VIDEO STIMULI BASED EMOTION RECOGNITION USING BRAIN WAVES

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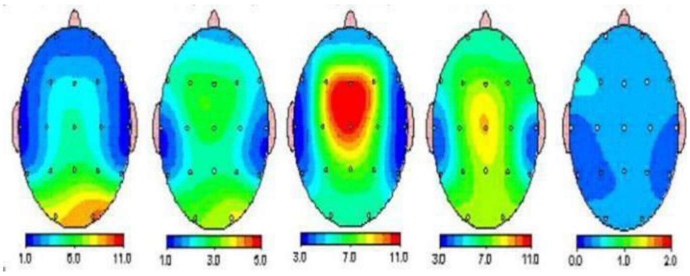
Abstract - Electroencephalograph (EEG) data is that the recording of brain electro-chemical activities, which is usually utilized in emotion recognition. We make use of multimodal dataset (DEAP: A Database for Emotion Analysis using Physiological Signals), for the analysis of human emotional states (valence, arousal). The electroencephalogram (EEG) and peripheral physiological signals of 32 participants recorded at 512Hz and preprocessed at 128Hz were wont to extract alpha and gamma bands using Park"s Mc-Clellan algorithm, which is an optimal FIR filter design method. Designing optimum FIR filters reduces adverse effects at the cut -off frequencies and also offers more control over the approximation errors in several frequency bands than other FIR filter design techniques, like designing FIR filters by windowing, which provides no control over the

approximation errors in several frequency bands. Statistical features like mean and the square root of variance are calculated for every of the alpha and gamma bands. These extracted features are utilized in supervised learning classifiers like Support vector machine (SVM) and K-nearest neighbor (K-NN) to classify human spirit into either valence or arousal. The extraction of frequency bands, calculation of statistical features and Classification of emotions are all performed using MATLAB Software.

***Key Words*:** DEAP, Park"s Mc-Clellan algorithm, FIR filters, KNN(K-Nearest Neighbor), SVM (support vector machine), Electroencephalogram(ECG).photonics, light, lasers, templates, journals

1. INTRODUCTION

Recognition of human emotion and providing appropriate response is a crucial criteria within the development of human machine interface (HMI). This will present an summary of the work carried out as the part of the project. The primary section deals with the motivation behind for selecting the EEG signal as a source to acknowledge the emotions. The second and third section describes the target and a quick outline of the work. An emotion may be a psycho-physiological process triggered by conscious and/or unconscious perception of an object or situation and is usually related to mood, temperament, personality and disposition, and motivation. Emotions play a crucial role in human communication and may be expressed either verbally through emotional vocabulary, or by expressing non-verbal cues like 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 shortage of emotional intelligence. In other words, they're unable to spot human emotional states and use this information choose upon proper actions to execute. This project fills this gap by recognizing human emotions using Electroencephalography (EEG), where EEG is an electrophysiological monitoring method to record electro-chemical activity of the brain. The five different frequencies in the EEG waves of human brain is as below-



(a) Delta (b) Theta (c) Alpha (d) Beta (e) Gamma

Fig 1: Five Different Frequencies in the EEG waves of Human Brain

- **Delta waves:** Abnormality in walking adults, accompaniment of deep sleep.
- **Theta waves:** The waves are strictly rhythmic or highly irregular. This shows the criteria of awake and drowsiness or light sleep stages.
- **Alpha waves:** Posterior-dominant, awake, eyes closed, mental inactivity, physical relaxation.
- **Beta waves:** Sharp spike-waves over 35 Hz. The signals are emitted from frontocentral, precentral and posterior part of the brain. This shows the criteria of light sleep stages.
- **Gamma waves:** These waves have high frequency compared to all other EEG bands. Highly active.

when in states of universal love, altruism, and the „higher virtues".

Problem Formulation:

✓ The raw dataset of brain waves is represented by D{bwi}, where D is the available EEG emotion recognition dataset. bwi is the EEG of i th participant, subscript i (=1,2,3,….32) indicates the participants number.

✓ In this project pre-processed data of D{bwi} are considered and are represented by P{bwi}, where P represents Pre-Processed data.

✓ From pre-processed data P{bwi} statistical features F{(bwj)i} are extracted, where (bwj)i represents the statistical feature j(= 1,2) of ith participant.

✓ Extracted features are used to classify emotion into valence and arousal using SVM and K-NN classifiers. Classification is represented by C{ F{(bwj)i}}. Where C is the classifier.

