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A Survey and Comparative Analysis of Various Existing Techniques used to Develop an Intelligent Emotion Recognition System Using EEG Signal Analysis

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ABSTRACT

In today's age there is intense need of recognizing emotions with the help of technological tools due to increase in cases of mentally challenged/autistic people. Emotions are believed to be extremely potential for analyzing condition of mind. Emotion related research helps computer scientist in the development of emotion based Brain Computer Interface. BCI provides the way for communication and interaction with the outside world using brain signals. Non-invasive electroencephalogram (EEG)-based brain-computer interfaces (BCI) is the technique used to measure brain activity and different brain signals are translated into commands which will help to read hidden brains of people in need that most of us take for granted. The research is in process to recognize basic emotions like happy, sad, relax, non relaxed. Autistic children may have greater difficulty with subtle emotions like shame, pride, things that are much more socially oriented and they face greater difficulty in understanding emotions of other people. The success of the research depends on the selection of methods for brain signal processing in each phase of the emotion detection system. This research paper addresses various techniques proposed in each stage of emotion detection system and also presents the comparative analysis of existing work and future direction in this area.

Keywords: EEG, Brain Signal Processing, BCI, Emotion Detection System, Non-invasive electroencephalogram 2

1. INTRODUCTION

Emotions allow animals to express themselves beyond the verbal communication. Emotions can be detected by analyzing various parameters like facial expressions, eye movements, speech signal and brain waves. These detection methods can be concealed by individuals using misleading facial expressions or change the tone of speech which may be a problem in some applications. Emotions can also be detected from physiological signals originating from the peripheral nervous system, such as galvanic skin response, skin temperature and electrocardiogram and from EEG originating from the central nervous system.[1] To understand the mind of the people in special need, emotion detection by analyzing brain waves is more beneficial owing to continuous and inconsistent movement of eyes and face expression. Emotion could be developed through "inner thinking " process by refereeing to the brain from the human senses for example: visual, audio, factile, odor and taste. There are various methods to capture the brain signals such as CT-SCAN, PET (Positron Emission Tomography), fMRI (functional Magnetic Resonance Imaging), MEG(Magneto Electroencephalography) and EEG(Electroencephalography. Researcher prefers EEG because it is high speed and non invasive method. There is growing interest in the use of brain signals for communication and operation of devices particularly for people in need. This paper focuses on study of methods to detect emotions using EEG.

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2. RELATED WORK

In this section we have included stepwise emotion detection system. We have considered each step and included related research. We have also included comparative analysis of different techniques used in each stage. In section 1.3 we have presented performance comparison. In the next section 1.4 research challenges and issues are covered. Conclusion and future scope is mentioned in section 1.5. 3

