**EEG SIGNAL PROCESSING AND EMOTION RECOGNITION USING CONVOLUTIONAL NEURAL NETWORK**

**CHAPTER -1**

**ABSTRACT**

As an important task in the advanced stage of artificial intelligence, the research of emotional EEG has received more and more attention in recent years. In order to improve the accuracy of EEG signal emotion recognition, in this paper, Fast Fourier Transform (FFT) and Continuous Wavelet Transform (CWT) are used to extract the features of EEG signals on the DEAP data set and build two CNN models for emotion recognition. The results show that the proposed algorithm is effective for EEG signal emotion recognition. The average recognition accuracy of emotion valence can reach 75.9%; the arousal can reach 79.3%; the like/dislike can reach 80.7%. This research can provide practical application reference for continuous dimension emotion automatic analysis and machine recognition.

Index Terms: component; EEG; FFT; CWT; CNN; emotion recognition

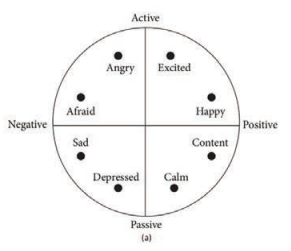
**CHAPTER-2**

**INTRODUCTION**

Enabling human-machine interfaces to interpret emotional states paves the path towards emotionally capable machines that offer more natural interactions and better performance in the fields of rehabilitation robotics, multimedia content characterization, personalized recommender systems etc. Several approaches to emotion detection have been proposed. Characterizing emotional data from facial expressions have been explored. However, such methods may be prone to deception as the associated parameters vary easily, subject to different situations. Use of physiological signals (especially electroencephalogram (EEG)) have gained a lot of interest. Time-frequency domain features such as power spectral density (PSD) and frequency power ratios have been employed with relative success 6,7. Given the non-Guassian nature of EEG signals, it makes sense to explore higher order spectral features. In this paper, we explore derived features of bispectrum for quantification of emotions using a Valence-Arousal emotion model. Classification of emotional states viz. Low/High Arousal (calm/bored to excited/stimulated) and Low/High Valence (unhappy/sad to happy/joyful) have been considered. Classification experiments were performed over EEG signals from the DEAP dataset. The choice of the Valence-Arousal model has been inspired by the circumplex model of affect. Preliminary classification experiments were conducted using EEG pertaining to Fp1 and Fp2 channels. Linear Kernel Least Square Support Vector Machine (LS-SVM) and back-propogation Artificial Neural Networks (ANN) were used. Further experiments were conducted by performing backward sequential feature selection.

**Modelling Emotions:**

Emotion is a psychological state or a process that functions in maintaining the balance of information process in the brain and the relevant goals. Every time an event is evaluated as relevant to a goal, an emotion is elicited. A model of emotion can be characterized by two main dimensions called valence and arousal. The valence is the degree of attraction or aversion that an individual feels toward a specific object or event. It ranges from negative to positive. The arousal is a physiological state of being awake or reactive to stimuli, ranging from passive to active. The valence arousal dimensional model, represented in Figure 1(a) is the accepted model. EEG and Emotion. Emotional data can be captured by means of EEG, acquired by measuring the electrical activities at different electrode positions on the scalp. The 10-20 system of electrode placement is used. See figure 1(b). Brain wave is the composition of five main frequency bands called delta (1-3 Hz), theta (4-7 Hz), alpha (8-13 Hz), beta (14-30 Hz) and gamma (31-50 Hz). Soleymani et al. employed EEG and peripheral physiological signals to classify emotions into three levels of valence and arousal. Using a support vector machine (SVM) with PSD Soleymani et al. arrived at accuracy rates of 57.0% and 52.4% for valence and arousal respectively. In another study, 66.05% and 82.46% accuracy rates for valence and arousal respectively was achieved by Huang et. al using an Asymmetrical Spatial Pattern technique to extract features. Other machine learning techniques have also been applied.



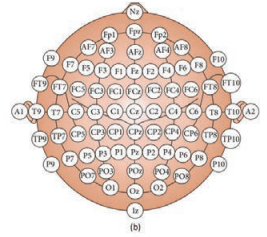


Fig.1 (a) Valence-Arousal Model; (b) 10-20 system of electrode positions

**Materials:**

**EEG Signal:**

Signals were acquired from the DEAP dataset 2, which is a multimodal dataset for analysis of human affective states. EEG and peripheral physiological signals of 32 subjects were recorded as each subject watched oneminute long excerpts of music videos designed to elicit peak emotional responses (For detailed discussion refer to DEAP dataset 2). Figure 2 shows the organization of the trials vis-a-vis the section and complete experiment; the protocol followed for elicitation of emotion is marked in the trail.

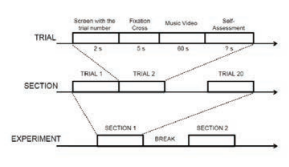


Fig.2 Protocol of signal acquisition

**Valence / Arousal:**

Each participant went through 40 trials of stimuli presentation (music videos). During the presentation, EEG signals were recorded at a sampling frequency of 512 Hz using 32 active AgCl electrodes, placed in accordance to the international 10-20 system. For self-assessment, the subjects selected values in the continuous scale of 1-9 to indicate their emotion states in each category. This study mapped the scales (1-9) into two levels of each valence and arousal states. The valence/arousal scale rating from 1-5 was mapped to Low valence/arousal state and the valence/arousal scale rating of 5-9 was mapped to High valence/arousal states.The choice of two level mapping (with a threshold of 5 on a scale of 1-9) is based on the analysis carried out by Koelstra et. al 2 on the DEAP dataset. According to the new scale mapping, the system provides 4 state emotion classification: High Valence, Low Valence, High Arousal and Low Arousal. The adopted mapping scheme is illustrated in Figure 3.

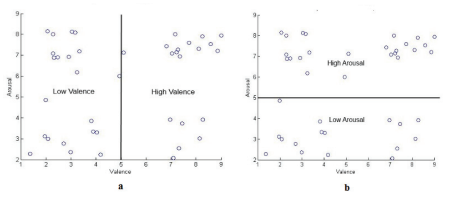


Fig. 3. Mapping of scales. (a)Low/High Valence states. (b)Low/High Arousal states. Each point represents a trial rating given by a subject for an experienced emotion in the valence and arousal dimensions

Human emotion is a complex phenomenon that comes from human brain, but there is no clear knowledge on its generation mechanism. Physiologists and computer scientists have been studying it for decades. For example, Ekman et al proposed the notion of 6 basic emotions that were universal and found across cultures.

Posner et al. proposed a two-dimensional model in which emotions were given coordinates denoting the degree of valence (the positive or negative quality of emotion) and arousal (how responsive or energetic the subject is). Other models include the Plutchik wheel of emotions, a tree of emotions, etc. In relation to engineering applications, the definition and classification of emotions are of importance in deciding what variables should be considered and what measurements are required during the design of a system.

A person's emotions can be gauged from external features such as facial expressions and the tone of voice. These can be captured via photographs, video, and audio recordings. However, emotion also results in other bodily changes such as variation in heart rate, muscle tension, respiration and skin conductance, and, of course, brain activity. Emotion detection through electroencephalogram (EEG) signals has a wide variety of practical applications, evidenced by medicine and scientific research, and the field of affective computing.

The latter refers to the incorporation of emotions in human-computer interaction giving machines a degree of emotional intelligence. It has been proposed, for the use of these machine learning systems, to include multimedia environments that recognize the emotions of the users such as recommendation and tagging systems, games and films that respond to the user emotions, and biofeedback devices that can be worn in the manner of headsets and might help users gain control over their emotional states.

This echoes objections made at a much earlier stage by Picard et al to emotion recognition based on external displays. Among these are that emotions are frequently concealed or masked or even unknown to the subjects themselves, the disparity between posed and spontaneous emotion, the practical and ethical obstacles to recording spontaneous emotion, as well as matters that can limit applications such as privacy in relation to video-based detection.

They recorded a variety of peripheral physiological signals including heart rate, respiration, skin conductance, blood volume pressure, and facial muscle tension and achieved 81% accuracy, which was amongst the highest at that time. In this paper, a new emotion detection system is proposed. Firstly, multiple feature extraction methods are used to produce different types of features from different domains. Secondly, we applied a new hybrid dimension feature reduction scheme, which used the combination of supervised and unsupervised reduction methods to fuse the different features in order to get the best feature. Advanced machine learning methods are used and evaluated on a public available dataset DEAP (Database for Emotional Analysis using Physiological Signals). Experimental results are given on all different features and different feature selection methods for the emotion information extraction from EEG signals. It is compared with other state-of-the-art methods at the same setting up on the public DEAP dataset.

An emotion detection system from EEG signals can be treated as a classification problem since the goal of the system is to predict the correct label of emotion. It is thus often a supervised learning task since labels are already assigned to the data by humans, although clustering methods have also been employed. Detailed information about the current research in this area can be found in the work of Alarcao and Fonseca. An important part of the study of emotion via machine learning involves the choice of features.

Researchers have made use of a variety of features from EEG recordings. Jenke et al made a survey on feature selection and extraction across a variety of studies and classified these as time domain, frequency domain, time-frequency domain, and multi-electrode features. Time domain features include event-related potentials, signal statistics, Hjorth features, non-stationary index, fractal dimension, and higher-order crossings. Frequency domain features include band power and higher-order spectra, time-frequency domain features include the Hilbert-Huang spectrum and discrete wavelet transforms, and multi-electrode features include magnitude-squared coherence estimate and differential and rational asymmetries.