2. LITERATURE SURVEY

The Authors in the paper presented a multimodal dataset 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 or dislike, dominance and familiarity. For 22 of the 32 participants, frontal face video was also recorded. A novel method for stimuli selection was used, utilizing retrieval by affective tags from the last.fm website, video highlight detection & an online assessment tool [3].

Open Problems:

Computers are often made more users friendly with emotional responses and services. Within the past decades, most of the emotion recognition based researches have only focused on using facial expressions and speech. However, it is very easy to fake the facial expressions or change tone of speech and these signals aren't continuously available and that they differ from using different physiological signals, which occurs continuously and are hard to hide, like Galvanic Skin Response (GSR), Electrocardiogram (ECG), Skin Temperature (ST) and also the particularly Electroencephalogram (EEG). In order to beat this problem many researchers have already been administered with the EEG signals. A number of the previous research works are tabulated below-

Year of publication	Dataset	Emotions	Features	Classifier
2013	No. of participants: 10 subjects Neuroheadset: EMOTIV Stimulus: 100 pictures from 2 classical musical pieces	2:happy and unhappy	PSD (power spectral density)	Gaussian SVM
2015	No. of participants: 4 subjects Neuroheadset: B-alert X10 from ABM Stimulus: 40 pictures: 20 per emotion	2: pleasant and unpleasant	ERDS/ERD (event related syncronization/desyncronization)	SVM KNN
2016	DEAP datasets No. of participants: 32 subjects Neuroheadset: EMOTIV and GENOVE Stimulus: 40 videos per subject	2: arousal and valence	Statistical features: Mean and standard deviation of EEG frequency bands	SVM KNN

Table 1: Comparison with prior studies on different datasets

3. PROPOSED SYSTEM

The use of publicly available EEG emotion recognition dataset, so as to extract the statistical features from them and use the extracted features to classify the emotions into valence and arousal using supervised learning based Support vector machine (SVM) and K-Nearest Neighbors (KNN) classifiers. Fig 2 shows the diagram of video stimuli based emotion recognition using brain waves.

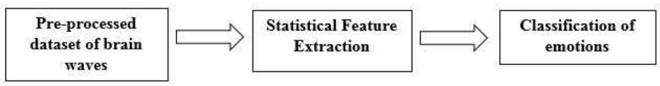


Fig 2: Block Diagram of video stimuli based Emotion recognition using brain waves.

The Main Objective of the system and the project is

- ✓ EEG data analysis and feature extraction.
- ✓ Classifier model selection and simulation.
- ✓ Analysis of results with respect to datasets.

The below Block diagram represents the video stimuli based Emotion recognition using brain waves.

4. WORKING WITH THE SYSTEM

4.1 Dataset Information:

A number of datasets are available for public research activities. EEG dataset may be a collection of related sets of EEG and peripheral physiological signal information. These datasets are collected by counting based on the specific problem i.e., the participants or scenario considered for a specific circumstance. Since the gathering of dataset requires sophisticated, expensive laboratory setup and time consuming process, so during this project, DEAP: A Database for Emotion Analysis using Physiological Signals[2] is also considered into account for emotion recognition. We might wish to thank DEAP database and its associated members for providing the chance to use their dataset for our project.

Online subjective annotation	
Number of videos	120
Video duration	1 minute affective highlight (section 2.2)
Selection method	60 via last.fm affective tags, 60 manually selected
No. of ratings per video	14 - 16
Rating scales	Arousal Valence Dominance
Rating values	Discrete scale of 1 - 9
Physiological Experiment	
Number of participants	32
Number of videos	40
Selection method	Subset of online annotated videos with clearest responses (see section 2.3)
Rating scales	Arousal Valence Dominance Liking *(how much do you like the video?)* Familiarity *(how well do you know the video?)*
Rating values	Familiarity: discrete scale of 1 - 5 Others: continuous scale of 1 - 9
Recorded signals	32-channel 512Hz EEG Peripheral physiological signals Face video (for 22 participants)

Fig 3: The Block diagram of the Database content Summary

4.2 Filter Design:

In general, there are two types of digital filters: Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) Filters. In the following chapter, we discuss about one of the FIR digital filter and the algorithm used to implement the same. We will also discuss in detail about the design parameters and its constraints.

FIR filters have the following characteristics[4]:

- ✓ FIR filters can achieve linear phase because of filter coefficient symmetry in the realization.
- ✓ FIR filters are always stable.
- ✓ FIR filter allows filtering of the signals using convolution. Therefore, you can generally associate a delay with the output sequence, as shown in the following equation:

  Delay = (n-1)/2 …………(1)

  Where n is the number of FIR filter coefficients.