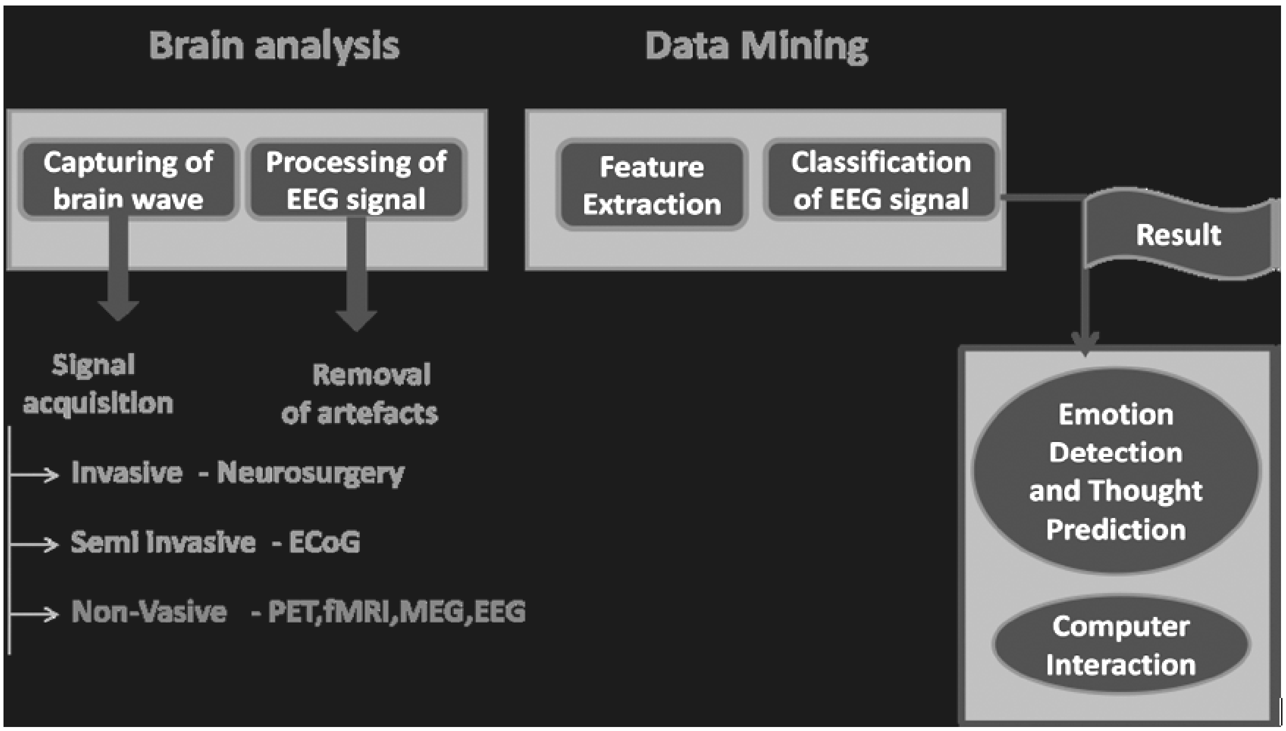

Figure 1: Model of Emotion Recognition System

The process of emotion detection contains following steps.

2.1. Capturing Brain Signal

There are various methods to capture the brain signals such as CT-SCAN, PET (Positron Emission Tomography), fMRI (functional Magnetic Resonance Imaging), MEG(Magneto Electroencephalography) and EEG(Electroencephalography. Researcher prefers EEG because it is high speed and non invasive method. This step consists in using various types of sensors in order to obtain signals reflecting the user's brain activity. Here we are presenting comparative study of Signal Acquisition Methods.

EEG has several strong points as a tool for exploring brain activity compared to other approaches such as Positron Emission Tomography (PET) and Functional magnetic resonance imaging (FMRI) as it give immediate response, high time resolution and low cost [2]. Electroencephalography is a medical imaging technique that reads scalp electrical activity generated by brain structures. The electroencephalogram (EEG) is defined as electrical activity of an alternating type recorded from the scalp surface after being picked up by metal electrodes and conductive media [3]. Weak electrical signals detected by the scalp electrodes are massively amplified, and then displayed on paper or stored to computer memory. Due to capability to reflect both the normal and abnormal electrical activity of the brain, EEG has been found to be a very powerful tool in the field of neurology and clinical neurophysiology. The EEG measured directly from the cortical surface is called electrocortiogram while when using depth probes it is called electrogram. Thus electroencephalographic reading is a completely non-invasive procedure that can be applied repeatedly to patients, normal adults, and children with virtually no risk or limitation [4]

Table 1
Comparative study of Signal Acquisition Methods

Type *Method of Acquisition*	*PET* *Positron Emission Tomography*	*FMRI* *Functional Magnetic Resonance Imaging*	*MEG* *Magnetoence – Phalography*	*EEG* *Electroence phalography*
Technique	Scanning a visual display of brain activity that detects where a radioactive form of glucose goes while the brain performs a given task.	For revealing blood flow and brain activity by comparing successive MRI scans	Functional neuroimaging technique for mapping brain activity by recording magnetic fields produced by electrical currents occurring naturally in the brain	An amplified recording of the waves of electrical activity that sweep across the brain's surface
Measure	Display blood flow associated with neural activity.	Measures changes in blood flow associated with neural activity.	Measures magnetic signals generated by electrical activities	Measures electrical potentials at the scalp which original from electrical currents involved in the generation of action potentials
Spatial Resolution	Good	Good (3-6mm)	Very good	Bad
Temporal Resolution	No	Bad (in order of seconds)	Very good	Good
Speed	Very slow	Very slow	Slow	High speed
Dependent Measure	Regional Cerebral Blood Flow	On the magnetic properties of blood	Magnetic properties depends on electrical activity	Electrical activity in different brain regions.
Radioactive Tracers	Needed	Not needed	Not needed	Not needed
Technique	Semi Invasive	Non invasive	Non invasive	Non invasive
Setup	Setup cost is more	Setup cost is more	Bulky setup Expensive	Safe and easy technique