Frequency domain features are prevalent and appear in the majority of the studies surveyed in the paper, in particular spectral power, but it was also found that its performance scores is lower compared to other features. A very high level of performance was achieved in the study by Valenzi et al who analyzed EEG data from nine participants in response to video stimuli intended to induce the emotional states of amused, disgusted, sad, and neutral. A key difference in the use of video stimuli in this study was that between stimuli, a distraction task rather than a relaxation task was used to neutralize the emotional state of the participant and was considered to be more effective than a relaxation task.

Data were recorded from 32 electrodes. The features extracted from the EEG were spectral power in delta (0.16-4 Hz), alpha (8-13 Hz), lower beta (14-21 Hz), upper beta (21- 30 Hz), and gamma (30-40 Hz) bands. A linear discriminant analysis was used to reduce the dimensionality of the feature space. Both supervised and unsupervised learning methods were used. Supervised learning methods were the error back propagation and support vector machine (SVM).

Unsupervised learning algorithms used were vector quantization, fuzzy c-means clustering (FCM), k-means, and k-medians. A maximum average accuracy of 97.2% was achieved for supervised learning (for SVM) and a maximum average accuracy of 95.2% was achieved for unsupervised learning (for FCM). The average EEG power was computed across the stimuli for the different electrodes and showed larger frontal right symmetry for negative emotions. An electrode reduction was attempted, using only 8 electrodes (6 frontal and 2 temporal), yielding a best rate (using SVM) of 92.5% for individual classification and an average classification rate of 87.5%.

It was noted, however, that the method in its current state was designed only to work offline. Using all the features, an average classification accuracy of 87.5% was achieved when features from all the bands were used. For individual bands, higher frequency alpha, beta and gamma bands yielded better results compared with lower frequency bands. After the feature reduction, the classification accuracy, in fact, increased slightly when using the top one hundred subject-independent features and was at 89.2%.

It was noted that the selected subject independent features were mainly in the higher frequency bands, and this was consistent with studies relating human emotional response to these bands. Noticed by Othman et al,10 one possible application for this area is intervention in cases of brain developmental disorders such as ADHD and autism. Their study involved 5 child participants, who were shown emotional faces whilst EEG recordings were made. Two different dimensional models were used for the classification of the emotions known as rSASM and 12-PAC.

Recordings were taken only from the F3 and F4 frontal electrodes, and only the theta and alpha bands were considered. For the purposes of feature extraction, Mel-frequency cepstral coefficients and kernel density estimation were used, and a multi-layer perception was used for classification. The best performance achieved was for the 12-PAC with Kernel Density Estimation, at a mean squared error range (among the participants) of 0.07 to 0.09. Another study used the connectivity between the EEG channels.

Chen et al considered the relationship between each channel, and calculated the mutual information, person correlation coefficient, and phase coherence connectivity13 between each channels and use these information as the extracted features and then used the Fisher linear discriminant method as the feature selection method, which is at the same setting with the one in the DEAP paper dataset.6 They use an SVM as the classification method and obtained 76% on valence and 73% on arousal.

Meanwhile, Gupta et al14 also applied connectivity features for the DEAP dataset.6 This method is inspired by the work of Pablo et al.15 For their work, Welchs t-test and PCA used the two-step feature reduction methods, which applied for the fusion of spectral power and mutual information. At the DEAP dataset, a total of 880 features were extracted from 32 channels. ForWelch's t-test, they used 0.01 increase step as the threshold, and best features were selected. Then, they applied PCA for the second step reduction. In order to reduce the effect of different classifiers, they used SVM-RBF, SVM-Sigmoid, and Naive Bayes as the classification methods. The presented results show that arousal reaches 67.7 ± 11.3% and valence reaches 69.6 ± 9.3% for the best classification accuracy.

The reigning experimental paradigm in affective neuroscience research posits that emotions can be divided into discrete and independent categories and that specific neural structures and pathways subserve each of these emotional categories. This theory of basic emotions has yielded significant advances in the understanding of affect and yet, in the fields of clinical psychology and psychiatry, it has left unsettled many important questions.

The theory of basic emotions, for example, has not explained the near ubiquitous comorbid illnesses among mood disorders, nor has it resolved confusion over the neurophysiological underpinnings of affective disorders. Moreover, basic emotion theory is largely incompatible with recent findings in behavioral genetics and temperament research.

Given these empirical and heuristic limitations of the theory of basic emotions, we propose that a shift is needed in the conceptual approaches taken to the study of emotion. We propose that clinicians and researchers move away from a strictly basic emotion model of affective states, where each emotion is thought to emerge from independent neural systems, to more dimensional models of emotions, in which all affective states areunderstood to arise from common, overlapping neurophysiological systems.

Although poorly represented in psychiatry, dimensional models have a long history in psychology ~Larsen & Diener, 1992; Russell, 2003; Schlosberg, 1952; Watson, Wiese, Vaidya, & Tellegen, 1999!. One particular dimensional approach, termed the circumplex model of affect, proposes that all affective states arise from two fundamental neurophysiological systems, one related to valence ~a pleasure–displeasure continuum! and the other to arousal, or alertness ~Russell, 1980!. Each emotion can be understood as a linear combination of these two dimensions, or as varying degrees of both valence and arousal ~see Figure 4!. Joy, for example, is conceptualized as an emotional state that is the product of strong activation in the neural systems associated with positive valence or pleasure together with moderate activation in the neural systems associated with arousal.

Affective states other than joy likewise arise from the same two neurophysiological systems but differ in the degree or extent of activation. Specific emotions therefore arise out of patterns of activation within these two neurophysiological systems, together with cognitive interpretations and labeling of these core physiological experiences.

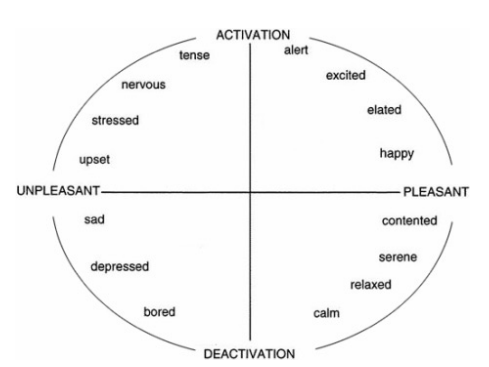


Figure 4. A graphical representation of the circumplex model of affect with the horizontal axis representing the valence dimension and the vertical axis representing the arousal or activation dimension

In addition to reviewing the literature relevant to dimensional theories of emotion, we will discuss the implications that dimensional approaches hold for psychiatric research and clinical practice. The circumplex model of affect in particular offers a conceptual and experimental framework for exploring the neural basis of affect that is also likely to provide insight into the neurophysiology of affective disorders.

It also provides a theoretical basis for understanding the widespread comorbidities among mood and anxiety disorders, and its dimensional approach makes available powerful statistical and methodological tools for use in genetic, neuroimaging, and neurobiological studies of affective disorders.

**Theories of Basic Emotions**

The dominant theory of emotion in psychiatric and neuroscience research posits that humans are evolutionarily endowed with a discrete and limited set of basic emotions ~Ekman, 1992; Panksepp, 1998; Tomkins, 1962, 1963!. Each emotion is independent of the others in its behavioral, psychological, and physiological manifestations, and each arises from activation within unique neural pathways of the central nervous system ~CNS!. Fear, by this account, produces aversive feelings and behaviors that are related to activation within specific neural pathways. Other emotions are produced through activation in separate neural pathways distinct from the fear system, and likewise they produce subjective feelings, peripheral nervous systems patterns, and behaviors associated with that specific emotional state. This is a theory in which each specific emotion maps to one neural system.

**Animal studies**

The conceptualization of emotions as discrete and independent has arisen largely from affective research with animals. By selectively stimulating neural pathways and observing subsequent behaviors, or conversely by eliciting behaviors in highly constrained experimental circumstances and measuring neural activity, animal researchers have constructed taxonomies of the basic emotions and proposed specific neural pathways associated with each putative basic emotion ~Panksepp, 1998!.

Although this experimental approach has helped researchers begin to explore the neural basis of emotion, it is inherently limited in the information that it provides about affective experiences and the neural systems that support them. Researchers are forced to attribute affective states to animals based on the behaviors that the animals exhibit.

Affective behaviors, however, are neither sufficient nor necessary to characterize emotional states ~Kagan, 2003; Panksepp, 1998!. Anxiety, for example, can be felt without any overt changes in behavior, just as affective behaviors, such as frowning and smiling, can be elicited without any obvious changes in subjective feeling.

An animal, therefore, could experience feelings without demonstrating any overt changes in behavior, and conversely, through experimental manipulation, could display affective behaviors without any associated feeling. As Damasio ~2003! notes, paramecium will flee from predators, but to argue that single-celled organisms experience fear makes little sense. Aware of these limitations in their experimental paradigms and the possible difficulties with interpreting their results, emotion researchers assert that the validity of many of the findings from animal research must ultimately be confirmed through human studies of emotion ~Panksepp, 1998!.

This confirmation, however, has proved elusive, and inconsistencies between the findings from human studies of emotion and those predicated from animal research abound ~Berridge, 2003; Davidson, 2003!. In short, and at the risk of oversimplification, these inconsistencies might be summarized as follows: animal research emphasizes the role of subcortical and other evolutionarily primitive structures in the processing of emotions, whereas human research demonstrates the importance of neocortical structures in emotional experience ~Berridge, 2003!. Given animal researchers’ necessary reliance on overt behavior, their results could reasonably be interpreted as delineating neural systems related primarily to affective behaviors rather than subjective feelings as described in the human literature.