Algorithm:

The Parks–McClellan Algorithm is implemented using the following steps:

1. **Initialization:** Choose an extremal set of frequences {ωi(0)}.
2. **Finite Set Approximation:** Calculate the best Chebyshev approximation on the present extremal set, giving a value δ(m) for the min-max error on the present extremal set.
3. **Interpolation:** Calculate the error function *E(ω)* over the entire set of frequencies Ω using (2).
4. Look for local maxima of |*E(m)(ω)*| on the set Ω.
5. If max(ωεΩ)|*E(m)(ω)*| > δ(m), then update the extremal set to {*ωi(m+1)*} by picking new frequencies where |*E(m)(ω)*| has its local maxima. Make sure that the error alternates on the ordered set of frequencies as described in (4) and (5). Return to Step 2 and iterate.
6. If max(ωεΩ)|*E(m)(ω)*| ≤ δ(m), then the algorithm is complete. Use the set {ωi(0)} and the interpolation formula to compute an inverse discrete Fourier transform to obtain the filter coefficients.

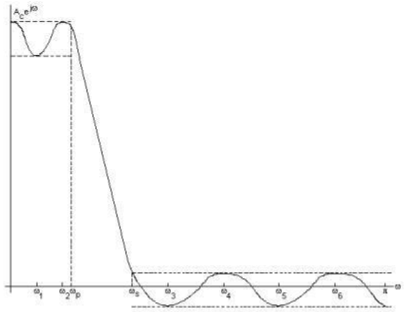


Fig 4: Representation of Pass and stop bands of a filter designed by the Parks –McClellan algorithm

paramters	**Alpha Band**	**Gamma band**
Sampling Frequency	256 Hz	256 Hz
First stop band frequency	7.5 Hz	25.5 Hz
First pass band frequency	8 Hz	30 Hz
Second pass band frequency	12 Hz	47 Hz
Second stop band frequency	12.5 Hz	47.5 Hz
First stop band attenuation	0.0001 dB	0.0001 dB
Second stop band attenuation	0.0001 dB	0.0001 dB
Pass band ripple	0.0575011277855 dB	0.0575011277855 dB

Table 2: filter design parameters

4.2.1 **The Frequency Design Parameters on Order**

The design specification of a band-pass filter can be defined by the six tuple(Fc , Fp , ΔFl , ΔFr,∂p, ∂s) where Fc is the pass-band centre frequency, Fp is the width of pass-band, ΔFl and ΔFr are the left and right transition bandwidths , ΔFr, ∂p and ∂s are the pass-band and stop-band ripples. These quantities are illustrated in figure below

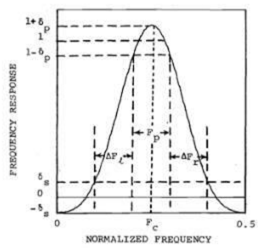


Fig 5: Representation of Band-pass filter

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6.3 Classifier Model

KNN:

Nearest neighbors can be used to determine the class label of the test example. The justification for using nearest neighbors is best exemplified by the following saying: "If it walks like a duck, quacks like a duck, and looks like a duck, then it's probably a duck." A nearest neighbor classifier represents each example as a data point in a d-dimensional space, where d is the number of attributes. Given a test example, we compute its proximity to the rest of the data points in the training set, using one of the proximity measures. The k-nearest neighbors of a given example z refer to the k points that are closest to z. Figure 5.1 illustrates the 1-, 2-, and 3-nearest neighbors of a data point located at the center of each circle. The data point is classified based on the class labels of its neighbors. In the case where the neighbors have more than one label, the data point is assigned to the majority class of its nearest neighbors.

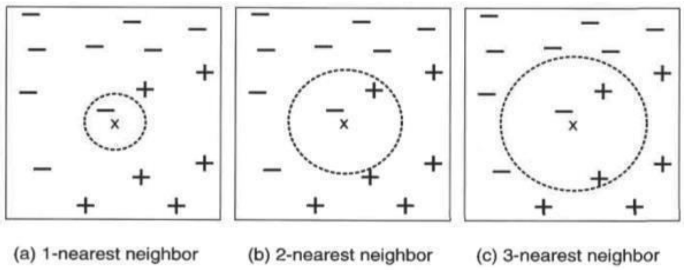


Fig 6: Representation of 1-,2,3- nearest neighbor for an instance

In the above figure, the l-nearest neighbor of the data point is a negative example. Therefore the data point is assigned to the negative class. If the number of nearest neighbors is three, as shown in Figure 5(c), then the neighborhood contains two positive examples and one negative example. Using the majority voting scheme, the data point is assigned to the positive class. In the case where there is a tie between the classes (see Figure 5(b)), we may randomly choose one of them to classify the data point.