The measurement of electrical activity of human brain scalp through electrodes is called as Electroencephalography (EEG). The use of EEG signals is powerful as a vector of communication between men and machines measuring emotions as the signals measured from the central nervous system will give a relationship between psychological changes and emotions.

Various ways of elicitation emotions in human subjects have been employed in order to develop datasets of brain waves for different emotions. The basic method is known as Ground Truth Method. In this method subject is asked to invoke a particular emotion by remembering some of his life incidents or by providing some audio and visual stimuli. Another approach is to provide the combination of visual and audio stimuli. This method is capable of producing responses that are closer to real life. After providing the visual stimuli, subject is allowed to stabilize so as to invoke particular emotion and then the EEG is captured with the closed eyes. EEG is recorded by differential amplifier (difference between two inputs). It is averaging method. 6

The EEG signal has excellent temporal resolution, but it has poor spatial resolution. The skull behaves like a low-pass filter and distorts the underlying brain electrical activity over a large area of the scalp. Potentials recorded at the scalp are likely generated by multiple groupings of cortical and subcortical generators spread across a relatively wide area. Thus, a scalp electrode is likely detecting electrical activity generated from non-local groups of neurons, which is why it is better to discuss EEG activity at a specific electrode location rather than resulting from a particular brain area. Use of dense electrode arrays (typically considered to be a minimum of 64 electrodes) may alleviate some of the concerns with spatial resolution.

Indeed, dense arrays allow calculation of the source of the electrical signal [5]. The Source localization is the big problem in EEG. To solve this problem EEG systems use caps with as many as 256 active electrodes. The cost of an EEG system is correlated with the number of electrodes. Some EEG systems can be used for simultaneous EEG/MEG or EEG/fMRI recordings. Researchers are also working on wireless acquisition and on dry electrode technologies that do not use conductive gel[6]

2.2. Pre-processing

This step consists in cleaning and de-noising input data in order to enhance the relevant information embedded in the signals. After capturing all the EEG signals for different emotions, they are filtered using a band pass filter. The most frequently used methods are ICA Independent Component Analysis (ICA), CAR Common Average Referencing (CAR), SL Surface Laplacian (SL), PCA Principal Component Analysis (PCA), CSP Common Spatial Patterns (CSP) and Adaptive Filtering. EEG wave contains certain range for different waves from 0-100Hz. In which delta is present for 0-3Hz, theta for 3-7Hz, alpha for 8-13Hz, beta for 13-30 Hz and gamma above 30Hz. Therefore, to get the particular set of waves from EEG, a band pass filter of 3-35Hz is applied. This filter removes power lines 50Hz noise as well as DC offset of each electrode. Also it helps to preserve the frequency band of interest for emotions. After capturing the required EEG, trimming of the part of signal that contains artifacts is possible. Also the manual selection of signal of our own interest is possible. In the “Effect of Noise Removing on Emotional Classification” by Maziyar molavi, Jasmy bin Yunus, Paper for pre-processing and 7

rejection of noise Wavelet transform, ICA, PCA were used. It is mentioned in the paper that ICA could provide the most accurate result for classifying emotional states in brain activity than other methods and PCA was not shown a very different and inaccurate classification results[7].In the “Classification of human emotions from EEG signals using SVM and LDA Classifiers” paper, ICA techniques is used for preprocessing. To perform ICA in EEG signal, we can used EEGLAB, a matlab toolbox.It is an open source environment and is freely available. EEGLAB is useful in performing ICA, in rejection of artifacts, time/frequency analysis provides various modes of visualizing dynamic properties of components present in an EEG signal.[8]

