A Review on Classifiers for Emotion Studies

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Abstract--- In recent years the research interest is improving in the field of human computer interaction Two different Human-Machine Interfaces (HMIs) were developed, both based on electro-biological signals. One is based on the EMG signal and the other is based on the EEG signal. The Electroencephalogram (EEG) is one of the useful biosignals to detect human emotions which uses an electrical activity of the neurons inside the brain. Electromyography (EMG) is a technique for evaluating and recording the electrical activity produced by skeletal muscles. Emotions allow people to express themselves beyond the verbal domain. This paper attempts to review the different classifiers which attempts to classify the emotions using EEG and EMG signals.

Keywords--- Electroencephalogram, Electromyogram, emotion

I. INTRODUCTION

Emotions and their expression are a key element in social interactions, being used as mechanisms for signalling, directing, attention, motivating and controlling interactions, situation assessment, construction of self and others image, expectation formation, inter subjectivity etc[1]. It plays a central role in decision making, problem solving, communicating, negotiating and adapting to unpredictable environments. Recently, a constellation of findings from neuroscience, psychology and cognitive science suggests that emotion plays surprising critical roles in rational and intelligent behaviour.

Emotion assessment has recently attracted the attention of many researchers from different fields. The research of emotion recognition consists of facial expressions, vocal, gesture and physiological signal recognition and so on. The emotion recognition systems in speech or facial expressions which have been used include several emotional states such as joy, fear, sadness, disgust, anger, surprise and neutral. Emotion recognition in humans is an important research area.

In Neuro-physiological works, the signals measured from the central nervous system give a relationship between physiological changes and emotions. The electrical potential measured by electrodes on the scalp is rich in information on the brain activity and proper signal processing would allow us to collect global information about mental activities and emotional states. The goal of emotion classification is to recognize the emotional state of interest into number of emotional feature inputs. The accuracy of emotion classification and the time taken for training through an intelligent network are important factors for emotions classification.

Emotion is an important aspect in the interaction and communication between people. Even though emotions are intuitively known to everybody, it is hard to define emotion. Emotion is a complex set of interactions among subjective and objective factors, mediated by neural/hormonal systems, which can:

1. Give rise to affective experiences such as feelings of arousal, pleasure/displeasure;
2. Generate cognitive processes such as emotionally relevant perceptual effects, appraisals, labelling processes;
3. Activate widespread physiological adjustments to the arousing conditions;
4. Lead to behavior that is often, but not always, expressive, goal directed, and adaptive.

II. EMOTION CLASSIFICATION

Two different approaches to classification will be applied towards the development of the Emotion Classifier. The first would integrate the data from all three sensory channels into a high dimensional vector before attempting classification. The second would be to individually classify each sensory channel, and then integrate the classifications of each channel into a super classifier, in order to output a single emotion

2.1 Standard Classifiers

Standard Classifiers include a list of tried and tested mechanisms, each with a set of limitations. They can be divided into broad categories such as Decision Tree Induction, Bayesian Classification, Neural Network approaches, Fuzzy Classifiers, Genetic Algorithm Based Classifiers, etc. Each category itself consists of several classification algorithms.
2.2 Biologically Motivated Classifiers

Biologically motivated model for a classifier preserves information when composed into classification networks. The classifier propagates and aggregates information about feature relationships. The K-set hierarchy is a biologically inspired model of neural population dynamics developed by Freeman and associates. They have designed and parameterized a model that replicates experimentally recorded data of the dynamic behavior in the olfactory system. The network has been tested by simulating temporal and spatial properties of neural populations.

III. Electroencephalography

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. The variation of the surface potential distribution on the scalp reflects functional and physiological activities emerging from the underlying brain. The surface potential variation can be recorded by affixing an array of electrodes to the scalp and measuring the voltage between pairs of these electrodes, which are then filtered, amplified and recorded. The resulting data is called the EEG[2].

The first recordings were made by Hans Berger in 1929 although similar studies had been carried out on animals in 1870. The EEG is used in the evaluation of brain disorders. Most commonly it is used to show the type and location of the activity in the brain during a seizure. It also is used to evaluate people who are having problems associated with brain function. These problems might include confusion, coma, and tumors, long-term difficulties with thinking or memory, or weakening of specific parts of the body.

