B. TECH. PROJECT REPORT

On

Automated Identification of Human Emotions based on Non-stationary EEG Signal Processing

BY

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Automated Identification of Human Emotions based on Non-stationary EEG Signal Processing

A PROJECT REPORT

Submitted in partial fulfillment of the requirements for the award of the degree

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BACHELOR OF TECHNOLOGY
in
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Submitted by:

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CANDIDATE'S DECLARATION

I hereby declare that the project entitled **"Automated Identification of Human Emotions based on Non-stationary EEG Signal Processing"** submitted in partial fulfillment for the award of the degree of Bachelor of Technology in 'Electrical Engineering' completed under the supervision of **Dr. Ram Bilas Pachori, Professor, Electrical Engineering**, IIT Indore is an authentic work.

Further, I declare that I have not submitted this work for the award of any other degree elsewhere.

Signature and name of the student with date

CERTIFICATE by BTP GUIDE

It is certified that the above statement made by the students is correct to the best of my knowledge.

Signature of BTP Guide with date and their designation

Preface

This report on **"Automated Identification of Human Emotions based on Non-stationary EEG Signal Processing"** is prepared under the guidance of **Dr. Ram Bilas Pachori, Professor, Electrical Engineering, IIT Indore.**

Through this report, I have tried to present an automated identification of human emotions using flexible analytic wavelet transform (FAWT) based on electroencephalogram (EEG) signals. The main motivation behind this work is to provide a better automated classification system for human emotions. The proposed methodology can be helpful to identify emotions in persons unable to express the emotions facially. The methodology designed by us is a novel method for the computer-aided identification of human emotion which provides higher accuracy as compared to the existing method. The proposed method also provides channel specific emotion classification which can give an insight to the emotional sensitivity of different persons across brain regions when the similar stimuli are present. Thus, brain sensitivity of different persons can be compared using the proposed method.

I have tried my best to explain the proposed concepts, techniques, results, and conclusion in detail along with the comparison of our method with the already existing method.

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I would also like to express my sincere gratitude towards my parents and friends for their kind co-operation and encouragement which helped me in completion of this project. Finally, I thank to God for enlightening my mind to carry out this work.

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Abstract

Human emotion is a physical or psychological process which is triggered either consciously or unconsciously due to perception of any object or situation. The electroencephalogram (EEG) signals can be used to record ongoing neuronal activities in the brain to get the information about the human emotional state. These complicated neuronal activities in the brain cause non-stationary behavior of the EEG signals. Thus, emotion recognition using EEG signals is a challenging study and it requires advanced signal processing techniques to extract the hidden information of emotions from EEG signals. Due to poor generalizability of features from EEG signals across subjects, recognizing cross-subject emotion has been difficult. Thus, our aim is to comprehensively investigate the channel specific nature of EEG signals and to provide an effective method based on flexible analytic wavelet transform (FAWT) for recognition of emotion. FAWT decomposes the EEG signal into different sub-band signals. Further, we applied information potential (IP) to extract the features from the decomposed sub-band signals of EEG signal. The extracted feature values were smoothed and fed to the random forest and support vector machine (SVM) classifiers that classified the emotions. The proposed method is applied to two different publicly available databases which are SJTU emotion EEG dataset (SEED) and database for emotion analysis using physiological signal (DEAP). The average classification accuracies on SEED dataset for positive, neutral, and negative emotions obtained using 12 level decomposition of FAWT on 6 effective channels are 91.53% (FT7), 90.63% (FT8), 93.46% (T7), 92.84% (T8), 91.06% (C5), and 91.22% (TP7). On DEAP database, the average classification accuracies obtained using 11 level decomposition on 2 effective channels are 80.53% (T7), 80.42% (T8) for high arousal (HA)/low arousal (LA), 80.64% (T7), 80.15% (T8) for the high valence (HV)/low valence (LV), and 72.07% (T7), 71.70% (T8) for HVHA/HVLA/LVLA/LVHA. Thus, the proposed method has shown better performance for human emotion classification as compared to the existing method. Moreover, it yields channel specific subject classification of emotion EEG signals when exposed to same stimuli.

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Chapter 1

Introduction

1.1 Human emotion

Emotion is psycho-physiological process triggered consciously or unconsciously perception of any object or situation [1]. Emotions play a vital role in human life and are one of the crucial features of humans [2]. The everyday activities like communication, decision-making, etc., get highly affected by emotional behavior.

1.2 Electroencephalogram (EEG) signals

The EEG signals measure the electrical activity in the brain generated by the neurons. The EEG signals can help us diagnose focal epileptic seizure [3], sleep disorders [4], etc.

1.3 Literature survey

For decades, brain-computer interfaces (BCI) [5] have been one of the emerging and interesting bio-medical engineering research field that allows human being to control the external devices using their brain waves. To achieve precise and natural interaction, computers and robots must possess the ability of emotion processing [6, 7]. The study of emotions has drawn attention of researchers from various disciplines like psychology, bio-medical science, neuroscience, etc. In the field of computer science, emotion study is inclined towards the development of applications such as task workload assessment and vigilance of operator [8, 9]. An automated emotion recognition system enriches the computer interface more user-friendly, effective, and enjoyable. The approaches to recognize human emotions vary from facial images, gesture, speech signals, to other physiological signals [10]. An inherent ambiguity exists in recognition of emotions using facial images, gesture, or speech signals because it might be a pretended emotion not the real ones. To resolve this ambiguity, emotion recognition using EEG signals gained significant attention of researchers due to its accurate assessment of the emotions and objective evaluation in comparison with facial expressions and gestures based techniques [11]. It has been proven that EEG signals can be helpful in effectively identifying the different emotions [12, 13, 14, 15]. For effective medical care, the consideration of emotional state is important [16, 17]. The process of recognition of emotion requires suitable signal processing techniques, feature extraction, and machine learning based classifiers for automated classification.