Indeed, abundant data from lesion studies and neuroimaging investigations demonstrate that activation of the prefrontal cortex participates centrally in the experiencing of positive and negative emotions ~Davidson, Ekman, Saron, Senulis, & Friesen, 1990!. Facial expressions and the human physiological correlates of basic emotions In addition to conducting animal studies of putative affective processes, basic emotion theorists have investigated emotional processes in humans by exploring facial expressions and peripheral physiological responses to affective stimuli.

These investigators have assumed that patterns of autonomic activation and facial innervation are specific to each basic emotion ~Ekman, 1992; Ekman, Levenson, & Friesen, 1983!. Evidence to support this hypothesis, however, is limited. In a metaanalysis of studies correlating autonomic activity with affective states, for example, Cacioppo concludes that the basic emotions have not been found to be associated with specific patterns of autonomic activation ~Cacioppo, Berntson, Larsen, Poehlmann, & Ito, 2000!.

The physiological measures associated with a single basic emotion often differ significantly depending on the nature of the eliciting stimuli ~Hamm, Gerlach, Globisch, & Vaitl, 1992!. Similar problems plague animal models of emotion, in that dissimilar physiological responses are observed in association with a single basic emotion ~Iwata & LeDoux, 1988!. Conversely, disparate basic emotions in both animal and human studies are often associated with similar physiological responses ~Cacioppo et al., 2000!

**CHAPTER-3**

**LITERATURE REVIEW**

**[1] Posner J, Russell JA, Peterson BS:** The circumplex model of affect proposes that all affective states arise from cognitive interpretations of core neural sensations that are the product of two independent neurophysiological systems. This model stands in contrast to theories of basic emotions, which posit that a discrete and independent neural system subserves every emotion. We propose that basic emotion theories no longer explain adequately the vast number of empirical observations from studies in affective neuroscience, and we suggest that a conceptual shift is needed in the empirical approaches taken to the study of emotion and affective psychopathologies. The circumplex model of affect is more consistent with many recent findings from behavioral, cognitive neuroscience, neuroimaging, and developmental studies of affect. Moreover, the model offers new theoretical and empirical approaches to studying the development of affective disorders as well as the genetic and cognitive underpinnings of affective processing within the central nervous system.

**Summary:** We have argued for a conceptual shift in the theory and experimental approaches to the study of emotion and affective illness. We have suggested that the dimensional model of the affective circumplex helps explain current research and clinical findings that are at odds with models of basic emotions. The circumplex model of affect posits that the two underlying neurophysiological systems of valence and arousal subserve all affective states, and upon this substrate are layered various cognitive processes that interpret and refine emotional experience according to salient situational and historical contexts.

**[2] Abelson, R. P., & Sermat, V:** This paper presents an experimental modeling framework Thirty women gave nine-point rating scale judgments of the dissimilarity of emotional expression of each of 78 pairs of facial poses formed from combinations of 13 diverse stimuli of the Lightfoot Series. The dissimilarity ratings were converted to interstimulus distances. Comparison of these distances with the distances one would expect on the basis of the three Schlosberg scales of facial expression yielded the following conclusions: (a) The pleasant-unpleasant scale explains 50% of the variance in the distance data; the pleasant-unpleasant (Vi) and tension-sleep (Va) scales together account for almost 75% of the variance; the attentionrejection (Vi) adds little more to prediction. (6) If the V2 scale is omitted, the Vt and Vs scales should be calibrated in approximately the ratio 5:4. (c) Standard multidimensional factoring techniques applied to the distance matrix yielded stimulus coordinates on five dimensions, with the major dimension essentially identical to Schlosberg's pleasantunpleasant scale, the second dimension, a compromise between Schlosberg's other two scales, correlating extremely highly with both, and the remaining three dimensions not readily interpretable. (d) The shape of the configuration of stimuli in the space of the first two dimensions is approximately an equilateral triangle with a sleep stimulus at one corner and actively pleasant and unpleasant expressions at the other two corners. (e) If the Lightfoot Series has indeed captured the full range of potential expressions, then for usage a two-dimensional system would appear to be adequate: pleasant-unpleasant and tension-sleep, or perhaps a slight variant of the latter.

**Summary:** The present study provides evidence that the Schlosberg scales are sound: they predict the dissimilarity data fairly well, and the extra dimensions that appear in the multidimensional scaling operation do not suggest new meaningful scales to replace or supplement the old ones.

**[3] Ahern, G. L., & Schwartz, G. E.:**

The present experiment utilized EEG spectral analysts to investigate laterahzatlon for emotional processes in the human brain. In frontal zones, a differential lateralization for positive and negative emotion was observed. with relative left-hemispheric acti\ ation (as measured by decreases in alpha abundance) for positive emotions and relative right-hemispheric activation for negative emotions. In parietal zones. a differential laterakation for verbal and spatial processes was obberved. with relative left-hemispheric actl\,ation for verbal questlons and relatwe right-hemispheric activation for spatial questions. Examination of EEG bands other than alpha (i.e. delta. theta, beta, and total power) suggested that emotional and cognitive processes are further distingmshed by different EEG spectral patterns. The filtered signals from the first 4 set of the period following the posing of the question were sampled by a PDP I I,‘03 microcomputer. Using a sampling rate of 64 points per set, this resulted in 256-points samples collected per channel per trial. Thedata for each trial were then submitted to spectral analysis via the Fast Fourier Transform. The filtered signals were monitored for artifact on two Tektronix oscilloscopes (5103N). For each ofthe 66 trial epochs, the power at each electrode site in the various EEG bands, i.e. delta (l--3 Hz), theta (4 7 Hrj, alpha (8-12 Hz). beta (13-31 Hz), and total power (I-31 Hzj, was calculated. In order to increase the reliability of the EEG data, the power spectra for the six trials comprising each question type, as well as the rest trials, were averaged after those epochs with artifact or where the subjects had failed to be engaged by the question (see below) were eliminated. Lateralization ratios were then computed from these averaged power data using the formula: (L-R/L+R)x 100. As EEG lateralizatlon studies have been criticized for failing to control various confounding factors [19], it is important to discuss the efforts made in this experiment to correct for such variables. Trials w-ith obvious artifact were eliminated. artifact being defined here as one or more of the following: (1) a baseline shift or other obvious abnormality in the EEG trace; (2) EMG values in either frontal channel whose value after Z-transformation was greater than or equal to 2.00; or (3) a lateral eye movement greater than 10 of arc. Another criterion for rejection ofa trial was subject movement during the recording period. This is particularly important, insofar as GEVINS ef d. [ IY] have claimed that EEG lateralization effects are largely dependent on concurrent motor activity during task performance. rather than on cerebral specialization, per se. In this experiment, no movement was required or allowed during the recording periods and when such movement did occur (as noted by the experimenter on the closed-circuit TV system), the trial was eliminated from the analysis.

**Summary:** The results of this experiment support the hypothesized specialization of the cerebral hemispheres for emotional processes. Furthermore, the data suggest that differential lateralization for positive vs negative emotion is a characteristic of frontal zones, while the results of other studies [S, S] in conjunction with the marginally significant results reported here, suggest that parietal zones show a right-hemispheric specialization for emotion regardless of affective valence. Thus, the two different groups of results that have been reported in the past can be unified by assuming the existence of two different types of lateralization for emotion.

**[4] Kumar N, Khaund K, Hazarika S M.:** Emotion recognition from electroencephalogram (EEG) signals is one of the most challenging tasks. Bispectral analysis offers a way of gaining phase information by detecting phase relationships between frequency components and characterizing the nonGaussian information contained in the EEG signals. In this paper, we explore derived features of bispectrum for quantification of emotions using a Valence-Arousal emotion model; and arrive at a feature vector through backward sequential search. Crossvalidated accuracies of 64.84% for Low/High Arousal classification and 61.17% for Low/High Valence were obtained on the DEAP data set based on the proposed features; comparable to classification accuracies reported in the literature. In this paper we performed the classification of human emotions using EEG data via two classification tasks resulting in four-state classification of emotions. Initial experiments revealed that a window of the last 30 seconds of the recordings have greater discriminating power. Also filtered brain rhythms (Theta, Alpha and Beta) showed better classification accuracy than unfiltered EEG signals. Experimental results also showed that reduced feature sets obtained by backward feature selection, for the Theta and Alpha rhythm yielded best cross-validated accuracy results for the Low/High Arousal and Low/High Valence classification tasks respectively. The accuracy percentages obtained in this work however are valid for offline classification of emotions. Building predictors for online classification is part of on-going research.

**Summary:** A combination of time-frequency domain and bispectrum features from different channels along with ensemble classifiers (Random Forest, AdaBoost etc.) may be explored to achieve higher accuracy rates.

**[5] S. Koelstra, C. Muehl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, I. Patras:** In this work, we have presented a database for the analysis of spontaneous emotions. The database contains physiological signals of 32 participants (and frontal face video of 22 participants), where each participant watched and rated their emotional response to 40 music videos along the scales of arousal, valence, and dominance as well as their liking of and familiarity with the videos. 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 last.fm website, 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.