![Figure 1: EEG Electrode Placement Locations](image)

![Figure 2: Basic Diagram for Human Emotion Recognition using EEG Signals](image)

3.1 Emotion Classification

Many methods are available to classify the features from the EEG signal. The classification can be performed by using Support Vector machine (SVM), Neural Networks (NN), Linear Discriminant Analysis (LDA), Genetic Algorithm (GA) and so on. The Multi Layer Perceptron Network is also used to classify the EEG signal features. Because it has an ability to learn and generalize, smaller training set requirements, fast operation, ease of implementation and therefore most commonly used neural network. It has been an ability to describe the alertness level of arbitrary subject.

Normally, SVM have very good solid foundation in statistical learning theory, and guarantees to find the optimal decision function for a set of training data, given a set of parameters determining the operation of SVM. Hence it performs better classification on emotional features derived from the EEG signal than LDA and conventional NN [3]. The Genetic Algorithm also performs well on classifying the features. Recent day classifications are dealt with Radial basis Function (RBF) networks for EEG signal classification. Because the networks train rapidly, usually orders of magnitude faster than MLP, while exhibiting none of its training pathologies such as paralysis or local minima problems.

3.2 Review of Classifiers of EEG

Petrantonakis, P.C[4] presented a novel emotion evocation and EEG-based feature extraction technique. In particular, the mirror neuron system concept was adapted to efficiently foster emotion induction by the process of imitation. In addition, higher order crossings (HOC) analysis was employed for the feature extraction scheme and a robust classification method, namely HOC-motion classifier (HOC-EC), was implemented testing four different classifiers [quadratic discriminant analysis (QDA), k-nearest neighbor, Mahalanobis distance, and support vector machines (SVMs)].
in order to accomplish efficient emotion recognition. Compared with other feature extraction methods, HOC-EC appears to outperform them, achieving a 62.3% (using QDA) and 83.33% (using SVM) classification accuracy for the single-channel and combined-channel cases, respectively, differentiating among the six basic emotions, i.e., happiness, surprise, anger, fear, disgust, and sadness.

Xiao-Wei Wang[5] introduced an emotion recognition system based on electroencephalogram (EEG) signals. Experiments using movie elicitation are designed for acquiring subject’s EEG signals to classify four emotion states, joy, relax, sad, and fear. After pre-processing the EEG signals, we investigate various kinds of EEG features to build an emotion recognition system. To evaluate classification performance, k-nearest neighbor (kNN) algorithm, multilayer perceptron and support vector machines are used as classifiers. Further, a minimum redundancy maximum relevance method is used for extracting common critical features across subjects. Experimental results indicate that an average test accuracy of 66.51% for classifying four emotion states can be obtained by using frequency domain features and support vector machines.

Reza Khosrowabadi[6] presented an EEG-based emotion recognition system using self-organizing map for boundary detection. Features from EEG signals are classified by considering the subjects’ emotional responses using scores from SAM questionnaire. This paper investigates the performance of a proposed EEG-based emotion recognition system that employed self-organizing map to identify the boundaries between separable regions. EEG features were extracted using the magnitude squared coherence of the EEG signals. The boundaries of the EEG features were then extracted using SOM. 5-fold crossvalidation was then performed using the k-nn classifier. The results showed that proposed method improved the accuracies to 84.5%.

Ruo-Nan Duan[7] focussed on the variation of EEG at different emotional states. Pure music segments as stimuli is used to evoke the exciting or relaxing emotions of subjects. EEG power spectrum is adopted to form features, power spectrum, differential asymmetry, and rational asymmetry. A linear dynamic system approach is applied to smooth the feature sequence. Minimal-redundancy-maximal-relevance algorithm and principal component analysis are used to reduce the dimension of features. Performance of support vector machine, k-nearest neighbor classifiers and least-squares classifiers is evaluated. The accuracy of the method reaches 81.03% on average. Yuan-Pin Lin[8] applied machine-learning algorithms to categorize EEG dynamics according to subject self-reported emotional states during music listening. A framework was proposed to optimize EEG-based emotion recognition by systematically 1) seeking emotion-specific EEG features and 2) exploring the efficacy of the classifiers. Support vector machine was employed to classify four emotional states (joy, anger, sadness, and pleasure) and obtained an averaged classification accuracy of 82.29% ± 3.06% across 26 subjects. Further, this study identified 30 subject-independent features that were most relevant to emotional processing across subjects and explored the feasibility of using fewer electrodes to characterize the EEG dynamics during music listening. The identified features were primarily derived from electrodes placed near the frontal and the parietal lobes, consistent with many of the findings in the literature. This study might lead to a practical system for noninvasive assessment of the emotional states in practical or clinical applications.