Several techniques for automated classification of human emotion using EEG signals are proposed in the literature [18, 19, 20, 21, 22, 23, 24, 25]. The technique based on discrete wavelet transform (DWT) is used in [18] to extract features from the EEG signals for emotion recognition. The features like energy and entropy are computed from the wavelet coefficients of the emotion EEG signals and the fuzzy c-mean and fuzzy k-mean clustering algorithms are used for classification purpose. In [19], the authors presented a method for user-independent emotion recognition based on EEG signals, gaze distance, and pupillary response. The reported classification accuracy is 68.5% for three valence labels and 76.4% for three arousal labels using modality fusion strategy, and support vector machine (SVM). The EEG signals pertaining to emotions of happiness and sadness are classified using common special patterns (CSP) and linear-SVM classifier. They also presented a strategy to choose an optimal frequency band and gamma band which is found suitable for EEG-based emotion classification [21]. The three time-frequency distributions namely, Hilbert-Huang, Zhao-Atlas-Marks, and spectrogram are used to compute the features based on time-windowing approach for discrimination between music appraisal responses [22]. The fast Fourier transform (FFT) based features are extracted and classification is performed by employing a classifier depending on Bayes theorem and perceptron convergence algorithm [23]. Differential entropy based features are computed from the EEG signals for emotion recognition. These features are found appropriate for recognition of emotion categories namely, positive, neutral, and negative [24]. In another work, the differential entropy computed in different frequency bands is related to EEG rhythms. The beta and gamma rhythms are found most effective for emotion recognition [25]. Recently, the authors investigated 18 different kinds of linear and non-linear features out of which nine are time-frequency domain features and others are dynamical system features from EEG measurements and studied the different aspects which are important for cross-subject emotion recognition e.g., different EEG channels and achieved average classification accuracies of 59.06% and 83.33% on the database for emotion analysis using physiological signals (DEAP) and SJTU emotion EEG dataset (SEED) databases, respectively [26].

1.4 Objectives

The objective of this dissertation is to design a computer-aided identification method for human emotions from EEG signals using non-stationary signal processing technique.

1.5 Contributions

The contributions of this work is that a computer-aided identification method for human emotion from EEG signals using a non-stationary signal processing method namely, flexible analytic wavelet transform (FAWT) has been developed. FAWT is applied to extract the sub-band signals from EEG signals. Further, information potential (IP) have been computed from the sub-band signals followed by classifier. The performance of the proposed method is better than the existing method.

1.6 Organization of the report

The remaining portion of this report is organized as follows: In chapter 2, the description about the datasets is given. The explanation about the designed methodology for classification of human emotions is given in chapter 3. It also provides description about the FAWT, IP, and studied classifiers. In the chapter 4, results and discussions have been provided. Finally, the whole work is concluded in chapter 5. The direction of future research work is also provided in chapter 5.

Chapter 2

Datasets description

The two publicly available datasets namely, SEED and DEAP are used in this work to validate the proposed methodology. The description of these datasets are as follows:

2.1 SJTU emotional EEG dataset (SEED)

The SEED dataset is available online for the research purpose [25, 27]. It consists EEG signals recorded from 15 subjects (7 males and 8 females). Each participant contributed to the experiment thrice at an interval of one week or longer. The emotion EEG signals were collected by showing fifteen Chinese film clips for positive, neutral, and negative emotions. These films contain both scene and audio to elicit strong emotion in subject. Every emotion contains five film clips with each 4 minutes long in one experiment. The subject's emotion reactions were recorded through a questionnaire after watching each emotion film clip. The 62-channel electrode cap was used for recording the EEG signals according to the international 10-20 system at 1000 Hz sampling rate. The recorded EEG signals were preprocessed with down-sampling rate of 200 Hz followed by a band pass filter between 0.5 Hz to 70 Hz to remove the noise and artifacts. The detailed information related to the dataset can be found in [27].

In [25], the authors presented the appropriate number of channels for emotion EEG signals classification and it was observed that 12 channels were most effective for classification of emotions. These channels are as follows: C5, C6, CP5, CP6, FT7, FT8, P7, P8, T7, T8, TP7, and TP8. We have considered each channel separately, and extracted one second epochs from the last 30 seconds of the recorded EEG signals. The authors in [1], have suggested the use of last 30 seconds of each trial (video) for emotions identification from EEG signals. On the other hand, the human emotions normally fall in the duration of 0.5-4 seconds [28]. It should be noted that the suitable selection of the duration is an important factor in the identification of human emotions from EEG signals. The selection of too long or too short duration may lead to misclassification of human emotions. For these reasons, the optimal duration of one second has been suggested in [29, 30] for identification of human emotions.

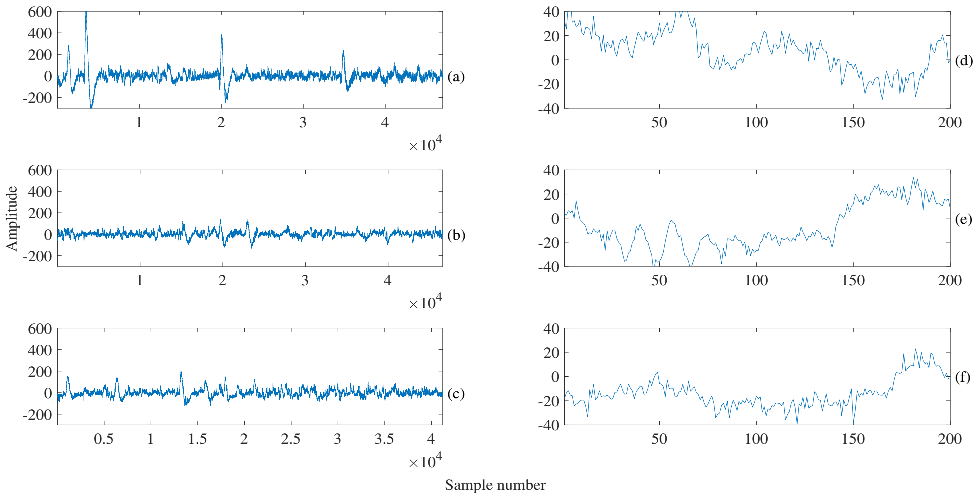

Figure 2.1: Plots of emotion EEG signals from SEED database: (a) positive, (b) neutral, and (c) negative. Plots of last 1 second epoch corresponding to (d) positive, (e) neutral, and (f) negative emotion EEG signals.

The SEED database contains recordings from 62 channels but we considered only those mentioned in [25]. Fig. 2.1(a)- 2.1(c) shows emotion EEG signals of positive, negative, and neutral whereas Fig. 2.1(d)- 2.1(f) shows the epoch of corresponding last one second extracted from positive, negative, and neutral emotion EEG signals from FT7 channel (first session of first subject), respectively.

2.2 Database for emotion analysis using physiological signal (DEAP)

We have also studied the DEAP emotion database available online for the research purpose [1]. It consists recording of 32 subjects and the recording from each subject contains 32 EEG and 8 peripheral signals corresponding to 40 channels. These EEG signals were recorded by showing 40 pre-selected music video each with duration of 60 seconds and baseline recording of 3 seconds duration. The sampling frequency of these recorded EEG signals is 128 Hz. The detailed information about database can be found in [1].