**Summary:** We presented a novel semi-automatic stimuli selection method using affective tags, which was validated by an analysis of the ratings participants gave during the experiment. Significant correlates were found between the participant ratings and EEG frequencies. Single-trial classification was performed for the scales of arousal, valence, and liking using features extracted from the EEG, peripheral, and MCA modalities. The results were shown to be significantly better than random classification. Finally, decision fusion of these results yielded a modest increase in the performance, indicating at least some complementarity to the modalities.

**[6] Z. Zeng, M. Pantic, G.I. Roisman, and T.S. Huang:** Automated analysis of human affective behavior has attracted increasing attention from researchers in psychology, computer science, linguistics, neuroscience, and related disciplines. However, the existing methods typically handle only deliberately displayed and exaggerated expressions of prototypical emotions, despite the fact that deliberate behavior differs in visual appearance, audio profile, and timing from spontaneously occurring behavior. To address this problem, efforts to develop algorithms that can process naturally occurring human affective behavior have recently emerged. Moreover, an increasing number of efforts are reported toward multimodal fusion for human affect analysis, including audiovisual fusion, linguistic and paralinguistic fusion, and multicue visual fusion based on facial expressions, head movements, and body gestures. This paper introduces and surveys these recent advances. We first discuss human emotion perception from a psychological perspective. Next, we examine available approaches for solving the problem of machine understanding of human affective behavior and discuss important issues like the collection and availability of training and test data. We finally outline some of the scientific and engineering challenges to advancing human affect sensing technology. Research on the machine analysis of human affect has witnessed a good deal of progress when compared to that described in the survey papers of Pantic and Rothkrantz in 2003 and Cowie et al. in 2001. At those times, a few small-sized data sets of affective displays existed, and almost all methods for the machine analysis of human affect were unimodal based on deliberate displays of either facial expressions or vocal expressions of six prototypical emotions. Available data was not shared among researchers, multimedia data and multimodal human affect analyzers were rare, and the machine analysis of spontaneous displays of affective behavior seemed to be in a distant future. Today, several large collections of acted affective displays are shared by the researchers in the field, and some data sets of spontaneously displayed expressions have been recently made available. A number of promising methods for vision-based, audio-based, and audiovisual analysis of human spontaneous behavior have been proposed. This paper focused on surveying and discussing these novel approaches to the machine analysis of human affect and on summarizing the issues that have not received sufficient attention but are crucial for advancing the machine interpretation of human behavior in naturalistic contexts. The most important of these issues yet to be addressed in the field include the following: . building a comprehensive readily accessible reference set of affective displays, which could provide a basis for benchmarks for all different efforts in the research on the machine analysis of human affective behavior, and defining the appropriate evaluation procedures, . Developing methods for spontaneous affective behavior analysis, which are robust to observed person’s arbitrary movement, occlusion, and complex and noisy background, Devising models and methods for human affect analysis, which take into consideration the temporal structures of the modalities and the temporal correlations between the modalities (and/or multiple cues) and context (subject, the task, and environment), and Developing better methods for multimodal fusion.

**Summary:** Since the complexity of these issues concerned with the interpretation of human behavior at a deeper level is tremendous and spans several different disciplines in computer and social sciences, we believe that a large interdisciplinary international program directed toward computer understanding of human behavioral patterns should be established if we are to experience true breakthroughs in this and the related research fields. The progress in research on the machine analysis of human affect can aid in the creation of a new paradigm for HCI (affect-sensitive interfaces and socially intelligent environments) and advance the research in several related fields, including psychology, psychiatry, and education.

**CHAPTER-4**

**EXISTING METHOD**

Emotions recognition Research of human emotional states via physiological signals involves recording and statistical analysis of signals from central and parietal cortex. A popular physiological signal that is highly adopted for human emotion assessment is the EEG, etc. Unlike other physiological signals, EEG is a non-invasive technique with good temporal and acceptable spatial resolution. Thus, EEG might play a major role on detecting an emotion directly from the brain at higher spatial and temporal resolution.

A major problem with recognizing emotions is that people have different subjective emotional experiences as responses to the same stimuli. Accordingly, emotions can be classified into two taxonomy models:

(1) Discrete model: it is based on evolutionary features that include basic emotions (happiness, sadness, fear, disgust, anger, surprise), and mixed emotions such as Motivational (thirst, hanger, pain, mood), Self-awareness (shame, disgrace, guilt), etc.

(2) Dimensional model: it is expressed in terms of two emotions provoking people: Valence (disgust, pleasure) and Arousal. Emotion recognition enables systems to get non-verbal information from human subjects so as to put events in context based on underlying captured emotions. Humans are capable of recognizing emotions either from speech (voice tone and discourse) with an accuracy around 60% or from facial expressions and body movements with an accuracy of 78–90%. However, the recognition task is strongly dependent on the context and requires facial expressions to be deliberately performed or even in a very exaggerated manner, which is far away from the natural way a user interact with intelligent interfaces.

Other kinds of techniques use audio signals, obtaining classification accuracy close to 60–90% (Calvo & D’Mello, 2010), whereas some other methods use non-linguistic vocalizations (i.e., laughs, tears, screams, etc.) to recognize complex emotional states such as anxiety, sexual interest, boredom. Bi-modal methods also combine audio inputs and facial expressions based on the assumption that a human emotion can trigger multiple behavior and physiological responses whenever he/she experiences this emotion.

Nevertheless, most of these methods require humans to express their emotional (mind) states in a deliberated and exaggerated manner, so that emotions cannot spontaneously be expressed. On the other hand, extracting information from facial expressions requires monitoring a subject by using one of several cameras, whereas for audio-based approaches, emotions are very hard to recognize whenever a subject does not speak or produce any sounds (Giakoumis, Tzovaras, Moustakas, & Hassapis, 2011; Sourina et al., 2011). A popular and effective non-invasive technique to measure changes on brain activity is called (EEG), which transforms brain activity into images of variations of electrical potential by using small low-cost devices (AlMejrad, 2010). There are several approaches for EEG-based emotion recognition which are usually based on four main tasks (Calvo & D’Mello, 2010):

(1) Signal preprocessing: an EEG device can directly get signals from the brain. However, there are some noise sources that are not neurologically produced known as artifacts (i.e., blinking, muscular effects, vascular effects, etc.), so digital signal processing techniques must be applied to represent signals using frequencies and harmonic functions (Petrantonakis & Hadjileontiadis, 2010; Yisi et al., 2010).

(2) Feature extraction: EEG signals are highly dimensional so computational processing becomes very complex. Hence different features must be extracted in order to simplify the further emotion classification task so to create input Feature Vectors (FV). Typical methods include statistical metrics of the signal’s first difference (i.e., median, standard deviation, kurtosis symmetry, etc.), spectral density (i.e., EEG signals with specific frequency bands) Zhang, Yang, and Huang (2008), Logarithmic Band Power (Log BP) (i.e., power of a band within the signal based on its oscillatory processes) Brunner, an C. Vidaurre, and Neuper (2011), Hjorth parameters (i.e., EEG signals described by activity, mobility and complexity) Zhang et al. (2008), wavelet transform (i.e., decomposition of the EEG signal) Petrantonakis and Hadjileontiadis (2010), fractal dimension (i.e., complexity of the fundamental patterns hidden in a signal) Zhang et al. (2008).

(3) Feature selection: one little used technique of feature selection for emotions recognition combines a metaheuristic method known as Genetic Algorithms (GA) and a Support Vector Machines (SVM). This GA-SVM approach heuristically searches for the best sets of features initially represented as chromosomes of features which evolves as the GA goes on, so that these can then be provided as an input to an SVM classifier (Wang et al., 2011). A major drawback with this method is the time spent to converge toward good results and the redundancy of the selected features assessed in each iteration of the GA. In order to deal with this issue, other EEG feature selection technique known as minimum-Redundancy-MaximumRelevance (mRMR) selects the features that correlate the strongest with a classification variable, reducing information redundancy. This method selects features that are mutually different from each other while still having a high correlation make up the selection task of mRMR (Polat & Cataltepe, 2012), by reducing redundancy between bad and good features using Mutual Information (MI) methods, so that a subset of features that represents best the dataset can be obtained.

(4) Emotions classification: once the FVs are extracted from the previous task, emotions must be classified according to previously identified classes of emotions. Despite the large number of features used by these methods, no feature selection is usually carried out. There are plenty of state-of-the-art classifiers for automatic emotion identification. For example, Nearest Neighbor classifiers used features such as FFT and Wavelets to recognize 4 types of emotions (i.e., joy, sad, angry, relaxed) achieving accuracies ranging from 54% to 67%. On the other hand, statistical methods such as Quadratic Discriminant Analysis (QDA) used several statistical features for negative and positive arousal levels with an average accuracy of 63% (Koelstra et al., 2012; Petrantonakis & Hadjileontiadis, 2010; Wu et al., 2010; Yisi et al., 2010).

An adaptive BCI-based emotions recognition model:

In this work, a novel approach that combines minimumRedundancy-Maximum-Relevance (mRMR) based feature selection tasks and kernel classifiers for emotions recognition is proposed. The method takes EEG signals received from BCI devices and incorporates relevant features in order to detect several kinds of emotional states by using state-of-the-art classifiers. The main contribution of this research is that unlike other automatic emotion recognition methods our approach

(1) Incorporates a feature selection task into the classification task.

(2) Uses multi-label classifiers to simultaneously recognize a wider range of emotion types based on a dimensional model. The overall model is composed of three tasks: signal preprocessing, feature extraction and selection, and emotions classification (see Fig. 5).