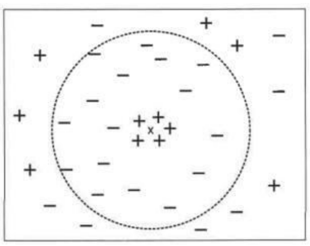


Fig 7: Representation of k-nearest classification with large k

KNN Algorithm

1. Let k be the number of nearest neighbours and D be the set of training examples.
2. For each test example z = (x`,y`) do
3. Compute d(x`,x), the distance between z and every example, (x`,y`)∈ D.
4. Select DZ C D the set of k closest examples to z.
5. y`= argmax Σ (xi, yi) ε Ds I (v = yi).

The Advantages of the Algorithm are as mentioned below-

- Simple to implement
- Flexible to feature / distance choices
- Naturally handles multi-class cases
- Can do well in practice with enough representative data

SVM:

The SVM classification technique[7] has its roots in statistical learning theory and has shown promising empirical results in many practical applications, from handwritten digit recognition to text categorization. SVM also works very well with high-dimensional data and avoids the curse of dimensionality problem. Another unique aspect of this approach is that it represents the decision boundary using subset of the training examples, known as the support vectors. The concept of maximal margin hyper plane is used which explains the rationale choosing of a hyper plane.

SVM Algorithm:

The data for training is a set of points (vectors) *xj* along with their categories *yj*. For some dimension *d*, the *xj* ε *Rd*, and the *yj* = ±1. The equation of a hyperplane is represented in equation 5.1.

f(x)=x′β+b=0……….……………(1)

where *β* ε *Rd* and *b* is a real number.

The following problem defines the *best* separating hyperplane (i.e., the decision boundary). Find *β* and *b* that minimize ||*β*|| such that for all data points (*xj*,*yj*),

yjf(xj)≥1.

The support vectors are the *xj* on the boundary, those for which yjf(xj)=1.

For mathematical convenience, the problem is usually given as the equivalent problem of minimizing ||β||. This is a quadratic programming problem. The optimal solution (^β ,^b)enables classification of a vector *z* is represented by equation 2.

class(z)=sign(z'^ β+^b)= sign(^f(z))…………..(2)

ˆf(z) is the classification score and represents the distance *z* is from the decision boundary.

The Main Advantages of the algorithm is as fallows -

1. It has a regularization parameter, which makes the user think about avoiding over-fitting.
2. It uses the kernel trick, so you can build in expert knowledge about the problem via engineering the kernel.
3. SVM is defined by a convex optimization problem (no local minima) for which there are efficient methods (e.g. SMO).

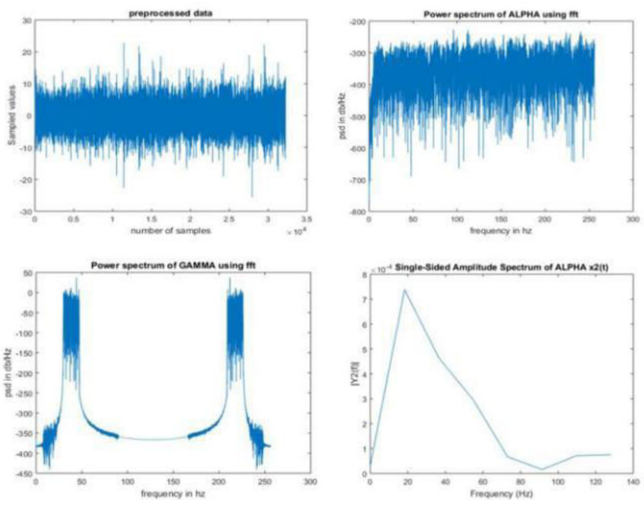
4. It is an approximation to a bound on the test error rate, and there is a substantial body of theory behind it which suggests it should be a good idea.