2.3. Feature extraction

After obtaining the noise-free signals from the signal enhancement phase, essential features from the brain signals were extracted. Feature extraction aims at describing the signals by a few relevant values called “features”.[9] With the help of feature extraction the original EEG data is retrieved with reduced number of variables so as to find a difference in the different brain states during different tasks. Features like the mean, median, Analysis of variance, Standard Deviation, Average Energy and Average Power were extracted from the EEG signals. Various temporal and spatial approaches have been applied to extract features from the physiological signal. For feature extraction from EEG signals use methods like PCA, ICA, Genetic Algorithms (GA), Wavelet Transformations (WT), Wavelet Packet Decomposition (WPD) ,DWT are mostly used.

Wavelet analysis allows the use of long time intervals where we want more precise low frequency information, and shorter-regions where we want high frequency information. Discrete Wavelet Transform (DWT) has emerged as a powerful technique in diverse areas such as Multi-Resolution Analysis (MRA), peak detection and feature extraction of physiological signals and biomedical images. Normally, the EEG signals are non linear and complex in nature. The non linearity and complexity of EEG signals can signify the different emotions of the human [10]. Different types of emotions have different waveform characteristics. Hence it is not always the optimal wavelet function which is suitable for detecting all the emotions. Moreover, the classical wavelet basis method does not improve the further properties of the wavelet basis. The conventional convolution based implementation of the DWT has high computational complexity and memory requirements.

For feature extraction wavelet packet decomposition (WPD) can be used. Since the EEG is a time-varying and space-varying non stationary signal, this makes both wavelet transform (WT) and wavelet

Table 2
Comparison between DWT and WPD

DWT	*WPD*
It does not change the information content present in the signal	In WPD the results are in the form of approximations and details. The approximations are the high- scale, low-frequency components of the signal. The details are the low-scale, high frequency components
B-Spline parameters is used	Fisher's criterion is used
This function can act as low pass filter as well as high pass filter and with these filtering characteristics	the signal is passed through more filters than the DWT.
DWT can extract features in time domain	WPD can extract features in both time and frequency domain with the coefficients mean of WT.
In the DWT, each level is calculated by passing the previous approximation coefficients though a high and low pass filters.	the WPD, both the detail and approximation coefficients are decomposed
The DWT is computed by successive low pass and high pass filtering of the discrete time-domain signal	Wavelet packets are the particular linear combination of wavelets. The coefficients in the linear combinations are computed by a recursive algorithm making each newly computed wavelet pack

packet decomposition (WPD) excellent candidates for feature extraction from such data. Many literatures have demonstrated that WPD is one of the most promising methods to extract features from the EEG signals wavelet decomposition is used to decompose EEG signal into low frequency and high frequency component [11]. High frequency component are noise because EEG signal is very small in Hz. So our signal is in low frequency. Here comparison between DWT and WPD is presented.

Classification parameters achieved both by the DFT provide similar results but features of the dominant cluster are closer together in the case of the DWT use in most cases.[12]

2.4. Classification

The classification step assigns a class to a set of features extracted from the signals. Every Classification technique has its own advantage and disadvantage. The choice of classifier generally depends on various factors leading to type of data and sample size to objective of classification. Sometimes a better data beats a better classification technique. Independent Component Analysis (ICA) and Machine Learning techniques such as Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) can be used to classify EEG signals into different emotions. Advantage of SVM includes high accuracy, prevents over-fitting and works very well with non- linear data with appropriate choice of kernel. LDA is generally not good with few category variables though it performs very well with linear data. The k-Nearest Neighbor works well on basic pattern recognition problems; however it is a slow learner in the sense that that it does not learn anything from the training data. It is also not efficient to noisy data.[8]. It is important to achieve a very high accuracy to enable applications to be built around human computer interaction in the future.