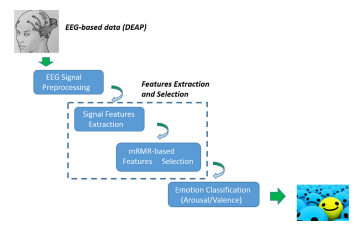


Fig. 5. Steps in our emotions recognition approach

**1. EEG signal pre-processing:**

In order to train the emotions classifier, a set of previously emotion-labeled EEG data extracted from subjects self-assessing their emotional states was taken. It Arousal and Valence dimensions that were triggered from external stimuli. Since EEG brain signals contain much noise, the following basic preprocessing steps were performed:

• Resolution reduction: it optimizes the used memory by reducing a signal resolution. Since useful data for emotions recognition are found under 40 Hz (Yisi et al., 2010), resolution can be reduced to 128 Hz, preserving the original signal’s information.

• Electrooculography removal: electrooculography (EOG) measures the corneo-retinal standing potential that exists between the front and the back of the human eye. In order to remove the noise produced from this kind of eyes movement, a method for removing EOG artifacts in the EEG called Automatic Removal of Ocular Artifacts is applied.

• Band filter: it filters EEG signals by generating bands that are useful for emotion recognition (e.g., 4 Hz–45 Hz).

2. Feature extraction and selection EEG signals are highly dimensional data which may contain a lot of useless features. In order to reduce dimensionality, a large set of relevant features are extracted to create easy-to-process FVs for each stimuli. These included statistical features (S), band power (BP) for different frequencies, Hjorth parameters (HP) and fractal dimension (FD) for each channel. Statistical features included median, standard deviation, kurtosis coefficient, etc.

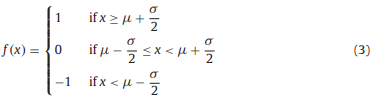
Furthermore, bands of frequency for each EEG channel correspond to theta (4–8 Hz), low alpha (8– 10 Hz), alpha (8–12 Hz), beta (12–30 Hz) and gamma (30–45 Hz). In order to select a relevant set of features from the previously extracted candidate features so that further classification can be more accurate, the minimum-Redundancy-Maximum-Relevance (mRMR) method was used (Wu et al., 2010; Yisi et al., 2010). It selects the features that correlate the strongest with the classification variable, reducing information redundancy between bad and good features using Mutual Information (MI) methods, so that the best set of features can be selected. It is based on two underlying conditions: minimum redundancy and maximum relevance. Let S be a set of features, the minimum redundancy condition is defined as:



Where I(fi, fj) is the MI between features fi and fj, and |S| = n is the number of features from the set. The discriminant power of each feature regarding the emotion classes is then measured as the MI between features and classes. Since I(C, fi) expresses the relevance of feature fi for a class C, the maximum relevance condition can be seen as:



Thus, finally obtained sets must accomplish the optimization conditions for Eqs. (1) and (2) simultaneously, into a single function, where the first and second condition are named MID and MIQ, respectively (max(VI − WI) and max(VI/WI)). In addition, each feature was converted into a discrete value by using the transformation function of Eq. (3), whereμis the median of a subject’s feature values, and σ is the standard deviation of values for the same feature (a common value of α = 0.5 is used).



Emotions classification In order to recognize different emotion classes, a multi-class Support Vector Machine (SVM) was trained for a set E = {xi, yi}N i=1, where N is the number of samples built from previously selected features, xi is composed of an FV and yi the dimension class of xi (i.e., Arousal and Valence). The classifier builds and trains k(k − 1)/2 SVMs, where k is the number of classes for yi. For our approach, three classes were considered for each dimension. Each of three SVM uses RBF kernels and the overall classification is then carried out by using a One-versus-One voting mechanism in which a finally assigned class label will become those having the higher accuracy among the voting SVMs.

Classes produced for each dimension are divided according to a range of values for each dimension [1, 9], into three sets: [1, 3.66], [3.66, 6.33] and [6.33, 9] based on Eq. (4), where r(i) indicates the point in which the i-th division of the range of values is created, max v − min v is the difference between the maximum and minimum value for each dimension, and k is the number of sets to be created.



Previously trained multi-class SVMs are then used to classify Arousal and Valence dimension classes for unseen FVs extracted from different EEG signals extracted from the same subject as our model is subject-dependent.

In this paper, an EEG feature-based emotion recognition method was proposed. Unlike other approaches, the approach uses the mRMR feature selection method as a signal preprocessing step so as to improve the predictive accuracy of an SVM emotion classifier based on two-dimension emotions model (i.e., Valence and Arousal). In addition, compared with state-of-the-art emotion recognition methods, our approach deals with a higher number of emotion classes (i.e., 8) on a standard DEAP dataset, which makes the problem more realistic but at the same time, the training task becomes more demanding.

Accordingly, one of the contributions of this research is that it incorporates a statistical-based feature selection task into the classification task. Furthermore, our approach which combines feature selection and kernel classifiers uses multi-label classifiers to simultaneously recognize a wider set of emotion classes based on a dimensional emotion model. In order to assess the effectiveness of our kernel-based classifier, several preliminary experiments were conducted so as to produce the best parameters settings.

It included tunning feature selection methods, emotion classifier, signal preprocessing tasks, etc. Preliminary experiments showed that our mRMR-based feature selection method outperformed the most popular feature selection strategy (GA-SVM) for both dimensions (Arousal and Valence) when classifying emotions (Accuracy of 60.72% and 62.4% versus 57% and 53.4%). In addition, for both dimensions, our method reduced the number of relevant features of almost to capable of reducing in 63% with a higher accuracy. Classification accuracy of our model was then compared against other competitive current approaches to emotion recognition: SVM-based spectral density and Bayes-based Band Power (BP).

An important issue with these two techniques is that either the EEG signal they analyse must be within very specific frequence bands (i.e., spectral density) or the power of the frequence band within a signal is strongly dependent on its oscillatory processes. Hence they might not very effective when attempting to classify a wider set of emotion classes (i.e., a higher number of classes per dimension).

Overall results showed that our methods outperformed those of the state-of-the-art for the same number of classes per dimension (i.e., 73% versus 62%). In addition, our approach was capable of classifying a higher number of classes per dimension whenever no other state-of-the-art method did it for em Valence (i.e., 62.33% versus no accuracy known in spectral density for 3 classes per dimension). Note that spectral density does it well for recognizing emotions within the Arousal dimension, but it has not been assessed for more than 5 classes/dimensions as for our research. Thus, our mRMR-based emotion classification approach outperformed other state-of-the-art methods.

Furthermore, the method is promising when considering a higher number of classes per dimension (i.e. 3 and 5), that had not been proven in the literature. This also showed our method recognizes a higher number of emotion classes without using additional emotions classifiers. Accordingly, combining features-selection methods (mRMR) and SVM classifiers using RBF kernels yield significant improvements in accuracy. In words, our method requires less work to classify based on a smaller set of selected so as to achieve higher accuracy than other techniques.

**DISADVANTAGES:**

1. One of the biggest disadvantage is increase in computer processing speed.

2. Increase of computing power.

3. Accuracy is less.

**CHAPTER-5**

**PROPOSED METHOD**

Emotion is a psycho-physiological process triggered by conscious and/or unconscious perception of an object or situation and is often associated with mood, temperament, personality and disposition, and motivation. Emotions play an important role in human communication and can be expressed either verbally through emotional vocabulary or by expressing nonverbal cues such as intonation of voice, facial expressions, and gestures. Most of the contemporary human-computer interaction (HCI) systems are deficient in interpreting this information and suffer from the lack of emotional intelligence.

The current data set is recorded with the goal of creating an adaptive music video recommendation system. In our proposed music video recommendation system, a user’s bodily responses will be translated to emotions. 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 stimuli (music video clips) have never been explored before, and the research in this field was mainly focused on images, music, or nonmusic video segment.

Dimensional scales of emotion have also been proposed, such as Plutchik’s emotion wheel and the valence-arousal scale by Russell. In this work, we use Russell’s valence-arousal scale, widely used in research on affect, to quantitatively describe emotions. In this scale, each emotional state can be placed on a 2D plane with arousal and valence as the horizontal and vertical axes.

While arousal and valence explain most of the variation in emotional states, a third dimension of dominance can also be included in the model. Arousal can range from inactive (e.g., uninterested, bored) to active (e.g., alert, excited), whereas valence ranges from unpleasant (e.g., sad, stressed) to pleasant (e.g., happy, elated).

Dominance ranges from a helpless and weak feeling (without control) to an empowered feeling (in control of everything). For selfassessment along these scales, we use the well-known selfassessment manikins (SAM).

Emotion assessment is often carried out through analysis of users’ emotional expressions and/or physiological signals. Emotional expressions refer to any observable verbal and nonverbal behavior that communicates emotion. So far, most of the studies on emotion assessment have focused on the analysis of facial expressions and speech to determine a person’s emotional state.

Physiological signals are also known to include emotional information that can be used for emotion assessment, but they have received less attention. They comprise the signals originating from the central nervous system (CNS) and the peripheral nervous system (PNS).

At present, in EEG signal emotion recognition, the accuracy of continuous emotion recognition based on the dimensional emotion model is generally not high, especially for the fourcategory emotion recognition research, which cannot meet the application needs, and the individual emotional physiological characteristics vary greatly. The characteristics of physiological signals related to emotions are not sufficient and the differences are not significant. Therefore, in response to these problems, this article uses two types of feature extraction tools on the dimensional emotional data set: fast Fourier transform (FFT) and continuous wavelet transform (CWT), and constructs two CNN models for classifying EEG signals.