7. RELATED RESULTS

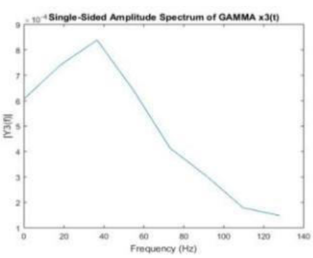
The results are calculated by considering 8 subjects randomly. For the calculation of the result at present report, subject number 1, 4, 6, 7, 8, 9, 10 and 11 are considered. For each of these 8 subjects results will be discussed in the following chapter along with their graphs for the pre-processed data, power spectrum of alpha and gamma bands and also the single sided amplitude spectrum for alpha and gamma bands have been shown. Each case represents one subject out of 8 total subjects. The variations among different subjects can be observed from each of their respective graphs. The Classification results of 8 subjects with two different videos for each will be discussed in the later sections. Note: Keeping in-mind the simplicity of report only the 8 subject‟s pre-processed data of the first video were considered for the graphical representation.

7.1 Subject 1

Here only the alpha and gamma bands associated with the 4 channels namely: FP1, FP2, F3, F4 were considered. The graph for pre-processed data, power spectrum of alpha band and gamma band, single-sided amplitude spectrum of alpha and gamma band are shown in figure 8.



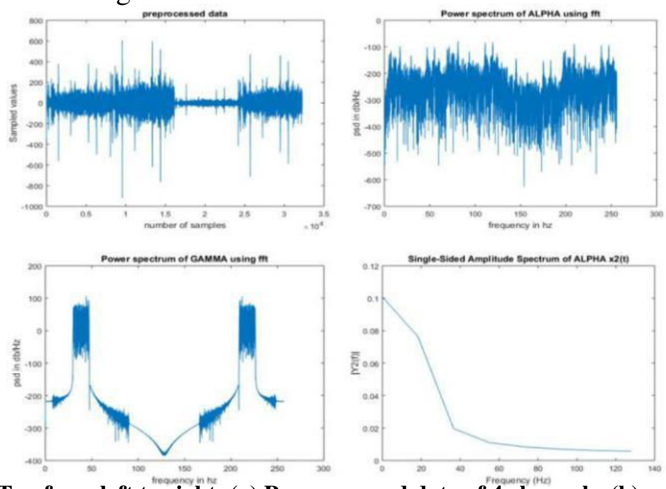
Top from left to right: (a) Pre-processed data of 4 channels, (b) Power Spectrum of Alpha Band
Bottom from left to right: (c) Power Spectrum of Gamma Band, (d) Single-Sided Amplitude of Alpha,



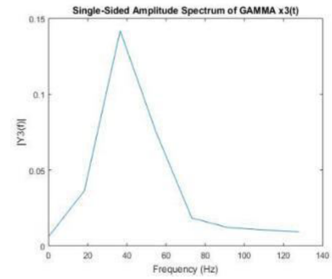
(e) Single-Sided Amplitude Spectrum of Gamma Band
Fig 8: The graph for subject 1

7.2 Subject 2

Here only the alpha and gamma bands associated with the 4 channels namely: FP1, FP2, F3, F4 are considered. The graph for pre-processed data, power spectrum of alpha band and gamma band, single-sided amplitude spectrum of alpha and gamma band are shown in figure 9.



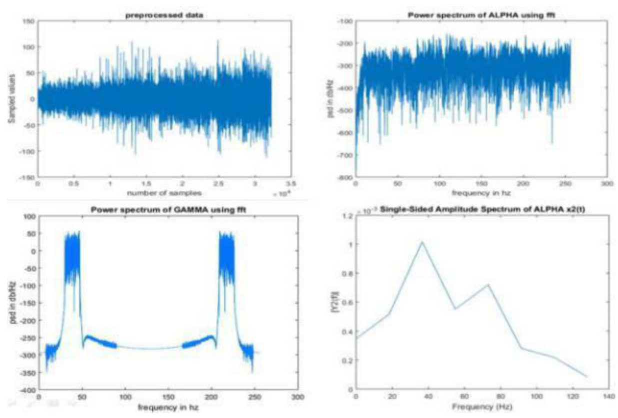
Top from left to right: (a) Pre-processed data of 4 channels, (b) Power Spectrum of Alpha Band Bottom from left to right: (c) Power Spectrum of Gamma Band, (d) Single-Sided Amplitude of Alpha



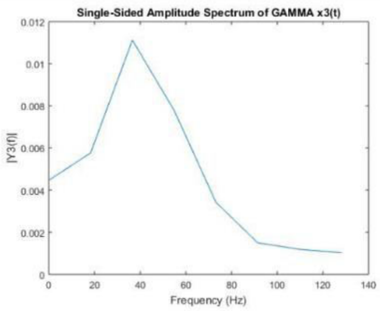
(e) Single-Sided Amplitude Spectrum of Gamma Band.
Fig 9: The graph for subject 2

7.3 Subject 3

Here only the alpha and gamma bands associated with the 4 channels namely: FP1, FP2, F3, F4 are considered. The graph for pre-processed data, power spectrum of alpha band and gamma band, single-sided amplitude spectrum of alpha and gamma band are shown in figure 10.