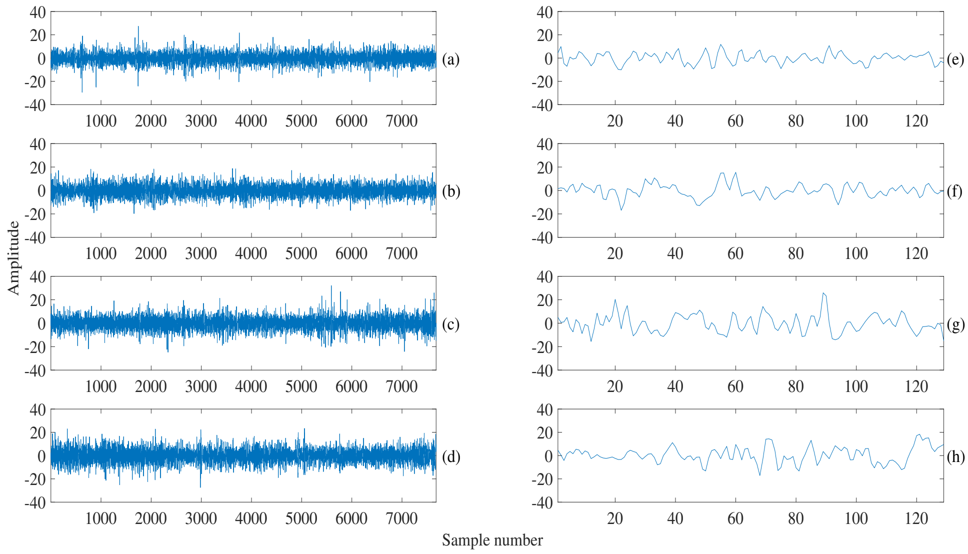

Figure 2.2: Plots of emotion EEG signals from DEAP database: (a) HVHA, (b) HVLA, (c) LVLA, and (d) LVHA. Plots of last 1 second epoch corresponding to (e) HVHA, (f) HVLA, (g) LVLA, and (h) LVHA emotion EEG signals.

In DEAP dataset, the channels T7, T8, CP5, CP6, P7, and P8 are considered in this work because these channels are more suitable for recognition of emotions as suggested in [25]. Fig. 2.2(a)- 2.2(d) shows the high valence high arousal (HVHA), high valence low arousal (HVLA), low valence low arousal (LVLA), and low valence high arousal (LVHA) EEG signals recorded from T7 channel, respectively. The epoch of last one second corresponding to HVHA, HVLA, LVLA, and LVHA EEG signals are shown in Fig. 2.2(e)- 2.2(h), respectively.

In this presented work, the methodology framework has been designed based on the SEED database. In order to show the effectiveness of the designed framework, we have considered DEAP database in addition to SEED database. It can be seen from Fig. 2.1(a)- 2.1(c) and Fig. 2.2(a)- 2.2(d) for SEED and DEAP databases that these signals are complicated in nature, respectively. Moreover, it is not easy to discriminate them based on the visual inspection. Due to this reason, we have proposed a technique based on the signal processing and machine learning algorithms for automated classification of the emotion EEG signals. In our proposed method, we have studied one second duration EEG signals, due to this reason the emotion EEG signals for SEED and DEAP databases corresponding to last one second are shown in Fig. 2.1(d)- 2.1(f) and Fig. 2.2(e)- 2.2(h), respectively.

Chapter 3

Methodology

In this work, the emotion EEG signals are first decomposed using FAWT method. The FAWT based decomposition of EEG signal results in sub-band signals. The FAWT method has many advantages over the conventional DWT method such as flexibility in the selection of parameters (fractional sampling, quality factor, dilation, and redundancy). Moreover, the FAWT provides a platform for analysis of transient and oscillatory nature of the signal. It should be noted that with these above mentioned specific features, the FAWT can also be implemented using iterative filter bank approach like DWT. The IP estimator is used to extract the feature values from different sub-band signals. These feature values are smoothen and fed to the random forest and SVM classifiers separately that classify the emotion EEG signals. The block diagram for the proposed automated emotion classification system is shown in Fig. 3.1.

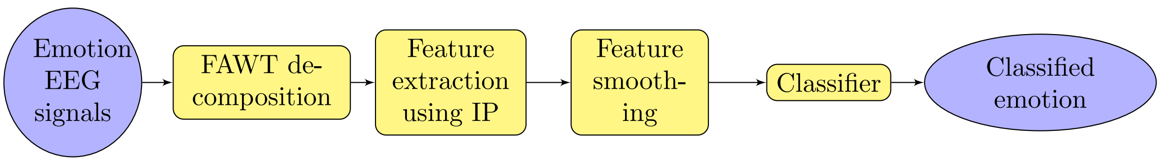

Figure 3.1: Block diagram representation of the proposed methodology for the automated classification of the emotion EEG signals.

3.1 Flexible analytic wavelet transform (FAWT)

FAWT [31, 32] is an advanced form of DWT that serves as an effective method for analyzing bio-medical signals [33, 34]. The time-frequency covering is one of the salient features of FAWT. The FAWT contains Hilbert transform pairs of atoms that make it suitable for analysis of signals which contain oscillations. The Q-factor (QF), number of decomposition level (J), and redundancy (r) are the input parameters for FAWT. The QF for an oscillatory pulse can be expressed as [31]:

$$\mathrm{QF} = \frac{\omega_0}{\Delta\omega}. \tag{3.1}$$

where ω_0 is central frequency and $\Delta\omega$ is the bandwidth of the signal.
Thus, QF is the controlling parameter of the number of oscillations in the mother wavelet. The redundancy controls the time localization of the wavelet. FAWT provides the facility to specify the dilation factor, QF, and redundancy through adjusting parameters namely, e, f, g, h, and β. We have e and f for up and down sampling of high pass channel while g and h are used for up and down sampling of low pass channel, respectively. The β is a positive constant which gives a measure for QF and it can be expressed as [31]:

$$\beta = \frac{2}{\mathrm{QF} + 1} \tag{3.2}$$

As per the definition of FAWT, the parameters e, f, g, h, and β control the number of oscillation in the wavelet. For a specific QF, the generated wavelet for different decomposition levels will have same number of oscillations. The shape of these wavelets will change with the variation of FAWT parameters [31]. The fractional sampling can also be done using these FAWT parameters in low and high pass channels. Implementation of J level decomposition using FAWT is done by iterative filter bank comprising of high pass and low pass channels at every iteration level. The high pass and low pass channels of the filter bank separate the positive and negative frequencies, respectively. The frequency response corresponding to high pass filter is expressed as [31]:

$$H(\omega) = \begin{cases} (ef)^{1/2}, & |\omega| < \omega_p \\ (ef)^{1/2}\theta\left(\frac{\omega-\omega_p}{\omega_s-\omega_p}\right), & \omega_p \le \omega \le \omega_s \\ (ef)^{1/2}\theta\left(\frac{\pi-(\omega-\omega_p)}{\omega_s-\omega_p}\right), & -\omega_s \le \omega \le -\omega_p \\ 0, & |\omega| \ge \omega_s \end{cases} \tag{3.3}$$

and the low pass filter frequency response is expressed as [31]:

$$G(\omega) = \begin{cases} (gh)^{1/2}\theta\left(\frac{\pi-\omega-\omega_0}{\omega_1-\omega_0}\right), & \omega_0 \leq \omega < \omega_1 \\ (gh)^{1/2} & \omega_1 < \omega < \omega_2 \\ (gh)^{1/2}\theta\left(\frac{\omega-\omega_2}{\omega_3-\omega_2}\right), & \omega_2 \leq \omega \leq \omega_3 \\ 0, & \omega \in [0, \omega_0) \cap (\omega_3, 2\pi) \end{cases} \tag{3.4}$$

where $\omega_p = \frac{(1-\beta)\pi+\epsilon}{e}$; $\omega_s = \frac{\pi}{f}$; $\omega_0 = \frac{(1-\beta)\pi+\epsilon}{g}$; $\omega_1 = \frac{e\pi}{fg}$; $\omega_2 = \frac{\pi-\epsilon}{g}$; $\omega_3 = \frac{\pi+\epsilon}{g}$; $\epsilon \leq \frac{e-f+\beta f}{e+f}\pi$.

The $\theta(\omega)$ can be given by [31]:

$$\theta(\omega) = \frac{[1+\cos(\omega)][2-\cos(\omega)]^{1/2}}{2}, \text{ for } \omega \in [0, \pi] \tag{3.5}$$

For perfect reconstruction, following condition must be satisfied [31]:

$$|\theta(\pi-\omega)|^2 + |\theta(\omega)|^2 = 1 \tag{3.6}$$

The constraint for selecting the QF parameter is expressed as:

$$1 - \frac{e}{f} \leq \beta \leq \frac{g}{h} \tag{3.7}$$

The redundancy parameter r can be expressed as:

$$\mathrm{r} \approx (g/h)\frac{1}{1-e/f} \tag{3.8}$$

Thus, the selection of parameter r is subjected to following constraint:

$$\mathrm{r} > \beta/(1 - \frac{e}{f}) \tag{3.9}$$

Figs. 3.2, 3.3, and 3.4 show the plots of the epochs and its corresponding reconstructed sub-band signals (SS_1-SS_{13}) obtained from FAWT decomposition for positive, neutral, and negative emotion EEG signals, respectively. These epochs are corresponding to last one second extracted from FT7 channel (first session of first subject) obtained with SEED database. It should be noted that SS_1 to SS_{13} denote the first to thirteenth reconstructed sub-band signals (SS) in their decreasing order

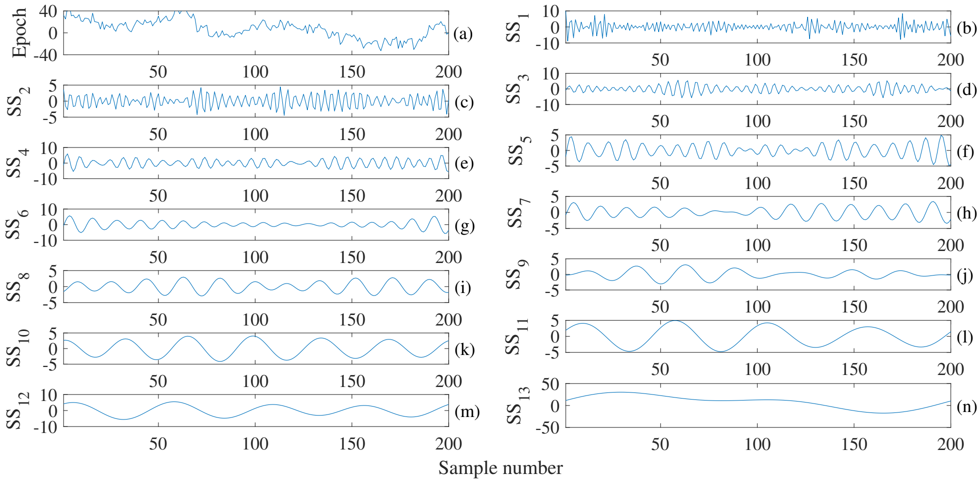

Figure 3.2: Plots of (a) an epoch from positive emotion EEG signal and (b)-(n) its corresponding reconstructed sub-bands ($SS_1 - SS_{13}$) obtained using FAWT decomposition.

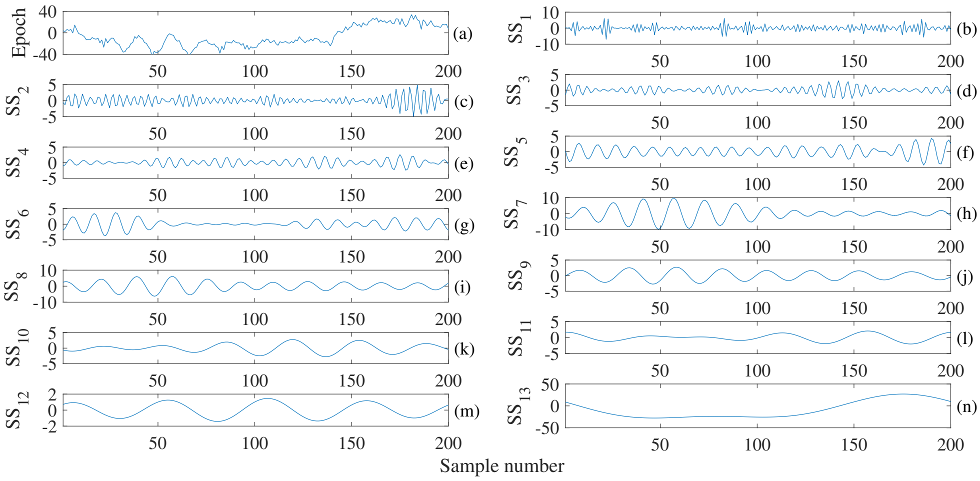

Figure 3.3: Plots of (a) an epoch from neutral emotion EEG signal and (b)-(n) its corresponding reconstructed sub-bands ($SS_1 - SS_{13}$) obtained using FAWT decomposition.

of frequency. These components are well behaved and suitable for features extraction for the classification of human emotion EEG signals. These obtained SS show the outcome of FAWT based analysis.