2.4.1. Survey of classifiers used in BCI research

Table 3
Types of classifiers

		Classifiers			
Generative	*Discriminative*	*Static*	*Dynamic*	*Stable*	*Unstable*
Bayes Quadratic	Support Vector Machines	Multi Layer Perceptrons	Hidden Markov Model	Linear Discriminant Analysis	MultiLayer Perceptrons

Linear Discriminant Analysis

LDA easily handles the case where the Within-class frequencies are unequal and their performance has been examined on randomly generated test data. This method maximizes the ratio of between-class variance to the within-class variance in any particular data set thereby guaranteeing maximal separability [13] and [14]. LDA fails if the discriminatory function is not in mean but in the variance of the data.

Support Vector Machine

It is a very popular supervised learning algorithm invented by Vapnik et.vl further modified by Corinna Cortes and Vapnik . SVM is used to analyze data and recognize pattern. SVM is a supervised learning algorithm. They infer a function or relationship from the given training data and recognize patterns and are frequently applied in the field of pattern regression analysis and classification. When provided with a set of training set or belonging to two different classes, on SVM algorithm design a model which can then efficiently assigns a new example point to one of the two classes.

K- nearest Neighbor

K-NN classification is an intuitive and simple method of classification used by researchers for the classification of signals. This classifier compares a newly labeled sample (testing data) with the baseline data (training data) and gives the decision accordingly. Training data set includes classes. For a given values from data set, k-NN finds the k i.e. closest neighborhood in training data set. Then it assigns a class which frequently appears in its neighborhood .

Artificial Neural Network

ANNs are non linear classifiers composed of large number of interconnected elements called neurons. Each neuron in ANN simulates the biological neuron and is capable of performing simple computational tasks. The most frequently used neural network is the Multi Layer Perceptron Neural Network (MLPNN) in which, the network is arranged into three layers viz., input layer, hidden layer and output layer. The advantage of MLPNN is that its fast operation, ease of implementation and requiring small training sets. The no. of inputs denotes the no. of features selected and, no. of outputs denotes the no. of classes formed. The complexity of an ANN is estimated by the no. of neurons in the hidden layer of it. The large the no. of neurons in hidden layer the more the complexity, less no. of neurons in hidden layer causes classification errors. No specific criterion was defined for making this decision in hidden layer. By using trial and error method the no. of neurons has to be decided.

HMM

Hidden Markov models (HMM) are introduced for the offline classification of single-trail EEG data in a brain-computer-interface (BCI). The HMMs are used to classify Hjorth parameters calculated from bipolar EEG data, recorded during the imagination of a left or right hand movement. The Hidden Markov model (HMM) is a statistical model that has been widely applied to many scientists and engineering areas. It can well model temporal or sequential structures of signals by combining the observation and hidden state in an elegant Manner. Therefore, it is particularly suitable for modeling temporal signals, such as Speech and bio-signals. On the other hand, support vector machine (SVM) is a maximum margin classier with solid background in statistical learning theory. In principle, SVM constructs a hyper plane in the kernel space so as to maximize the margin of separation between positive and negative examples. Thereby, it has a good generalization performance while retaining the advantage of discriminative approaches. Considering the advantage of HMM and SVM, a few recent endeavors resort to combining HMMs and SVM in a unified frame work which can capture well the temporal information as well as preserve the superior classification and generalization capability.[21]

Hjorth Parameters are indicators of statistical properties used in signal processing in the time domain introduced by Bo Hjorth in 1970. The parameters are Activity, Mobility, and Complexity. They are commonly used in the analysis of electroencephalography signals for feature extraction. The parameters are normalised slope descriptors (NSDs) used in EEG.[22]

COMPARATIVE PARAMETERS

Noise and outliers:

Regularized classifiers, such as SVM, seem appropriate to deal with outliers. It is also argued that discriminative classifiers perform better than generative ones in presence of noise or outliers.

HIGH DIMENSIONALITY: 12

SVM probably are the most appropriate classifier to deal with feature vectors of high dimensionality. If the high dimensionality is due to the use of a large number of time segments, dynamic classifiers can also solve the problem by considering sequence of feature vectors instead of a single vector of very high dimensionality. For instance, SVM and dynamic classifiers such as HMM are perfectly able to classify raw EEG. The kNN should not be used in such a case as they are very sensitive to the curse of dimensionality. Nevertheless, it is always preferable to have a small number of features. Therefore, it is highly recommended to use dimensionality reduction techniques and/or features selection.