Top from left to right: (a) Pre-processed data of 4 channels, (b) Power Spectrum of Alpha Band
Bottom from left to right: (c) Power Spectrum of Gamma Band, (d) Single-Sided Amplitude of Alpha

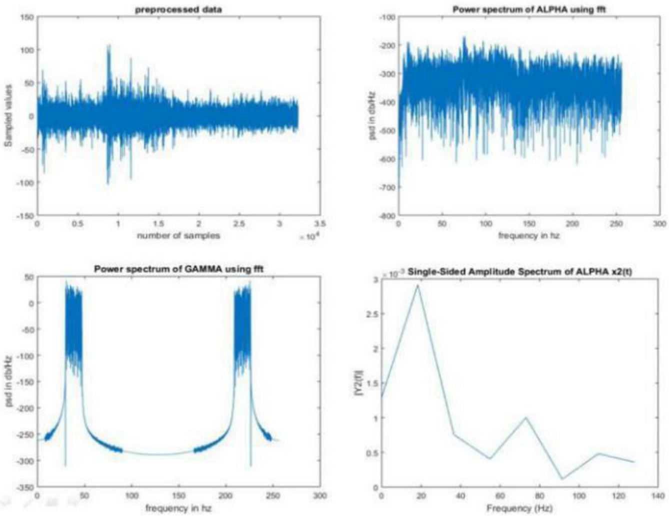


(e).Single-Sided Amplitude Spectrum of Gamma Band.

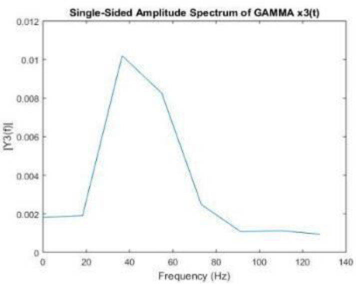
Fig 10: The graph for subject 3.

7.4 Subject 4

Here only the alpha and gamma bands associated with the 4 channels namely: FP1, FP2, F3, F4 are considered. The graph for pre-processed data, power spectrum of alpha band and gamma band, single-sided amplitude spectrum of alpha and gamma band are shown in figure 11.



Top from left to right: (a) Pre-processed data of 4 channels, (b) Power Spectrum of Alpha Band Bottom from left to right: (c) Power Spectrum of Gamma Band, (d) Single-Sided Amplitude of Alpha

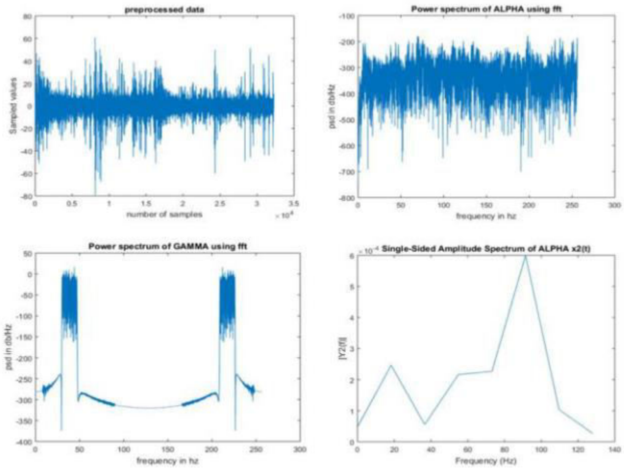


(e).Single-Sided Amplitude Spectrum of Gamma Band.

Fig 11: The graph for subject 4

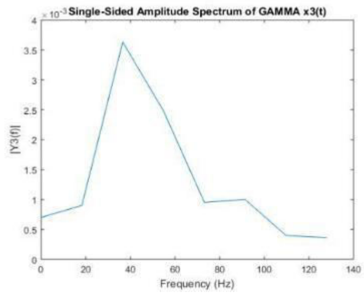
7.5 Subject 5

Here only the alpha and gamma bands associated with the 4 channels namely: FP1, FP2, F3, F4 are considered. The graph for pre-processed data, power spectrum of alpha band and gamma band, single-sided amplitude spectrum of alpha and gamma band are shown in figure 12.