In this work, we have used a fixed value of dilation factor ($\frac{e}{f} = \frac{3}{4}$) as suggested in [3] for EEG signals classification. On the basis of this fixed dilation factor, we have chosen the values of parameters (QF and r) for the FAWT decomposition subjected to constraints which are expressed in equations (3.8) and (3.9), respectively. The selected range of values for QF parameter are (3, 4, 5, and 6) and r parameter are (3, 4, 5, 6, 7, and 8). The value of J is selected from the range of (5, 6, 7, 8, 9, 10, 11, and 12) because J=12 is the maximum possible decomposition level using

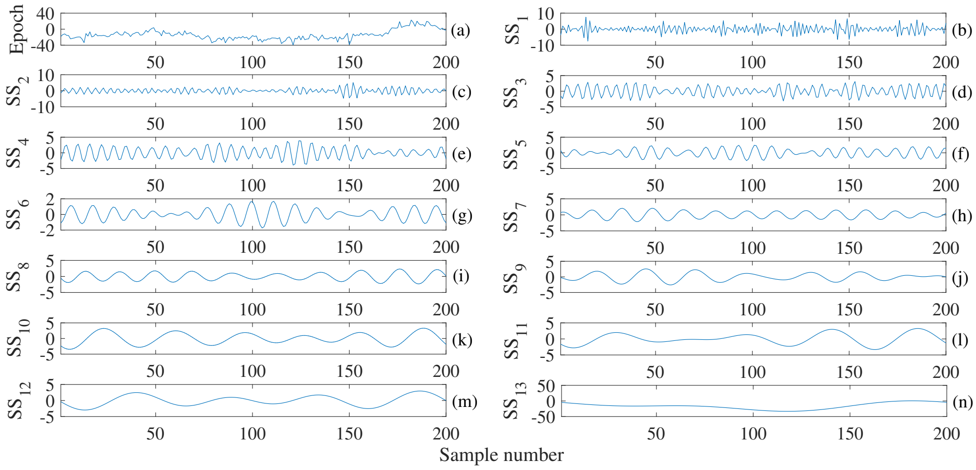

Figure 3.4: Plots of (a) an epoch from negative emotion EEG signal and (b)-(n) its corresponding reconstructed sub-bands ($SS_1 - SS_{13}$) obtained using FAWT decomposition.

FAWT on these parameters values for EEG signals of length 200 samples [31].

The FAWT is successfully applied for identification of atrial fibrillation electrocardiogram (ECG) signals [35], myocardial infarction ECG signals [33], coronary artery disease [36, 37], and focal EEG signals [3]. For the FAWT decomposition method, matlab toolbox is available at (`http://web.itu.edu.tr/ibayram/AnDWT/`).

3.2 Information potential (IP)

The IP is a kernel based non-parametric estimator to evaluate Renyi's quadratic entropy. For a random variable X, the IP of X is expressed as [36, 38]:

$$\hat{I}(X) = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} k_\sigma(x_j, x_i) \tag{3.10}$$

where $\{x_i\}_{i=1}^{N}$ are the data samples of random variable X and N is the total number of observations, k_σ represents the Gaussian kernel with bandwidth parameter σ.

In this work, computation of IP [38] feature from the SS obtained from FAWT decomposition of each epoch is done. Information theoretic learning (ITL) toolbox (`http://www.sohanseth.com/Home/codes`) is used for the faster implementation of IP that makes the use of incomplete Cholesky decomposition with parameter σ fixed to 1 [36].

3.3 Feature smoothing

As the human emotion changes gradually, the rapid fluctuations in raw feature values need to be removed. The feature smoothing process is useful for human emotion classification from EEG signals [24], due to this reason, we have used feature smoothing process in our proposed method. In this process, raw feature values obtained from IP of epochs have been smoothen using a moving average filter corresponding to window-length of 5 samples [24]. Fig. 3.5 shows the effect of moving average filter on the raw feature values obtained from positive emotion using FT7 channel of the first subject during the first session.

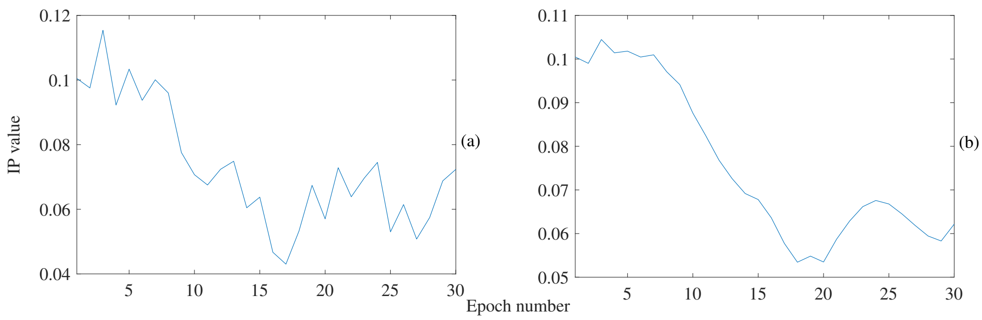

Figure 3.5: Plots of (a) raw feature values (b) smooth feature values using moving average filter.

3.4 Classification

In this work, random forest [39] and SVM [40] classifiers have been used for the classification purpose. The ten-fold cross validation is used for the effective calculation of the classification accuracy [41]. The Waikato environment for knowledge analysis (WEKA) [42] is used for the implementation of the random forest and SVM classifiers. These classifiers have been used with default parameters present in WEKA.

3.4.1 Random forest classifier

The working principle of random forest classifier is based on the aggregate decisions taken from different trees and each decision tree individually with assigned weight makes a decision about the class for the final decision. For building a tree, random tree method is employed [43]. The class decision from every tree determines overall classification output. The random forest classifier has been successfully utilized for the classification of ECG signals [44] and EEG signals [4, 45].

