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EEG Feature Extraction in Brain-Mobile Phone Interfaces

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Authors' contributions

This work was carried out in collaboration between both authors. Author ATP designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript and managed literature searches. Authors CRH managed the analyses of the study, literature searches and reviews. Both authors read and approved the final manuscript.

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ABSTRACT

Aims: The paper describes four methods for extracting features of brain signals in frequency and time domain that can be used as parameters for identifying the face images of people.
Place and Duration of Study: Human Computer Interface Lab, Karpagam University, India (July 2012-June 2014)
Methodology: The subject is asked to remember different known face images like father, mother and so on and the corresponding Electroencephalogram (EEG) signals are captured. Wigner Ville Distribution and other spectral methods are used for studying the features. The data was collected from 15 subjects having good mental health condition. Real EEG records from different subjects are taken for duration of 10 seconds in each trial. 10 such trials are taken from each test subject.
Results: It is noticed that the band of frequencies in the range 0-40 Hz shows higher spectral variations, due to "remembering" or retrieving memories possibly due to the presence of Alpha or Beta waves. Using Fourier spectrum analysis it is found that, the EEG signals corresponding to the

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face image of one person (e.g: Mother) was always giving a different range of values for the number of spectral crossings, in comparison to the second face image (eg: Father). During the Wigner Ville analysis the peak value of instantaneous power in one case was seen in the range of $2x10^5$ to $3x10^5$ for father's face whereas for mother's face in the range of $0.5x10^6$ to $1x10^6$. In the Power Spectral Density based analysis, the frequency range of 10-20 Hz showed a higher average value in case of mother's face than in father's. When the mean signal power was calculated from PSD for different trials, it is noticed that the signal power is significantly different in cases of father and mother and gavea 70-90% of correct classification result.

Conclusion: After identifying the features that are unique for a face image, the same is proposed to be used for the address book dialing in a smart phone which can be further used for helping physically disabled as well as normal people to interact with external world.

Keywords: Brain Machine Interface (BMI); Brain Computer Interface (BCI); EEG signal processing; power spectral density; instantaneous power; wigner-ville distribution; biomedical signal processing.

1. INTRODUCTION

Brain Machine Interfacing (BMI) has been a major research area in the field of biomedical researches over past years, which still continues its search for optimized algorithms and new protocols for an easy interface with the external world. The most important step in any Brain-machine Interface (BMI) is the identification of useful features from brain signals. People have been using a variety of signal processing algorithms for feature extraction using specific protocols defined in each case of study.

The major motivation behind the work is the lack of suitable EEG feature extraction protocols for the brain-mobile phone interface designs. Majority of the past researches do not specifically talk about the different use cases when a physically disabled person wants to communicate with external world over a smart phone.

The paper describes 4 methods for extracting features that may be used as parameters for identifying the faces of different people using EEG signal analysis. The main focus is on the investigation of methods using spectral parameters and quadratic transformations using Wigner Ville Distribution that can help in identifying features that are unique for a particular individual. Wigner Ville Distribution (WVD) is a quadratic time-frequency transformation that has many useful properties for signal analysis. One of the important properties is the time marginal property. The instantaneous signal power is obtained by integrating WVD of the EEG signal along the frequency axis at that time. The resultant of this integration does not depend on the time duration of the signal, instead it only represents the amplitude of the signal.

Among the various research that have been undertaken in the area, some of them required manual or PC intervention; like in the work by [1]. They used a scoring system approach in order to assess the condition of patients by using mobile phones which helps in early detection of diseases in a critical condition. The major disadvantage of this system is that it is not completely automated for helping physically disabled people; instead it requires a computer or human intervention in order to interface with the external world and no specific protocols are defined for this purpose. Another research was on controlling wheelchairs through Bluetooth interface based on wireless EEG signals [2]. Eye blinking and brain waves are used as triggering commands for the wheelchair control. Alpha waves are used for transferring the attention signals. Even though the communication is direct and there is no interface with a computer, it studies specifically about motor neuron diseases. There are no specific mention about any protocol used in signal acquisition and feature extraction. The research also doesn't focus on minimizing the number of electrodes to make it a practically feasible solution for rehabilitation of physically paralyzed.