By comparing the experimental results of the two proposed models with other emotion classification task models, the FFT CNN model obtained a better recognition accuracy, which laid a solid foundation for the automatic emotion analysis and recognition of physiological signals.

The steps of emotion recognition based on EEG signals generally include: emotion induction, EEG signal collection, signal preprocessing, EEG feature extraction and emotion learning classification. In this paper, the data set is DEAP. The overall design framework is shown in Fig. 6. First, a bandpass filter is used to preprocess the original EEG signal to filter out high-frequency clutter. Second, a fast Fourier transform (FFT) and continuous wavelet transform (CWT) perform feature extraction on EEG.

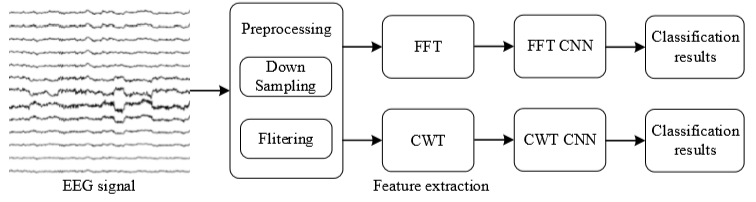


Fig.6. Overall design framework

**CNN Model with FFT Feature Extraction**

First, the raw EEG signal is preprocessed, and feature extraction is performed through the FFT algorithm. Split the processed data and labels into a training-test set at a ratio of 8020, apply one-hot encoding to the labels, and use a standard scalar to normalize the data in order to obtain better accuracy.

Maximum pooling is implemented for the convolution part, and the rectified linear unit (Relu) activation function is used for the dense layer. Several batch normalization and dropout layers were inserted to prevent overfitting. For the final classification layer, use the softmax activation function to output the probability estimate for each class. The convolution part is shown in Fig. 7(a).

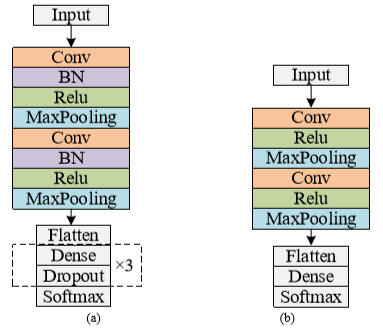


Fig.7 FFT model (a); CWT model (b)

**CNN Model with CWT Feature Extraction**

The CWT model utilizes the CWT algorithm from PyWavelets. This method uses the mother wavelet and the scale list of the inspection signal as the input signal. The mother wavelet is a "Morlet" wavelet. Similar to the FFT model, the CWT model is implemented through One-Hot and other methods of encoding, standard scalar normalization, and k-fold cross-validation. The model architecture is redesigned as shown in Fig. 7(b). In order to better adapt to the DEAP data set and produce better results. The CWT model reduces the number of dropout layers and the number of batch normalization layers to prevent large peaks and fluctuations in the verification loss.

**DEAP data set and preprocessing**

The DEAP data set contains 32 channels of EEG signals of 32 subjects and 8 channels of peripheral physiological signals. This article only uses 32-channel EEG signals as experimental data: EEG signals are first sampled at 512Hz, then the sampling rate is reduced to 128Hz, and the bandpass frequency filtering of 40-45.0Hz is used to remove EOG artifacts, as shown in Fig. 3. Each participant watched 40 emotional music videos, each with a duration of 1 minute. After the subjects watched each video, they scored the degree of arousal, valence preference and dominance, with a score of 1-9. The evaluation value from small to large indicates that the various indicators are from negative to positive, from strong to weak.

**CHAPTER-6**

**ADVANTAGES AND APPLICATIONS**

**Advantages:**

1. Power reduction.

2. Computation speed reduces.

3. Increase of accuracy

**Applications:**

1.industrial control

2.environmental monitoring,

3. military surveillance,

4.intelligent transportation systems and medical field.

5.Furthermore, it can function independently in harsh or high-risk places where human presence is not possible

6.Disaster relief operations.

7.Biodiversity mapping

8.monitoring of temperature, pressure, and humidity.

**CHAPTER-7**

**MATLAB**

**7.1 INTRODUCTION TO MATLAB**

**What Is MATLAB?**

MATLAB is an elite dialect for specialized registering. It incorporates calculation, representation, and programming in an easy to-utilize condition wherein issues and preparations are communicated in herbal numerical documentation. Run of the mill utilizes comprise

• Math and calculation

• Algorithm advancement

• Data obtaining

• Modeling, re-enactment, and prototyping

• Data examination, investigation, and representation

• Scientific and designing illustrations

• Application advancement, including graphical UI building

MATLAB is an intuitive framework whose important statistics aspect is an show off that does not require dimensioning. This allows you to tackle several specialized processing issues, particularly those with framework and vector info, in a small quantity of the time it'd take to compose a program in a scalar non intuitive dialect, as an instance, C or FORTRAN.

The call MATLAB stays for grid studies facility. MATLAB changed into first of all composed to present easy access to framework programming created by way of the LINPACK and EISPACK ventures. Today, MATLAB motors fuse the LAPACK and BLAS libraries, inserting the cutting side in programming for network calculation.

MATLAB has advanced over a time of years with contribution from several customers. In university situations, it's far the usual academic apparatus for early on and propelled guides in mathematics, designing, and science. In enterprise, MATLAB is the tool of choice for excessive-profitability studies, advancement, and exam.

MATLAB highlights a collection of more utility-specific arrangements known as tool booths. Important to most clients of MATLAB, device kits permit you to learnandapply particular innovation. Tool compartments are exhaustive accumulations of MATLAB capacities (M-records) that reach out the MATLAB condition to take care of precise training of problems. Territories in which tool stash are reachable include flag coping with, manipulate frameworks, neural structures, fluffy reason, wavelets, pastime, and severa others.

**The MATLAB System:**

The MATLAB system consists of five main parts.

**Development Environment:**

 This is the set of tools and centres that help you operate MATLAB features and files. Many of that gear are graphical person interfaces. It includes the MATLAB desktop and Command Window, a command history, an editor and debugger, and browsers for viewing assist, the workspace, files, and the hunt direction.

**The MATLAB Mathematical Function:**

This is a great collection of computational algorithms ranging from standard capabilities like sum, sine, cosine, and complex arithmetic, to extra sophisticated features like matrix inverse, matrix eigen values, Bessel functions, and speedy Fourier transforms.

**The MATLAB Language:**

This is a high-level matrix/array language with control flow statements, functions, data structures, input/output, and object-oriented programming features. It allows both "programming in the small" to rapidly create quick and dirty throw-away programs, and "programming in the large" to create complete large and complex application programs.

**Graphics:**

MATLAB has considerable centres for displaying vectors and matrices as graphs, as well as annotating and printing those graphs. It consists of high-stage functions for 2-dimensional and 3-dimensional records visualization, photograph processing, animation, and presentation graphics. It also consists of low-stage capabilities that will let you absolutely customise the appearance of graphics as well as to construct complete graphical person interfaces for your MATLAB programs.

**The MATLAB Application Program Interface (API):**

This is a library that allows you to put in writing C and Fortran applications that have interaction with MATLAB. It consists of facilities for calling workouts from MATLAB (dynamic linking), calling MATLAB as a computational engine, and for studying and writing MAT-documents.

**7.2 MATLAB WORKING ENVIRONMENT:**

## MATLAB DESKTOP:

Matlab Desktop is the principle Matlab application window. The desktop consists of five sub windows, the summon window, the workspace program, the existing catalog window, the order records window, and at the least one figure home windows, which can be proven simply while the consumer suggests a sensible.

The order window is the area the customer sorts MATLAB orders and expressions at the initiate (>>) and wherein the yield of these fees is shown. MATLAB characterizes the workspace because the association of factors that the customer makes in a work session. The workspace software demonstrates these elements and some statistics approximately them. Double tapping on a variable within the workspace application dispatches the Array Editor, which may be applied to get data and salary instances modify sure homes of the variable.

The present Directory tab over the workspace tab demonstrates the substance of the existing registry, whose way is seemed within the present index window. 1For case, within the windows running framework the manner may be as consistent with the subsequent: C:MATLABWork, demonstrating that registry "paintings" is a subdirectory of the primary catalog "MATLAB", which is delivered in pressure C. Tapping on the bolt inside the present index window demonstrates a rundown of as of past due utilized approaches. Tapping at the seize to one aspect of the window enables the client to exchange the existing catalog.

MATLAB utilizes an inquiry way to discover M-data and different MATLAB related documents, which might be sort out in catalogs within the PC file framework. Any file keep strolling in MATLAB must dwell inside the ebb and go with the flow registry or in an index that is on are trying to find manner. Of direction, the statistics supplied with MATLAB and math works device kits are included into the inquiry way. The least stressful method to look which indexes are at the inquiry manner. The handiest method to peer which catalogs are soon the quest way, or to encompass or regulate an inquiry manner, is to pick set manner from the File menu the computer, and after that utilization the set way exchange container. It is exquisite exercise to add any typically utilized catalogs to the pursuit way to hold a strategic distance from again and again having the exchange the existing index.