3.4.2 Support vector machine (SVM) classifier

In SVM classifier, the data is mapped to a higher dimensional space and an optimal hyperplane for separation of data is constructed in this space. This classifier basically solves a quadratic programming problem [40]. The SVM classifier is used in [46, 47], for classification of epileptic seizure EEG signals. In this work, the polynomial and radial basis function (RBF) kernels have been used with SVM classifier for evaluating the classification performance [48].

Chapter 4

Results and discussions

In this work, continuous epochs of 1 second duration are extracted from the last 30 seconds [1] of all the emotion EEG signals namely, positive, negative, and neutral from SEED database. Then, we have applied FAWT decomposition on each extracted 1s epoch of emotion EEG signal for 12 selected channels separately. The FAWT parameters J, QF, and r are selected from the range of 5 to 12, 3 to 6, and 3 to 8, respectively. IP is computed from each of the SS and the dimension of the feature set is dependent on J level of FAWT decomposition for an epoch and thirty such epochs are considered from the last 30 second duration of the emotion EEG signal. The size of total feature set is product of the number of SS used to extract features with number of epochs. For a channel, total feature set is $30 \times J+1$ for an emotion EEG signal. Extracted feature values were classified by the random forest and SVM classifiers.

Fig. 4.1 shows the variation of average classification accuracies for different channels with respect to J parameter on SEED database. It can be seen from the Fig. 4.1 that the classification accuracies increase with the increase in J parameter for all the channels. Therefore, we have selected J=12 which is maximum available decomposition level for selected FAWT parameters with signal length of 200 samples in order to select the QF and r parameters. The variation of average classification accuracies for different channels with respect to QF parameter on SEED database can be seen in Fig. 4.2. The selected value of QF parameter is 5 with the help of Fig. 4.2, because most of the channels have higher average classification accuracies at this QF parameter value. However, the variation of third parameter r shows no impact on the average classification accuracies at J=12 and QF =5 and this variation can

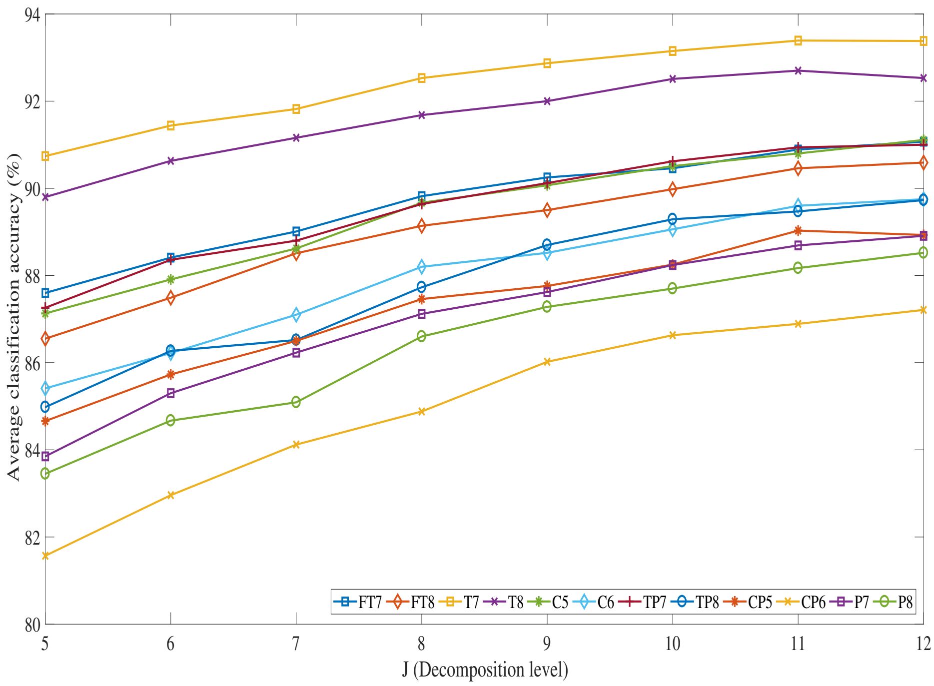

Figure 4.1: Plot of average classification accuracies on SEED database for different channels with respect to J values at QF=3 and r=3 using random forest classifier.

be seen in Fig. 4.3. Therefore, we have selected r=3 for FAWT decomposition in order to developed our methodology. Tables 4.1, 4.2, and 4.3 show achieved average classification accuracies on selected FAWT parameters on every channel for different subjects obtained with random forest and SVM classifiers on SEED. Table 4.4 shows the achieved average classification accuracies on selected FAWT parameters across channels obtained with random forest and SVM classifiers on SEED database. It can be observed from Table 4.4, that the highest average classification accuracies across channels are obtained with random forest classifier in comparison to SVM classifier for SEED database. It can also be observed from Table 4.4, that channels FT7, FT8, T7, T8, C5, and TP7 have shown higher average classification accuracies across channels obtained with SEED database using random forest classifier in comparison to other channels. Thus, we can clearly say that these channels are most efficient for cross-subject recognition of emotion with FAWT decomposition using EEG signals. The proposed methodology with selected FAWT parameters along with random forest classifier has been also tested on DEAP database to check the effectiveness of the proposed method. The selection of random forest classifier for DEAP database is based on the good performance of classification accuracies obtained on SEED

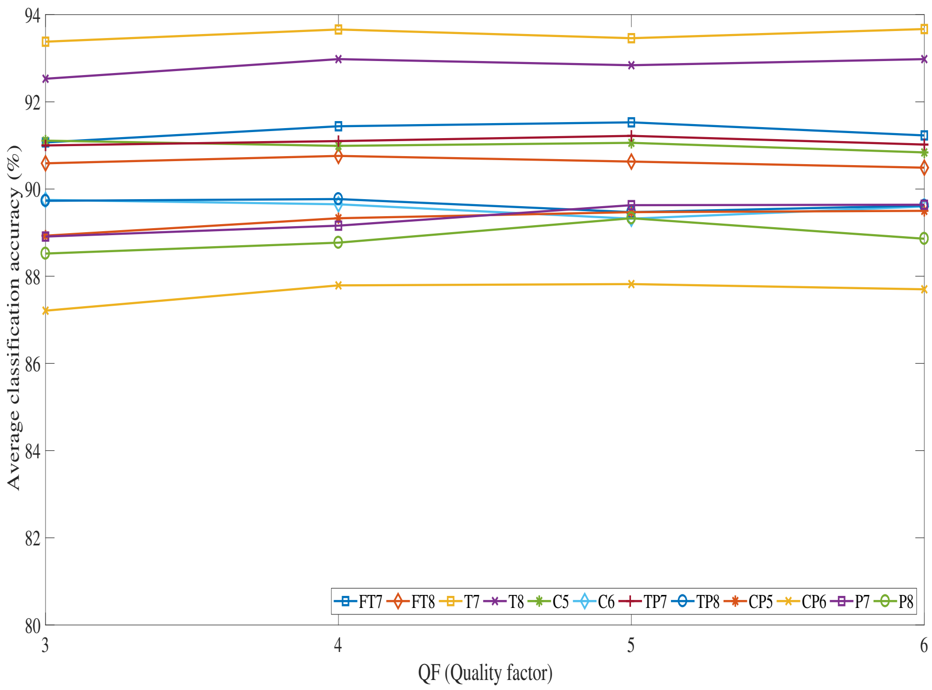

Figure 4.2: Plot of average classification accuracies on SEED database for different channels with respect to QF values at J=12 and r=3 using random forest classifier.