In the "Neurophone" project [3] brain signals are used to interface with mobile phones for human-mobile phone interaction. The brain controlled mobile phone dialing application is used for the address book dialing in the smart phone. A sequence of address book images are displayed on the smart phone LCD, which generates EEG signals over the patient's scalp. These brain signals are collected by EEG headset and processed accordingly. When the image matches with the person whom the patient wants to communicate to, the corresponding EEG signal strength and frequency are studied. The interface is designed in such a way that, the P300 signals triggered by any person's image causes his contact number to be dialed in the smart phone. In order to solve the power efficiency and resource issues in the Smartphone only a relevant set of EEG channels are supplied to the phone, instead of providing all the channels. This work also does not concentrate on a light weight algorithm so that an early battery drain can be avoided in smart phones.

The usage of Brain-machine interfaces for non-medical applications is studied by [4]. The work describes about some non-medical applications of a brain-machine interface including remote device control and gaming. Another research describes about a hybrid method of brain-computer interface (BCI) where the subjects control the navigation of a humanoid robot and recognize a desired object among candidates based on a low-cost system [5]. In another study some methods for detecting the drowsiness of driver and signaling through mobile phones is proposed. The driver will be wearing an EEG headset to capture live brain signals which is connected to mobile device and a mobile application classifies these live signals and capture sleep/drowsiness related signals. If mobile device identifies a drowsiness signal it will alert the driver to wake up [6]. The research doesn't target for any protocols for address book dialing, instead it just alerts the user. And there are no unique feature identification algorithms defined here. Another study concentrates on the practical aspects of moving a brain–computer interface (BCI) system from a laboratory demonstration to real-life applications. The study aims to integrate a mobile phone and wireless EEG system. Signal processing algorithms are implemented in a cell phone in order to detect steady-state visual evoked potentials [7].

Another work on non-invasive brain-computer interface describes how brain signals can be used to control a Windows desktop. But this work doesn't include any interface with mobile phones [8]. An investigated on the data acquisition sensors and remote device control as described in [9]. But the work doesn't describe about the feature extraction and classification algorithms. The work also doesn't talk about any protocols for helping physically disabled. The application of time-frequency transformation techniques for signal analysis and detection were discussed in [10]. The fundamentals of EEG measurements that are commonly used in medical field are described in the research [11]. Another work presents a method to design a four state Brain Machine Interface using EEG signals recorded from the C3 and C4 locations. Two novel classification algorithms are discussed here to study about the extracted features. The work just concentrates on motor imagery signals to control devices [12]. In another work a review on the progress of research efforts and challenges in BCI research meant for unblessed people is presented [13]. Another research work describes about the Brain Fingerprinting based on EEG signals to determine the falsely accused innocent suspects of a crime. The protocol doesn't concentrate on rehabilitation topics or brain-mobile phone interfaces. The protocols used are specific for the particular case study [14]. Comparison of the performance of a conventional P300 speller brain-computer interface (BCI) with one used in conjunction with a predictive spelling program is done in [15]. An approach using Inference System based on inverse model for classification in EEG based Brain Computer Interfaces is proposed by [16]. Evaluation of new approaches using commercial EEG devices for cutting-edge support for different user studies is conducted by [17]. Development of an e-Health monitoring application based on mobile phones is done in [18]. But the system is proposed for ECG signals and the mobile phone interface issues are discussed here like data management and user interfaces [18]. In another work, the past and recent research works on brain computer interface are studied and their usability in the field of BCI is analyzed [19]. Different aspects of BCI systems and practical solutions for the interfacing issues are discussed in [20].

