions on Rehabilitation Engineering, pp. 174-179, vol. 8 no. 2, June 2000.
[12] EEGLAB a Matlab tool box for EEG analysis Obtained through the Internet:http://sccn.ucsd.edu [accessed 12/11/2010].
[13] Hamid.N.H.A., Sulaiman.N, Aris.S.M.A, Murat.Z.H., and Taib.M.N., 2010 Evaluation of Human Stress Using EEG Power Spectrum, Paper Presented at the International Colloquium on Signal Processing & Its Applications (CSPA).
[14] Kim.S, Georgiou. P, Lee .S, and Narayanan.S, Real-time emotion detection system using speech: Multi-modal fusion of different timescale features, in IEEE 9thWorkshop on Multimedia Signal Processing, 2007. MMSP 2007, pp. 4851, 2007.
[15] Kiymik, K.M., Akin, M., and Subasi, A., "Automatic recognition of alertness level by using wavelet transform and artificial neural network", Journal of Neuroscience Methods, 2004.
[16] Niemic.C.P Studies of emotion: A theoretical and empirical review of psycho physiological studies of emotion. Journal of Undergraduate Research, 1:15–18, 2002.
[17] Nijboer.F, Furdea .A., Gunst. I, Mellinger. J, McFarland. D. J, Birbaumer. N, and K¨ubler. A. An auditory brain-computer-interface (bci). Journal of Neuroscience Methods, 2007.
[18] Olguin.D.O "Adaptive digital filtering algorithms for the elimination of power line interference in electroencephalographic signals. Master's thesis", Institute Technological y de Studios Superiors de Monterrey, Monterrey, Mexico, 2005.
[19] Storey. B. D. Computing Fourier series and power spectrum with Matlab, 2002. Lecture notes.
[20] Van Dun. B, Wouters. J, Moonen. M., "Improving Auditory Steady-State Response Detection Using Independent Component Analysis on Multichannel EEG Data," IEEE Transactions on Biomedical Engineering, vol.54, no.7, pp.1220-1230, July 2007.
[21] Wang H.L and Cheong .L.F., "Affective Understanding in Film," IEEE Trans. Circuits and Systems for Video Technology, vol. 16, no. 6, pp. 689-704, June 2006.
[22] A.Anbumani, " Emotion Analysis from Physiological Signal Using EEG "Assisant Professor, Mahendra Institute of Technology, Thiruchengode , (2014).
[23] A.Sathishkumar, " Emotion Analysis from Physiological Signal Using EEG", Assistant Professor, Vivekanandha College of Arts and Sciences for Women(Autonomous), Tiruchengode ,Tamil nadu, India, (2014).