database as compared to SVM classifier. In this DEAP database, J=11 is the maximum possible decomposition level due to signal length of 128 samples. Table 4.4 also shows the results of average classification accuracies across channels obtained with DEAP database using random forest classifier. Similarly, Table 4.4 shows the higher average classification accuracies across channels for T7 and T8 common channels on DEAP database. The proposed methodology obtained the average classification accuracies of 90.48% for positive/neutral/negative, 79.95% for high arousal (HA)/low arousal (LA), 79.99% for the high valence (HV)/low valence (LV), and 71.43% for HVHA/HVLA/LVLA/LVHA emotions classification using EEG signals. Our proposed methodology outperforms in comparison to methodology proposed in [26], which gives an average classification accuracies of 83.33% on SEED database and 59.06% on DEAP database.

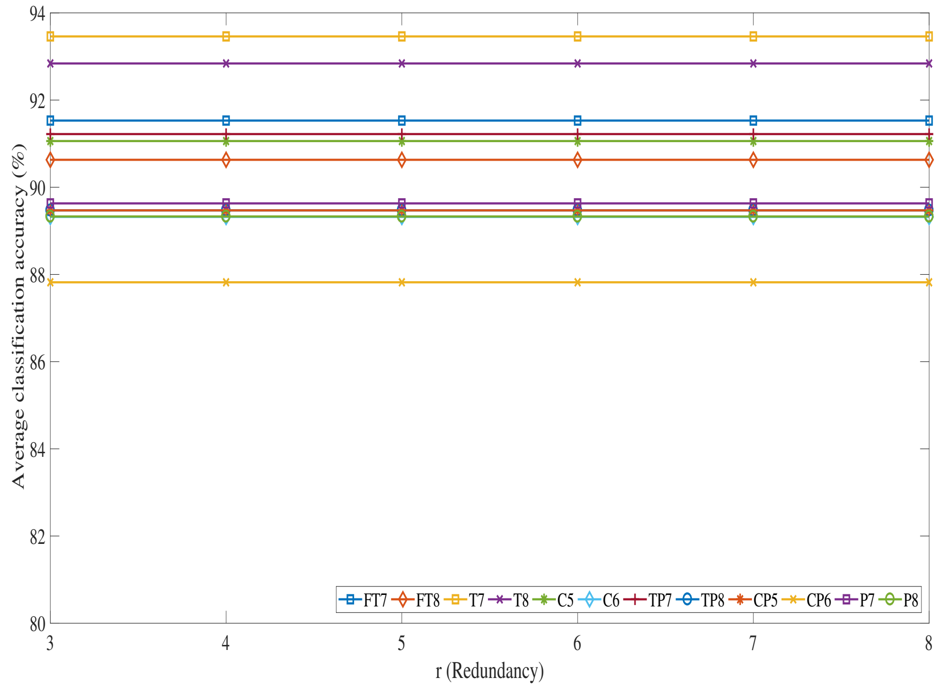

Figure 4.3: Plot of average classification accuracies on SEED database for different channels with respect to r values at J=12 and QF=5 using random forest classifier.

Table 4.1: Average classification accuracies (%) on SEED database of different subject across channels for J=12, QF=5, and r=3 with random forest classifier.

Subject	**Channel name**											
	FT7	FT8	T7	T8	C5	C6	TP7	TP8	CP5	CP6	P7	P8
1	87.10	90.07	94.83	91.70	88.13	86.23	90.00	88.87	85.77	88.20	89.67	86.30
2	88.83	87.93	90.43	90.30	86.90	85.87	92.13	85.40	87.17	83.57	88.50	85.57
3	92.77	89.53	92.60	94.23	90.07	90.73	91.50	89.63	87.13	87.63	88.67	88.90
4	88.33	90.07	90.37	90.47	89.57	84.43	87.33	84.23	87.63	82.07	86.97	84.53
5	95.70	92.10	95.17	93.97	95.27	93.93	93.97	93.83	91.93	92.23	93.27	93.40
6	96.77	97.23	93.77	95.90	92.97	91.33	93.20	92.50	93.27	90.23	93.10	89.87
7	92.10	87.27	94.87	90.43	92.67	90.03	88.30	88.97	87.40	89.83	87.83	88.63
8	89.47	82.77	92.83	89.27	89.50	81.77	91.07	86.43	86.13	80.23	90.67	88.63
9	90.83	93.17	94.97	93.77	92.17	88.87	92.17	89.47	93.83	88.27	89.80	88.47
10	91.33	90.83	91.17	91.33	90.23	90.77	89.97	85.93	89.13	86.40	89.10	88.23
11	94.60	94.17	92.60	94.93	90.90	92.83	90.27	94.67	91.40	88.77	89.20	91.10
12	88.47	89.37	91.27	92.13	89.40	89.20	88.67	88.97	87.17	89.00	88.20	89.83
13	90.77	90.20	95.27	93.90	93.03	91.47	92.97	91.20	89.97	91.20	86.67	91.53
14	90.97	91.10	94.67	94.00	91.70	88.57	93.20	91.03	92.10	88.47	91.63	93.27
15	94.97	93.70	97.13	96.23	93.47	93.83	93.60	90.90	92.07	91.23	91.13	91.63

Table 4.2: Average classification accuracies (%) on SEED database of different subject across channels for J=12, QF=5, and r=3 with SVM classifier along with polynomial kernel.