Top from left to right: (a) Pre-processed data of 4 channels, (b) Power Spectrum of Alpha Band

Bottom from left to right: (c) Power Spectrum of Gamma Band, (d) Single-Sided Amplitude of Alpha

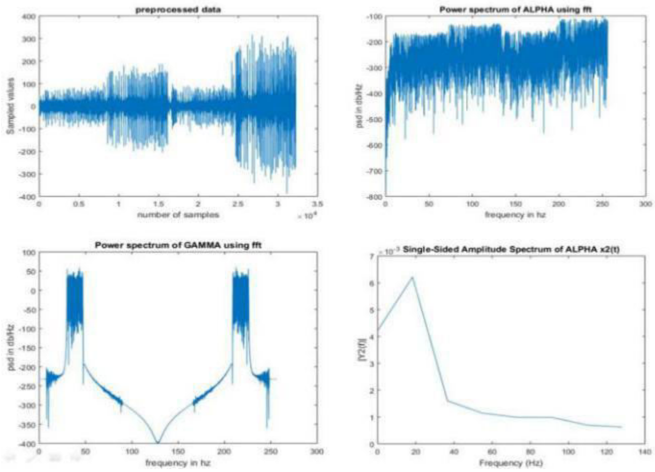


(e).Single-Sided Amplitude Spectrum of Gamma Band.

Fig 12: The graph for subject 5

7.6 Subject 6

Here only the alpha and gamma bands associated with the 4 channels namely: FP1, FP2, F3, F4 are considered. The graph for pre-processed data, power spectrum of alpha band and gamma band, single-sided amplitude spectrum of alpha and gamma band are shown in figure 13.



Top from left to right: (a) Pre-processed data of 4 channels, (b) Power Spectrum of Alpha Band

Bottom from left to right: (c) Power Spectrum of Gamma Band, (d) Single-Sided Amplitude of Alpha

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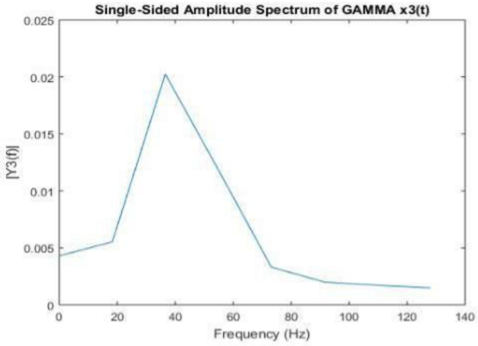
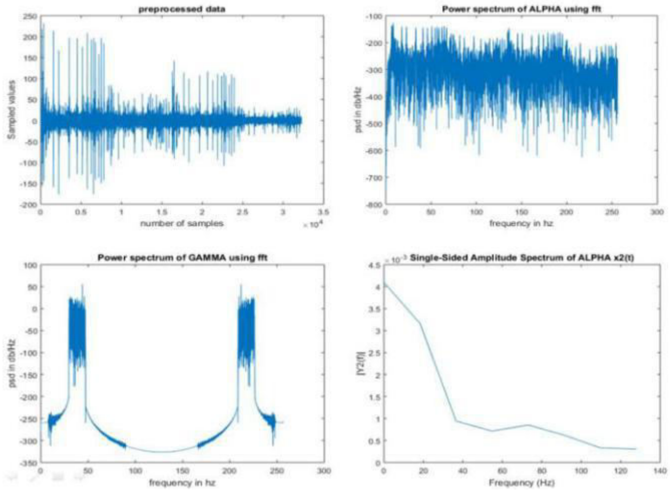


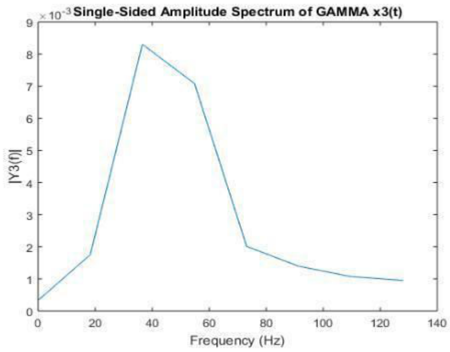
(e) Single-Sided Amplitude Spectrum of Gamma Band. Fig 13: The graph for subject 6

7.7 Subject 7

Here only the alpha and gamma bands associated with the 4 channels namely: FP1, FP2, F3, F4 are considered. The graph for pre-processed data, power spectrum of alpha band and gamma band, single-sided amplitude spectrum of alpha and gamma band are shown in figure 14.