The Command History Window contains a record of the orders a client has entered in the charge window, including both present and past MATLAB sessions. Already entered MATLAB orders can be chosen and re-executed from the charge history window by right

tapping on a summon or arrangement of orders. This activity dispatches a menu from which to choose different choices notwithstanding executing the orders. This is helpful to choose different choices notwithstanding executing the summons. This is a valuable component while trying different things with different orders in a work session

**Using the MATLAB Editor to create M-Files:**

The MATLAB manager is both a word processor unique for making M-statistics and a graphical MATLAB debugger. The proofreader can display up in a window without everybody else, or it could be a sub window in the laptop. M-facts are intended by means of the expansion .M, as in pixelup.M. The MATLAB editorial manager window has various draw down menus for errands, for instance, sparing, seeing, and troubleshooting documents. Since it plays out a few basic checks and furthermore utilizes shading to separate between exclusive additives of code, this content device is suggested as the equipment of selection for composing and changing M-capacities. To open the proofreader, sort regulate at the incite opens the M-report filename.M in a supervisor window, organized for altering. As referred to before, the record has to be inside the momentum catalog, or in an index within the pursuit manner.

**Getting Help:**

The important technique to get help on line is to utilize the MATLAB assist application, opened as a exclusive window both via tapping at the query mark image at the computing device toolbar, or by using writing help program on the provoke within the order window. The help Browser is an internet application coordinated into the MATLAB computing device that shows a Hypertext Markup Language (HTML) statistics. The Help Browser contains of two sheets, the assistance pilot sheet, used to find out data, and the show sheet, used to look the statistics. Clear as crystal tabs aside from pilot sheet are applied to play out a pursuit. Second, within the motion pictures taken via transferring camera setup, the state of affairs becomes extra complex because the heritage may additionally exchange by using shifting shot, we cannot tune item motion exactly inside the sum of distinction map. Therefore, in this situation, the purpose is executed through reusing the previous seam and applying it to the cutting-edge body. In order to discover the seams, we use the preceding seam from previous body to look the modern-day seam in contemporary frame. our method is using a seam computed in frame1 (in crimson) to go looking a comparable seam in frame2. For the pixels close by the area of previous seam, we decide how a lot the selected pixel might vary from the pixel of preceding seam. We use difference of the 2 pixels as the degree of temporal coherence. If the distinction value of first seam pixel is over the threshold, we can keep to go looking the next seam pixel on three feasible pixels (in yellow, blue and brown) in subsequent row, until we discover 5 consecutive pixels that also exceed the threshold.

When we can't search the matching seam, we recalculate the energy for a new seam. We assume a seam 𝑆l-1 has been calculated inside the previous body, and a seam must be calculated for the contemporary frame. For preserving the temporal coherence, we want to make a new seam close to the previous seam with the identical index. We use the distinction among preceding seam and all pixels at the current body as the measure

Thus we upload temporal coherence price Tc(i,j) to the strength map earlier than calculating a seam 𝑆L. The price Tc is zero while the body pixels have the equal fee as previous seam pixels. Using our temporal coherence price, we will calculate the seam which has least electricity and is more close to the preceding seam in previous frame. Consequently, we will decrease the jittery artifacts inside the films.

**COMMUNICATION:**

Communications System Toolbox™ offers algorithms and gear for the layout, simulation, and analysis of communications systems. These capabilities are furnished as MATLAB ® features, MATLAB System gadgets™, and Simulink ® blocks. The machine toolbox includes algorithms for source coding, channel coding, interleaving, modulation, equalization, synchronization, and channel modeling. Tools are supplied for bit blunders charge evaluation, producing eye and constellation diagrams, and visualizing channel characteristics. The machine toolbox additionally provides adaptive algorithms that allow you to version dynamic communications structures that use OFDM, OFDMA, and MIMO techniques. Algorithms support fixed-point facts arithmetic and C or HDL code era.

**Key Features**

▪ Algorithms for designing the physical layer of communications systems, which includes supply coding, channel coding, interleaving, modulation, channel fashions, MIMO, equalization, and synchronization

▪ GPU-enabled System objects for computationally intensive algorithms together with Turbo, LDPC, and Viterbi decoders

▪ Interactive visualization equipment, consisting of eye diagrams, constellations, and channel scattering capabilities

▪ Graphical tool for evaluating the simulated bit mistakes rate of a machine with analytical outcomes

▪ Channel models, consisting of AWGN, Multipath Rayleigh Fading, Rician Fading, MIMO Multipath Fading, and

LTE MIMO Multipath Fading

▪ Basic RF impairments, along with nonlinearity, section noise, thermal noise, and section and frequency offsets

▪ Algorithms available as MATLAB features, MATLAB System objects, and Simulink blocks

▪ Support for fixed-point modeling and C and HDL code technology

**System Design, Characterization, and Visualization:**

The layout and simulation of a communications gadget requires analyzing its reaction to the noise and interference inherent in real-world environments, reading its behavior the usage of graphical and quantitative manner, and determining whether the resulting overall performance meets requirements of acceptability. Communications System Toolbox implements a selection of obligations for communications machine layout and simulation. Many of the functions, System objects™, and blocks inside the device toolbox perform computations associated with a specific thing of a communications gadget, consisting of a demodulator or equalizer. Other talents are designed for visualization or evaluation.

**System Characterization**

The system toolbox offers several standard methods for quantitatively characterizing system performance:

▪ Bit error rate (BER) computations

▪ Adjacent channel power ratio (ACPR) measurements

▪ Error vector magnitude (EVM) measurements

▪ Modulation error ratio (MER) measurements

Because BER computations are fundamental to the characterization of any communications system, the system toolbox provides the following tools and capabilities for configuring BER test scenarios and accelerating BER simulations:

**BER tool**— A graphical user interface that enables you to analyze BER performance of communications systems. You can analyze performance via a simulation-based, semi analytic, or theoretical approach.

**Error Rate Test Console** — A MATLAB object that runs simulations for communications systems to measure error rate performance. It supports user-specified test points and generation of parametric performance plots and surfaces. Accelerated performance can be realized when running on a multi core computing platform.

**Multi core and GPU acceleration** — A capability provided by Parallel Computing Toolbox™ that enables you to accelerate simulation performance using multi core and GPU hardware within your computer.

**Distributed computing and cloud computing support** — Capabilities provided by Parallel Computing Toolbox and MATLAB Distributed Computing Server™ that enable you to leverage the computing power of your server farms and the Amazon EC2 Web service. Performance Visualization. The system toolbox provides the following capabilities for visualizing system performance:

**Channel visualization tool** — For visualizing the characteristics of a fading channel

**Eye diagrams and signal constellation scatter plots** — for a qualitative, visual understanding of system behavior that enables you to make initial design decisions

**Signal trajectory plots** — for a continuous picture of the signal’s trajectory between decision points

**BER plots** — for visualizing quantitative BER performance of a design candidate, parameterized by metrics such as SNR and fixed-point word size

**Analog and Digital Modulation**

Analog and digital modulation strategies encode the facts circulation into a sign this is appropriate for transmission. Communications System Toolbox presents some of modulation and corresponding demodulation abilities. These talents are available as MATLAB features and gadgets, MATLAB System Modulation sorts provided by the toolbox are:

**Source and Channel Coding**

Communications System Toolbox affords source and channel coding talents that can help you develop and compare communications architectures fast, enabling you to discover what-if eventualities and avoid the need to create coding competencies from scratch.

**Source Coding**

Source coding, also referred to as quantization or signal formatting, is a manner of processing facts a good way to lessen redundancy or prepare it for later processing. The system toolbox offers a diffusion of styles of algorithms for imposing source coding and interpreting, inclusive of:

▪ Quantizing

▪ Companding (*µ*-law and A-law)

▪ Differential pulse code modulation (DPCM)

▪ Huffman coding

▪ Arithmetic coding

**Channel Coding**

▪ orthogonal area-time block code (OSTBC) (encoder and decoder for MIMO channels)

▪ Turbo encoder and decoder examples

The gadget toolbox offers application functions for developing your personal channel coding. You can create generator polynomials and coefficients and syndrome deciphering tables, in addition to product parity-take a look at and generator matrices.

The system toolbox additionally presents block and convolutional interleaving and deinters leaving functions to reduce facts errors as a result of burst mistakes in a conversation machine:

**Block,** including General block interleaver, algebraic interleaver, helical scan interleaver, matrix interleaver, and random interleaver.

**Convolutional,** including General multiplexed interleaver, convolutional interleaver, and helical interleaver

**Channel Modeling and RF Impairments**

Channel Modeling

Communications System Toolbox provides algorithms and tools for modeling noise, fading, interference, and different distortions which might be commonly found in communications channels. The system toolbox supports the subsequent styles of channels:

▪ Additive white Gaussian noise (AWGN)

▪ Multiple-enter multiple-output (MIMO) fading

▪ Single-enter single-output (SISO), Rayleigh, and Rician fading

▪ Binary symmetric

A MATLAB channel object provides a concise, configurable implementation of channel models, enabling you to

specify parameters such as:

▪ Path delays

▪ Average path gains

▪ Maximum Doppler shifts

▪ K-Factor for Rician fading channels

▪ Doppler spectrum parameters

For MIMO systems, the MATLAB MIMO channel object expands these parameters to also include:

▪ Number of transmit antennas (up to 8)

▪ Number of receive antennas (up to 8)

▪ Transmit correlation matrix

▪ Receive correlation matrix

To combat the effects noise and channel corruption, the system toolbox provides block and convolutional coding and decoding techniques to implement error detection and correction. For simple error detection with no inherent correction, a cyclic redundancy check capability is also available. Channel coding capabilities provided by the system toolbox include:

▪ BCH encoder and decoder

▪ Reed-Solomon encoder and decoder

▪ LDPC encoder and decoder

▪ Convolutional encoder and Viterbi decoder

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**RF Impairments**

To model the effects of a non-ideal RF front end, you can introduce the following impairments into your communications system, enabling you to explore and characterize performance with real-world effects:

▪ Memory less nonlinearity

▪ Phase and frequency offset

▪ Phase noise

▪ Thermal noise

You can include more complex RF impairments and RF circuit models in your design using SimRF™.