Subject	**Channel name**											
	FT7	FT8	T7	T8	C5	C6	TP7	TP8	CP5	CP6	P7	P8
1	77.57	77.60	83.70	81.03	75.40	74.37	78.50	76.27	71.77	71.87	75.10	72.30
2	66.60	65.87	68.47	71.50	61.40	60.97	62.40	62.23	63.53	59.53	56.67	57.63
3	74.60	75.57	81.63	88.17	74.37	79.40	83.30	78.00	70.13	71.37	74.93	73.43
4	68.73	72.43	73.13	80.87	72.77	63.90	70.73	68.90	70.77	62.43	70.50	58.97
5	74.47	66.00	82.37	66.40	81.47	68.00	75.03	68.43	67.40	70.03	65.87	70.93
6	84.03	88.97	84.30	83.20	75.50	73.40	79.03	72.37	74.30	67.33	74.53	70.53
7	83.57	76.23	88.60	85.87	82.53	83.87	80.63	75.13	78.30	74.53	74.97	72.00
8	74.13	69.10	86.97	78.53	82.80	69.17	78.47	74.80	72.27	63.77	78.53	70.50
9	80.57	82.30	88.63	83.47	82.60	74.23	82.43	68.97	81.83	73.83	66.00	65.50
10	74.43	72.53	77.27	75.83	74.00	75.03	75.17	71.63	70.43	68.37	63.50	67.57
11	87.40	83.63	82.47	88.80	83.03	84.23	81.73	89.00	80.83	72.23	76.57	81.57
12	67.20	73.90	74.00	81.10	71.40	73.67	73.53	72.60	63.20	66.17	66.93	73.10
13	79.80	78.90	84.73	83.87	81.17	78.60	80.43	83.77	76.43	78.67	68.30	78.57
14	79.83	80.63	80.90	80.90	79.63	76.83	79.67	81.07	79.10	77.63	72.80	80.37
15	91.70	84.67	90.00	85.50	85.33	87.67	84.13	76.17	84.30	80.37	81.23	81.83

Table 4.3: Average classification accuracies (%) on SEED database of different subject across channels for J=12, QF=5, and r=3 with SVM classifier along with RBF kernel.

Subject	**Channel name**											
	FT7	FT8	T7	T8	C5	C6	TP7	TP8	CP5	CP6	P7	P8
1	68.23	71.83	72.97	75.03	66.43	60.20	68.97	62.70	55.83	50.37	63.80	57.20
2	57.33	55.03	58.87	57.70	52.13	46.07	51.47	48.87	43.77	46.07	49.43	46.23
3	55.87	61.87	71.93	81.53	59.83	62.07	67.57	60.17	47.77	46.93	57.23	53.27
4	55.93	59.33	64.23	74.90	61.10	46.47	60.67	55.30	49.67	48.60	52.77	44.43
5	54.07	55.13	58.40	52.97	57.60	55.07	64.50	58.87	53.03	55.07	55.90	58.63
6	73.40	81.40	75.37	72.17	65.53	57.90	65.03	59.77	55.27	49.47	64.53	59.47
7	70.77	61.40	81.20	79.43	70.60	64.77	66.43	58.00	62.60	59.40	55.10	51.63
8	61.70	46.73	78.00	70.07	74.23	54.97	70.90	65.80	61.90	52.17	63.33	60.23
9	68.80	75.57	79.73	74.00	74.07	61.87	76.77	53.77	69.00	60.63	50.30	56.07
10	67.63	69.70	68.23	62.37	63.03	67.00	61.87	56.37	58.67	54.97	53.63	56.07
11	80.10	76.00	75.83	71.77	71.27	70.00	70.97	76.63	62.20	50.93	62.83	62.23
12	54.67	61.80	59.57	71.83	54.03	64.00	58.03	57.37	55.77	54.50	57.40	60.07
13	69.57	68.17	75.00	75.90	70.17	69.27	70.47	68.30	64.60	59.87	56.00	61.57
14	71.17	71.77	66.30	71.23	63.77	68.43	61.63	70.17	67.93	59.87	58.67	69.67
15	82.43	78.43	77.13	75.10	77.57	77.83	78.87	67.83	70.17	62.17	76.40	74.07

Table 4.4: Average classification accuracies (%) across channels for J=12 and 11, QF=5, and r=3 on SEED and DEAP databases, respectively.

Database	**Classification problem**	**Classifier**	**Channel name**											
			FT7	FT8	T7	T8	C5	C6	TP7	TP8	CP5	CP6	P7	P8
SEED	Positve/negative/neutral	Random forest	91.53	90.63	93.46	92.84	91.06	89.32	91.22	89.47	89.47	87.82	89.63	89.33
		SVM (polynomial kernel)	79.56	77.78	83.50	81.21	79.75	76.63	78.99	75.71	75.17	71.96	71.69	73.68
		SVM (RBF kernel)	66.11	66.28	70.85	71.07	65.42	61.73	66.28	61.33	58.55	54.07	58.49	58.06
DEAP	HA/LA	Random forest	-	-	80.53	80.42	-	-	-	-	79.66	79.39	80.21	79.49
	HV/LV		-	-	80.64	80.15	-	-	-	-	79.64	79.85	79.73	79.95
	HVHA/HVLA/LVLA/LVHA		-	-	72.07	71.70	-	-	-	-	70.99	70.92	71.77	71.11

Chapter 5

Conclusion and future work

Emotions play a significant role in human life and are one of the important features of humans. In this work, we have presented a new method for the cross-subject classification of the emotion EEG signals. The proposed method explores the FAWT for identification of human emotions. The effect of variation in FAWT parameters have been studied in this work. The IP feature values of SS obtained using FAWT decomposition have been found useful for classification of the emotion EEG signals. On increasing the decomposition level (J) and QF parameter, the average classification accuracies are increased. The average classification accuracies achieved with random forest classifier are higher than SVM classifier. It has been shown that our method achieves higher classification accuracies in comparison to existing method for cross-subject channel specific classification of emotion EEG signals. Cross-subject classification using channel specific nature can provide an insight to the emotional sensitivity of different persons across brain regions when the similar stimuli are given.

In future work, many other publicly available datasets can be studied and even the data can be recorded using acquisition system and this method can be applied to get the classification of human emotion. Several new features can be studied and may be utilized with the extracted features in the present work so that the classification accuracy may be further improved. Also, some new kernel functions may be defined and used with SVM classifier to analyse the variation in classification accuracy. The proposed methodology can also be applied to other physiological signals like phonocardiogram (PCG), electromyogram (EMG), ECG etc., and the classification performance can be analysed. Emotions classification using channel specific nature can provide an insight to the emotional sensitivity of different persons across brain regions when the similar stimuli are provided. Thus, brain sensitivity of different persons can be compared using the proposed method.

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