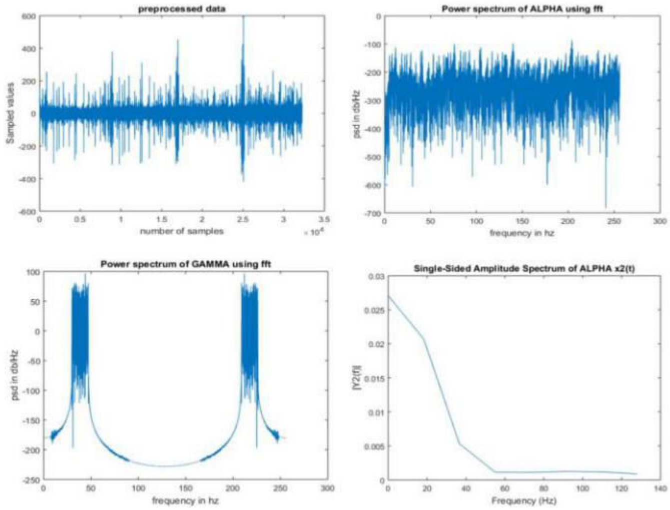
Top from left to right: (a) Pre-processed data of 4 channels, (b) Power Spectrum of Alpha Band
Bottom from left to right: (c) Power Spectrum of Gamma Band, (d) Single-Sided Amplitude of Alpha



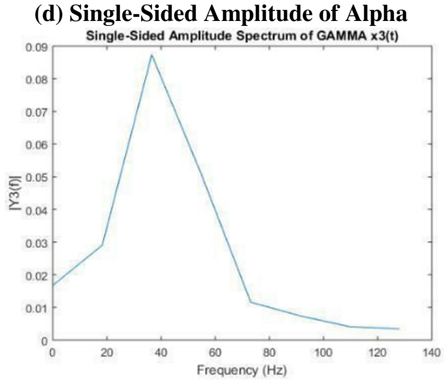
(e) Single-Sided Amplitude Spectrum of Gamma Band. Fig 14: The graph for subject 7

7.8 Subject 8

Here only the alpha and gamma bands associated with the 4 channels namely: FP1, FP2, F3, F4 are considered. The graph for pre-processed data, power spectrum of alpha band and gamma band, single-sided amplitude spectrum of alpha and gamma band are shown in figure 15.



Top from left to right: (a) Pre-processed data of 4 channels, (b) Power Spectrum of Alpha Ban
Bottom from left to right: (c) Power Spectrum of Gamma Band, (d) Single-Sided Amplitude of Alpha



(e) Single-Sided Amplitude Spectrum of Gamma Band. Fig 15: The graph for subject 8

7.9 Comparison of the Classification Results Based on: KNN and SVM Classifier

The Classification of 2 videos for 8 subjects was classified using K-NN classifier and SVM Classifier. The two classes considered here are: Valence and Arousal. The comparisons of these results are tabulated in the below table -

Video	Subjects	K-NN Classifier	SVM Classifier	Expected emotion state
1	1	A	V	V
	4	V	V	V
	6	A	V	V
	7	A	V	V
	8	A	V	V
	9	V	V	V
	10	V	V	V
	11	V	V	V
9	1	A	V	V
	4	V	V	V
	6	V	V	V
	7	A	V	V
	8	A	V	V
	9	V	V	V
	10	V	V	V
	11	V	V	V

V-Valence, A- Arousal

Table 3: Comparison of Results Obtained from K-NN and SVM Classifier

8. CONCLUSIONS AND FUTURE WORK

We gained a substantial amount of knowledge about Machine Learning and its categories. We have cultivated the method on how to handle the DEAP datasets. From the pre-processed data of eight subjects we extracted alpha and gamma bands using Optimal Filter Design Method which uses the Parks McClellan Algorithm and Chebyshev Finite Impulse Response Filter. Statistical features like mean and standard deviation are calculated for the extracted features of individual subjects. Finally, we classified the emotion state of subjects using KNN and SVM classifiers and compared their results obtained.

The datasets can further be used to calculate accuracy and can be tested by different neural network algorithms like ANN. It can be tested in higher Matlab versions. The classifiers can be used for real-time captured data.

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