Yisi Liu Olga Sourina[9] suggested that emotions recognized from Electroencephalogram (EEG) could reflect the real “inner” feelings of the human. Recently, research on real-time emotion recognition received more attention since it could be applied in games, e-learning systems or even in marketing. EEG signal can be divided into the delta, theta, alpha, beta, and gamma waves based on their frequency bands. Based on the Valence-Arousal-Dominance emotion model, we proposed a subject-dependent algorithm using the beta/alpha ratio to recognize high and low dominance levels of emotions from EEG. Three experiments were designed and carried out to collect the EEG data labeled with emotions. Sound clips from International Affective Digitized Sounds (IADS) database and music pieces were used to evoke emotions in the experiments. Our approach would allow real-time recognition of the emotions defined with different dominance levels in Valence-Arousal-Dominance model.

Ludmila I. Kuncheva,[10] introduced a system called AMBER (Advanced Multi-modal Biometric Emotion Recognition), which combines Electroencephalography (EEG) with Electro Dermal Activity (EDA) and pulse sensors to provide low cost, portable real-time emotion recognition. A single-subject pilot experiment was carried out to evaluate the ability of the system to distinguish between positive and negative states of mind provoked by audio stimuli. Eight single classifiers and six ensemble classifiers were compared using Weka. All ensemble classifiers outperformed the single classifiers, with Bagging, Rotation Forest and Random Subspace showing the highest overall accuracy. Olga Sourina[11] proposed and described a novel fractal dimension (FD) based emotion recognition algorithm using an Arousal-Valence emotion model. FD values calculated from the EEG signal recorded from the corresponding brain lobes are mapped to the 2D emotion model. The proposed algorithm allows us to recognize emotions that could be defined by arousal and valence levels. Only 3 electrodes are needed for the emotions recognition. Higuchi and box-counting algorithms were used for the EEG analysis and comparison. Support Vector Machine classifier was applied for arousal and valence levels recognition. The proposed method is a subject-dependent one. Experiments with music and sound...
stimuli to induce human emotions were realized. Sound clips from the International Affective Digitized Sounds (IADS) database were used in the experiments.

Hosseini[12] proposed a new emotional stress recognition system using multi-modal bio-signals. Since electroencephalogram (EEG) is the reflection of brain activity and is widely used in clinical diagnosis and biomedical research, it is used as the main signal. In order to choose the proper EEG channels the cognitive model of the brain under emotional stress is used. An efficient acquisition protocol to acquire the EEG and psychophysiological signals under pictures induction environment (calm-neutral and negative-excited) is designed for participants. Qualitative and quantitative evaluation of psychophysiological signals have been tried to select suitable segments of EEG signal for improving efficiency and performance of emotional stress recognition system. After pre-processing the signals, both Linear and nonlinear features were employed to extract the EEG parameters. Wavelet coefficients and chaotic invariants like fractal dimension by Higuchi's algorithm and correlation dimension were used to extract the characteristics of the EEG signal which showed that the classification accuracy in two emotional states was 82.7% using the Elman classifier. This is a great improvement in results compared with other similar published work.

Chung-Hsien Wu[13] presents an approach to emotion recognition of affective speech based on multiple classifiers using acoustic-prosodic information (AP) and semantic labels (SLs). For AP-based recognition, acoustic and prosodic features including spectrum, formant, and pitch-related features are extracted from the detected emotional salient segments of the input speech. Three types of models, GMMs, SVMs, and MLPs, are adopted as the base-level classifiers. A Meta Decision Tree (MDT) is then employed for classifier fusion to obtain the AP-based emotion recognition confidence. For SL-based recognition, semantic labels derived from an existing Chinese knowledge base called HowNet are used to automatically extract Emotion Association Rules (EARs) from the recognized word sequence of the affective speech. The maximum entropy model (MaxEnt) is thereafter utilized to characterize the relationship between emotional states and EARs for emotion recognition. Finally, a weighted product fusion method is used to integrate the AP-based and SL-based recognition results for the final emotion decision. For evaluation, 2,033 utterances for four emotional states (Neutral, Happy, Angry, and Sad) are collected. The speaker-independent experimental results reveal that the emotion recognition performance based on MDT can achieve 80.00 percent, which is better than each individual classifier. On the other hand, an average recognition accuracy of 80.92 percent can be obtained for SL-based recognition. Finally, combining acoustic-prosodic information and semantic labels can achieve 83.55 percent, which is superior to either AP-based or SL-Based approaches. Moreover, considering the individual personality trait for personalized application, the recognition accuracy of the proposed approach can be further improved to 85.79 percent.