TIME INFORMATION

For synchronous experiments, dynamic classifiers seem to be the most efficient method to exploit the temporal information contained in features. Similarly, integrating classifiers over time can efficiently utilize the time information. For asynchronous experiments, no clear superiority could be observed

NON-STATIONARY

A combination of classifiers may solve this problem as it reduces the Variance. Stable classifiers such as LDA or SVM can also be used but would probably be outperformed by combinations of LDA or SVM;

SMALL TRAINING SETS

If the training set is small, simple techniques with few parameters should be used, such as LDA [15]. LSVM had more accuracy than Naive Bayes classifier. Furthermore, the gamma band was the suitable frequency interval to detect arousal emotions. Nevertheless, the happy versus sad emotional features were classified with higher accuracy.[16]

3. COMPARISON OF PERFORMANCE

Table 4
Comparison of Performance

Author	*Feature Extraction*	*Classi-fication*	*Mental States*	*Remark*
S. Ramaraju [9]	PCA	LDA	Neutral Humour	FMRI studies have been useful in helping isolate different neural regions involved in humor processing and the brain mechanisms involved
Aayush Bhardwaj [8]	ICA	SVM LDA	Happy, Sad, Disgust,	SVM Classifier is better than LDA. Happy and sad emotions are recognized with best accuracy. Accuracy increases with increase in number of training samples

(*contd... Table 4*)

Author	*Feature Extraction*	*Classi-fication*	*Mental States*	*Remark*
			Neutral, Fear, Surprised Anger	
Vaishnavi L. Kaund-anya[20]	WT	KNN	Sad, Happy	The performance of k-NN classifier is observed which provides computationally good classification. It is based on distance function therefore for different values of 'k' different accuracies are obtained.
Bharti W. Gawali [17]	SST	LDA	Happy, Sad, Relaxed	When EEG signals of the subjects were in complete synchronization with the state of mind at that particular time 100% classification result for relaxed state and good result for happy and sad can be achieved. but in some cases due to low comfort level of the subject the same could not be noticed.
Hayfa Blaiech, Mohamed Neji[18]	FFT PBF	Fuzzy Rules	Neutrality, Joy, Sadness, Fear, Anger, Disgust, Surprise	Researcher have performed an emotional experience then extracted the three emotion features: arousal, valence and dominance. These features have been the inputs to our fuzzy classifier system. They have obtained a rate of recognition favorable to three emotions and an acceptable rate for four other emotions. As perspectives, they intend to refine the emotions recognition by analyzing a finer and more complex emotion.
M.Muru-gappan [23]	DWT	KNN	Disgust Happy Surprise Fear Neutral	Researchers have considered the classification of discrete emotions than dimensional emotions Valence/arousal. The multi-resolution analysis based non-linear feature works well with the context of discrete emotion classification. These results represent a possibility of determining the emotional changes of human mind through EEG signals. In addition, these results also confirm our hypothesis that it is possible to differentiate and classify the human emotions the linear and non-linear features.
Raja Majid Mehmood [24]	Hijroth Parameter	SVM	Happy, Calm, Neutral, Sad, Scare	Hijroth parameter, Band-pass filtering and combination of several EEG channels into specific brain lobes extracted the significant features for the SVM. Feature selection is a key challenge in affective computing. Accuracy in this experiments greatly increased on the small group of emotions

EEG signal classified into different categories according to the different mental states and frequency range, detailed in below table

EEG is already used in studies on autism in children to measure asymmetry in frontal electroencephalography (EEG) activity which is associated with motivational approach and avoidance