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**Equalization and Synchronization**

Communications System Toolbox lets you discover equalization and synchronization strategies. These techniques are usually adaptive in nature and tough to design and symbolize. The machine toolbox affords algorithms and tools that will let you swiftly select the proper approach on your communications machine. Equalization To compare one-of-a-kind techniques to equalization, the device toolbox offers you with adaptive algorithms which include:

▪ LMS

▪ Normalized LMS

▪ Variable step LMS

▪ Signed LMS

▪ MLSE (Viterbi)

▪ RLS

▪ CMA

These adaptive equalizers are available as nonlinear decision feedback equalizer (DFE) implementations and as

Linear (symbol or fractionally spaced) equalizer implementations.

**Synchronization**

The device toolbox provides algorithms for each service segment synchronization and timing phase synchronization. For timing section synchronization, the machine toolbox presents a MATLAB Timing Phase Synchronizer object that offers the following implementation techniques:

▪ Early-late gate timing method

▪ Gardner’s method

▪ Fourth-order nonlinearity method

**Stream Processing in MATLAB and Simulink**

Most verbal exchange structures cope with streaming and frame-primarily based statistics using a aggregate of temporal processing and simultaneous multi frequency and multichannel processing. This form of streaming multidimensional processing can be visible in superior communication architectures consisting of OFDM and MIMO. Communications System Toolbox enables the simulation of advanced communications structures via helping move processing and frame-based simulation in MATLAB and Simulink. In MATLAB, circulate processing is enabled by way of System items™, which use MATLAB objects to symbolize time-based and facts-driven algorithms, sources, and sinks. System objects implicitly manipulate many information of flow processing, including information indexing, buffering, and management of set of rules state. You can mix System gadgets with fashionable MATLAB functions and operators. Most System items have a corresponding Simulink block with the identical abilities. Simulink handles circulation processing implicitly with the aid of coping with the float of information thru the blocks that make up a Simulink model. Simulink is an interactive graphical environment for modeling and simulating dynamic systems that uses hierarchical diagrams to symbolize a machine version. It includes a library of widespread-reason, predefined blocks to represent algorithms, resources, sinks, and device hierarchy.

**Implementing a Communications System**

Fixed-Point Modeling Many communications systems use hardware that requires a fixed-point representation of your design.

Communications System Toolbox supports fixed-point modeling in all relevant blocks and System objects™ with tools that help you configure fixed-point attributes.

Fixed-point support in the system toolbox includes:

▪ Word sizes from 1 to 128 bits

▪ Arbitrary binary-point placement

▪ Overflow handling methods (wrap or saturation)

▪ Rounding methods: ceiling, convergent, floor, nearest, round, simplest, and zero

Fixed-Point Tool in Simulink Fixed Point™ facilitates the conversion of floating-point data types to fixed point. For configuration of fixed-point properties, the tool tracks overflows and maxima and minima.

**Code Generation**

Once you've got advanced your set of rules or communications device, you can robotically generate C code from it for verification, rapid prototyping, and implementation. Most System gadgets, functions, and blocks in Communications System Toolbox can generate ANSI/ISO C code the use of MATLAB Coder™, Simulink Coder™, or Embedded Coder™. A subset of System gadgets and Simulink blocks also can generate HDL code. To leverage present highbrow belongings, you can choose optimizations for specific processor architectures and integrate legacy C code with the generated code.

You can also generate C code for both floating-point and fixed-point data types.

DSP Proto typing DSPs are used in communication system implementation for verification, rapid prototyping, or final hardware implementation. Using the processor-in-the-loop (PIL) simulation capability found in Embedded Coder, you can verify generated source code and compiled code by running your algorithm’s implementation code on a target processor. FPGA Prototyping

FPGAs are used in communication systems for implementing high-speed signal processing algorithms. Using the FPGA-in-the-loop (FIL) capability found in HDL Verifier™, you can test RTL code in real hardware for any existing HDL code, either manually written or automatically generated HDL code.

**CHAPTER -8**

**HARDWARE & SOFTWARE REQUIREMENTS:**

**Software:**

• Matlab R2018a.

**Hardware:**

**Operating Systems:**

• Windows 10

• Windows 7 Service Pack 1

• Windows Server 2019

• Windows Server 2016

**Processors:**

Minimum: Any Intel or AMD x86-64 processor

Recommended: Any Intel or AMD x86-64 processor with four logical cores and AVX2 instruction set support

**Disk:**

Minimum: 2.9 GB of HDD space for MATLAB only, 5-8 GB for a typical installation

Recommended: An SSD is recommended a full installation of all Math Works products may take up to 29 GB of disk space

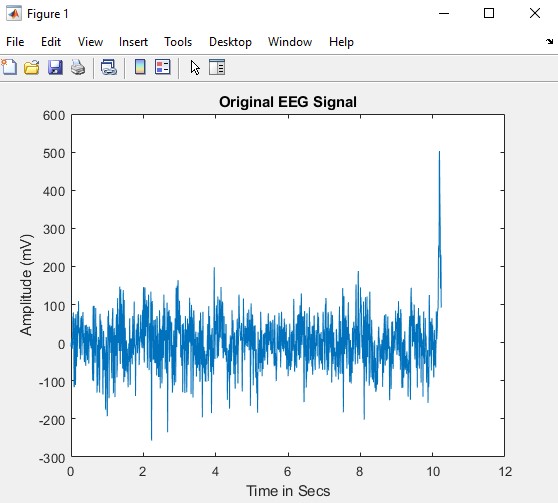
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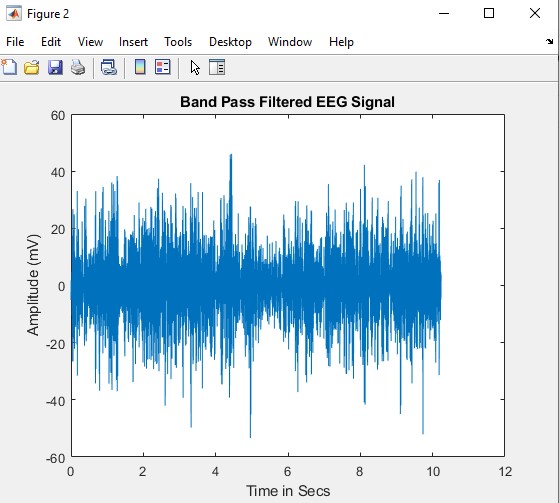
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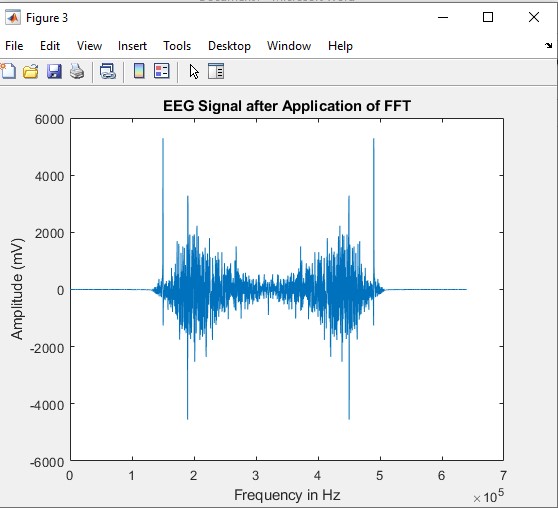
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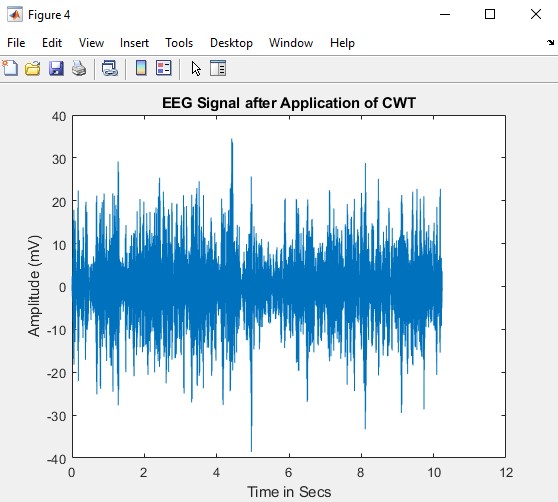
**CHAPTER-9**

**RESULTS**









**CHAPTER-10**

**CONCLUSION**

In this paper, basing on the DEAP data set, fast Fourier transform and continuous wavelet transform are used to extract the features of EEG original signals, and input the extracted shallow features into the convolutional neural network for learning and training. Emotions are classified and identified in three dimensions: arousal, valence and likes/dislike. By comparing two different feature extraction algorithms, it is proved that the fast Fourier transform CNN model achieves better classification and recognition effect. Comparing with other methods, FFT feature extraction algorithm has achieved higher recognition accuracy and is more suitable for emotion classification tasks. This research can be applied to EEG emotion recognition in medical treatment, education, human computer interaction and criminal investigation.

**CHAPTER-11**

**FUTURE SCOPE**

**CHAPTER-12**

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