<table>
<thead>
<tr>
<th>S.No</th>
<th>Classification Method</th>
<th>Features</th>
<th>Data Set</th>
<th>Nucleus Part</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>Support vector machine (SVM) classifier with a radial basis function (RBF) kernel is adopted to classify EEG segments. CA::(70-76)%</td>
<td>Through the weighed update of signal covariances, the most discriminative features related to the current brain states are extracted by the method of multi-class common spatial patterns (CSP).</td>
<td>No of Subjects:3 fs*:128 Hz No of Electrodes:15 No of Trials:3</td>
<td>Adaptive feature extraction for EEG signal classification for BCI Applications</td>
</tr>
<tr>
<td>2</td>
<td>In the SVM classifier, a Gaussian function was used as a kernel function that projects the data to high dimensional feature space. CA::41.7%</td>
<td>Mean, Variance, mean with first difference of raw signal and normalized signal, mean with second difference of raw signal and normalized signal</td>
<td>No of Subjects:12 No of Electrodes:3 No of Trials:2</td>
<td>Emotions namely joy, anger, sadness, fear and relax is trained and classified through multimodal bio-potential Signals EEM*:Commercial film clips</td>
</tr>
<tr>
<td>3</td>
<td>Using Neural Network-CA::62.3% Using SVM- CA::59.7%</td>
<td>Emotion Classification is done with features such as Power at each frequency band and mean of raw signal.</td>
<td>No of Subjects:10 No of Electrodes:3 No of Trials:5</td>
<td>Emotions namely Pleasure and Unpleasure are classified using NN and SVM. EEM*:Music or Sounds</td>
</tr>
<tr>
<td>4</td>
<td>Using Linear Mapping-CA::73.77% Using Neural Network-CA::91.74%</td>
<td>Differential signals between two electrodes (Y_i(t)=X_i(t)-X(t)) (X(t)) and (X(t)) are two signals in electrodes.</td>
<td>fs*:512 Hz (f_{0.10})Hz (f_{0.11})Hz No of Electrodes:19</td>
<td>Human emotions namely joy, anger, relaxation, sadness and worry is estimated using fractal-dimension of EEG and classification is done using NN and Linear Mapping network</td>
</tr>
</tbody>
</table>

Table 1: Previous Studies on Human Emotion Recognition using EEG
<table>
<thead>
<tr>
<th>No</th>
<th>Method/Details</th>
<th>Frequency Bands</th>
<th>Subjects</th>
<th>Electrodes</th>
<th>Trials</th>
<th>Classification/EDA</th>
<th>Description/Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>Using Naive Bayes Classifier CA*:54% Using Fisher Discriminant Analysis(FDA)</td>
<td>No</td>
<td>4</td>
<td>64</td>
<td>3</td>
<td></td>
<td>Emotions in two dimensional space namely valence &amp; arousal is detected. EEM*: a) Asking Actor to feel or express a particular mood b) External stimuli from images, sounds, videos and video games.</td>
</tr>
<tr>
<td>7</td>
<td>Emotions such as pleasant, aversive and neutral are classified according to its ANOVA values</td>
<td>No</td>
<td>4</td>
<td>254</td>
<td>2974</td>
<td></td>
<td>Electrodes are implanted in the human brain (amygdala) and are used for detecting the emotions. EEM*: International Affective Picture System (IAPS).</td>
</tr>
<tr>
<td>8</td>
<td>Depressed or Non-Depressed emotions are derived through MANOVA</td>
<td></td>
<td>2</td>
<td>64</td>
<td>30</td>
<td></td>
<td>Emotions are recognised from a 10 year old infant with his/her depressed mother.</td>
</tr>
<tr>
<td>10</td>
<td>Multi Layer Perceptron Neural Network (MLP), a feedforward artificial neural network model that maps sets of input data onto a set of appropriate output. CA*: 69.69%</td>
<td></td>
<td>5</td>
<td>32</td>
<td>28</td>
<td></td>
<td>Emotions namely angry, sadness, pleasure and joy are classified using MLP network. EEM*: Emotional Music from Oscar film sound tracks.</td>
</tr>
<tr>
<td>11</td>
<td>Binary Fisher Discriminant Analysis (BFDA), finds a discriminative feature transform on the set of support vectors. CA*: 90%</td>
<td></td>
<td>5</td>
<td>5</td>
<td>1</td>
<td></td>
<td>PCA is applied for feature selection and emotion is classified in two dimensional axis namely valence and arousal. EEM*: International Affective Picture System (IAPS) and International Affective Digital Sounds (IADS).</td>
</tr>
</tbody>
</table>