Table 5
Different mental states and frequency range

Brain wave type	*Frequency range(Hz)*	*Location*	*Mental states & conditions*
Delta wave	0-3.5 Hz	Frontal Lobe	Deep, dreamless sleep, non- REP sleep, unconscious
Theta wave	4-7.5 Hz	Midline, Temporal	Intuitive, creative, recall, fantasy, imaginary, dream
Alpha wave	8-12 Hz	Frontal, Occipital	Relaxed, but not drowsy, tranquil, conscious
Low Beta wave	12-15 Hz	Frontal	Formerly SMR, relaxed yet focused, integrated
Mid range Beta wave	16-20 Hz	Frontal,	Thinking, aware of self and surroundings
High Beta wave	21 to 30 Hz	Frontal , Central	Alertness, agitation
Gamma wave	30 to 100 Hz	Frontal , Central	Motor functions, higher mental activity

tendencies. During intense emotional activity, changes were noticed in the alpha signal in occipital and frontal regions of the brain. In case of very intense sad emotion display, Beta signals were also seen over Temporal and Frontal regions. 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 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 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. There are different regions of the brain. The electrodes are specific to the regions such as Prefrontal, Frontal, Temporal, Parietal, Central and Occipital. Alpha oscillations have been observed in memory processes where as Delta and Beta oscillations are observed in attention. In accordance with the literature survey we found that alpha signal showed changes in the occipital region and partially in the frontal regions as the emotions changes. It was observed that there was a relation between the different emotions and regions of the brain. Once the mental state is identified, a command is associated to this mental state in order to control a given application such as a speller (text editor) or a robot. This class corresponds to the kind of mental state identified. This step can also be denoted as “feature translation”.

4. CHALLENGES AND ISSUES

Despite numerous research efforts, the processes of emotion recognition still have limitations and margins for improvement.

1. Database for starting analysis is the biggest research challenge.
2. Non homogeneous properties of the skull, coherences between the sources and different orientation of the cortex sources increase the difficulty to locate exact location of the signal source. In the signal acquisition by EEG process, source localization is the big problem. This problem can be solved by using EEG cap with as many as active electrodes. This will lead to increase the cost of an EEG system. Some EEG systems can be used for simultaneous EEG/MEG or EEG/fMRI recordings. Researchers are also working on wireless acquisition and on dry electrode technologies that do not use conductive gel.
3. A very weak electrical signal EEG is detected by the scalp electrodes. Massive amplification should be performed for further analysis.
4. High impedance can lead to distortions which can be difficult to separate from actual signal. It may allow inducing outside electric frequencies on the wires used or on the body.
5. The immense research is going on to find basic emotions. The person lying in autistic spectrum have problem with subtle emotions. It is challenge to identify and classify such delicate emotions like love , pride, jealousy . The success of the research depends on the selection of methods for brain signal processing in each phase of the emotion detection system . Hybrid methodology can be used in each phase for the accurate and precise results.

5. CONCLUSION

Emotion Recognition System is still an open area of research due to the fact that we can improve the reorganization of many emotional states by using hybrid methodology at each level of BCI signal processing stage. In this paper a study of various signal processing methods used in each level of BCI signal processing is presented. The paper also addressed the research challenges and future scope in each phase 1. Signal acquisition 2. Pre-processing 3. Feature Extraction 4. Classification 5. External application of the emotion recognition system. The comparison of performance presented the success of researchers in identifying emotional state of the subject. This study may give guidance on finding the best method in accomplishing relevant experiments. Researcher addresses the issue of finding out basic emotions like happy, sad, excited, relaxed, non relaxed. To find of subtle emotions like pride, attitude, love, hate, comic etc. hybrid methodology can be used. With the use of various methods of BCI processing, human emotions can be identified, thought based games can be developed and significant improvements in BCI applications can be achieved . With the adequate knowledge of these new and efficient methods with mingled characteristics to always attain better performances. The ability to detect emotion from EEG may allow medical practitioners to obtain feedback from child patients suffering from conditions such as autism whereby facial features remain unreflective of emotional states. Studies suggested that humor might be another non-pharmacological lifestyle intervention to provide health, wellness & adjunctive therapeutic benefits. Further research can be carried out to see if it is possible to differentiate between several emotions. This would allow for more data rich feedback from patients, users and those seeking to use affective BCI with smart phone applications.

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