fs*: Sampling Frequency  
EEM*: Emotion  
Classification Accuracy f<sub>0</sub>: High Pass Filter Frequency  
f<sub>0</sub>: Low Pass Filter Frequency

### IV. ELECTROMYOGRAPHY

EMG is a technique for evaluating and recording the electrical activity produced by skeletal muscles. EMG is performed using an instrument called an electromyograph, to produce a record called an electromyogram. An electromyograph detects the electrical potential generated by muscle cells when these cells are electrically or neurologically activated. The signals can be analyzed to detect medical abnormalities, activation level, recruitment order or to analyze the biomechanics of human or animal movement. The electrical source is the muscle membrane potential of about 90 mV.
EMG potentials range between less than 50 μV up to 20 to 30 mV, depending on the muscle under observation. Typical repetition rate of muscle motor unit firing is about 7–20 Hz, depending on the size of the muscle (eye muscles versus seat (gluteal) muscles), previous axonal damage and other factors. EMG has many applications: For instance it is clinically used for the diagnosis of neurological and neuromuscular problems. Laboratory research applications are biomechanics, motor control, neuromuscular physiology, movement disorders, postural control and physical therapy. The first documented experiment dealing with EMG started with Francesco Redi’s works in 1666. The first actual recording of this activity was made by Marey in 1890, who also introduced the term electromyography. In 1922, Gasser and Erlanger used an oscilloscope to show the electrical signals from muscles. The capability of detecting electromyographic signals improved steadily from the 1930s through the 1950s, and researchers began to use improved electrodes more widely for the study of muscles. Clinical use of surface EMG (sEMG) for the treatment of more specific disorders began in the 1960s. Hardyck and his researchers were the first practitioners to use sEMG.

![Figure 3: EMG Electrode Placement Locations](image)

In the early 1980s, Cram and Steger introduced a clinical method for scanning variety of muscles using an EMG sensing device. Recent research has resulted in a better understanding of the properties of surface EMG recording. Surface electromyography is increasingly used for recording from superficial muscles in clinical or kinesiological protocols, where intramuscular electrodes are used for investigating deep muscles or localized muscle activity.

4.1 Review of Classifiers for EMG

Xiaowei Niu[24] discussed regarding the discrete emotion recognition as a pattern recognition problem, the idea of combinational mode optimization is employed on emotion recognition. For collecting physiological signals in four different affective states, joy, anger, sadness, pleasure, a music induction method which elicits natural emotional reactions from the subject is obtained. Four-channel biosensors are used to obtain electromyogram (EMG), electrocardiogram (ECG), skin conductivity (SC) and respiration changes. After calculating a sufficient amount of features from the raw signals, the genetic algorithm and the K-neigh bor methods are tested to extract a new feature set consisting of the most significant features for improving classification performance. Finally, the numerical results show that the performance is feasible and effective. It also turned out that it was much easier to separate emotions along the arousal axis than along the valence axis.

Jamieson, K,[25] proposed that when building a classifier from clean training data for a particular test environment, knowledge about the environmental noise and channel should be taken into account. He proposed training a support vector machine (SVM) classifier using a modified kernel that is the expected kernel with respect to a probability distribution over channels and noise that might affect the test signal. Comparison of the proposed expected SVM to an SVM that ignores the environment, to an SVM that trains with multiple random samples of the environment, and to a quadratic discriminant analysis classifier that takes advantage of environment statistics (Joint QDA) is made. Simulations classifying narrowband signals in a noisy acoustic reverberation environment indicate that the expected SVM can improve performance over a range of noise levels. Zhihong Liu Intell[26] proposed a novel electromyographic (EMG) motion pattern classifier using wavelet packet transform (WPT) and Learning Vector Quantization (LVQ) Neural Networks. This motion pattern classifier can successfully identify wrist extension, wrist flexion, hand extension and hand grasp, by measuring the surface EMG signals through two electrodes mounted on forearm extensor carpi ulnaris and flexor carpi ulnaris. The experimental results show that the proposed method achieves a 98% recognition accuracy. Furthermore, via quantitative comparison with other neural networks classifiers, LVQ method has a better performance. Consequently, the classifier is applicable to myoelectric hand control of 2 degrees of freedom (DOF) because of its high recognition capability.
Wee Ming Wong[27] proposed that a particle swarm optimization (PSO) of synergetic neural classifier for multimodal emotion recognition. In the experiments, a music induction method which elicits natural emotional reactions from the subject is used and four-channel biosensors are used to obtain electromyogram (EMG), electrocardiogram (ECG), skin conductivity (SC) and respiration changes (RSP) of the subject. The most significant features are extracted via testing several feature selection/reduction methods. Four classes of emotions, that is, joy, anger, sadness, and pleasure are considered and the synergetic neural classifier is used for multimodal emotion recognition. Weights are assigned to the different channels of the classifier and PSO is applied to optimize the weights for enhancing performance. Fast classification speed has been achieved and the experimental results look promising.

Shanxiao Yang[28] compared the emotional pattern recognition method between standard BP neural network classifier and BP neural network classifier improved by the L-M algorithm. Then comparison with the method Support Vector Machine (SVM) is made to them. Experiment analyzes wavelet transform of surface Electromyography (EMG) to extract the maximum and minimum wavelet coefficients of multi-scale firstly. The two kinds of classifier of the structural feature vector for emotion recognition are given as input. The experimental result shows that the standard BP neural network classifier, L-M improved BP neural network classifier and support vector machine’s overall pattern recognition rate is 62.5%, 83.33% and 91.67 respectively. Experimental result shows that feature vector extracted by the wavelet transform can characterize emotional patterns through the comparison with the BP neural network classifier and Support Vector Machine, indicating that the Support Vector Machine have a stronger emotional recognition effect.

Table 2: Previous Studies on Human Emotion Recognition using EMG

<table>
<thead>
<tr>
<th>S.No</th>
<th>Features</th>
<th>Classification Method</th>
<th>Data Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Separate the training data in feature space by a hyperplane defined by the type of kernel function used.</td>
<td>Support Vector Machine(SVM) CA:+9% (Amusement, Contentment, Disgust, Fear, Neutrality and Sadness) for subject1 (male) and subject2 (female), respectively</td>
<td>No.of Subjects:10 No of emotions:6 No of Trials:6</td>
</tr>
<tr>
<td>2</td>
<td>Technique used to reduce a high dimensional feature set, x, to a lower dimensional feature set y, such that the classes can be more easily separated in the lower dimensional space.</td>
<td>Fisher Linear Discriminant(FLD) CA:+92%</td>
<td>No.of Subjects:10 No of emotions:6 No of trials:6</td>
</tr>
<tr>
<td>3</td>
<td>Verifies the quality of achieved classification</td>
<td>Linear Discriminant Analysis(LDA) CA: Negative Pictures:99.3% Positive Pictures:97.4% Neutral:93.4%</td>
<td>No of Subjects:19(7 men and 12 women)</td>
</tr>
<tr>
<td>5</td>
<td>Fission process- Empirical Mode Decomposition (EMD) decomposes a signal into basis functions which are finite called the intrinsic mode functions. The intrinsic mode functions (IMFs) of interest are combined in an ad hoc or automated fashion in order to provide a greater knowledge. Fusion process- For the next classification stage, the information components of interest are then combined to create feature vectors Fission Based CA:+76% Fusion Based CA:+62% Fission Based CA:+76% Fusion Based CA:+62%</td>
<td></td>
<td>No of Samples:1024</td>
</tr>
</tbody>
</table>
V. Conclusion
Emotion recognition by computers is becoming very popular. This paper attempts to present various techniques that can be used to recognize emotions using EEG and EMG signals. Also a review on different classification techniques are discussed to classify the different types of emotions.

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