It is noticed that most of the above researches do not address the mobile phone interface aspects and protocols for the rehabilitation of physically disabled people by making use of EEG thought signals. When the person wants to communicate with the external world over a smart phone, the protocols need to be carefully defined. Among those who already worked on the interface protocols did not concentrate on the different kind of features that can be used for the analysis.

2. METHODOLOGY

A protocol or set of procedures is defined to help the subject as well as the researcher for generating and collecting the EEG data effectively and systematically. In this research, the protocol is defined for collecting the EEG data from the test subjects during their remembrance of different face images. The data is collected from the subjects having good mental health condition. The test subjects are from among the age groups of 17 years to 21 years. Out of the 15 different test subjects who participated in the test for collecting EEG signals, 6werefemales and 9weremales studying for graduate courses.The study was approved by any ethics committee in the university and consents were provided by the participants of the EEG signal acquisition.

Following the international 10-20 electrode placement system, the EEG records from different subjects are collected for 10 seconds in each trial. 10 seconds are taken in order to allow the test subject to completely remember the face of the known person, so that the EEG signal becomes richer with the needed information.10 such trials are taken for each of the test subjects by closing their eyes [11,21]. As marked in the Fig. 1 the signals are collected from the electrode locations O1 and O2 for signals arising from vision perception.2 electrodes are used to collect the signals from the locations using ADI instrument Power Lab data acquisition (DAQ) device and Lab Chart software version 7. In comparison with a P300 based system this method does not require visual stimuli for triggering an EEG signal. Instead, the EEG signals arising due to remembering the faces is studied, and hence the initiation of the telephone a call can be done though just a mental trigger by the physically disabled people.

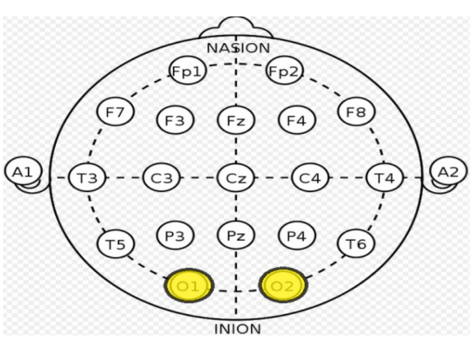

Fig. 1. International 10-20 electrode placement system

The EEG signals are classified according to their frequency ranges and the possible location of their presence. The study is concentrated in the frequency range of 0 to 50 Hz in order to analyze the presence of Alpha, Beta and Theta waves in the measured EEG signals. After identifying the features that are unique for a face image, the same is proposed to be used for the address book dialing in a smart phone. This will help in developing a hands-free method for brain-mobile phone interface, which can be further used for helping physically disabled as well as normal people to interact with external world.

The major steps involved in this work are signal acquisition, pre-processing, feature extraction and classification [22]. Signal acquisition step records the electrophysiological signals though EEG electrodes placed on the scalp of the subjects. EEG signal is sampled at a frequency of 200 samples per second. The pre-processing step does a preliminary processing of the recorded brain signals like removal of non-physiological artifacts. 50 Hz power line interference is removed using notch filters and signals are low pass filtered at 40 Hz in order to concentrate the study on the frequency range of 0-40 Hz. The feature extraction step involves the identification of a suitable parameter of brain data that simplifies the subsequent classification or detection of specific brain patterns.

The feature extraction is done using methods based on spectral analysis, quadratic transformation using Wigner Ville Distribution (WVD) and power spectral density.

2.1 Spectral Analysis

Spectral analysis is done using Fast Fourier Transform (FFT) and the study is concentrated on the frequency range of 0-40 Hz with many sub-ranges in between; for example 4-15 Hz. A specific threshold is decided for the frequency spectrum of each test subject. The number of times that particular threshold is crossed by the spectral components is counted within the sub-range of analysis. This number of spectral crossings can be used as a parameter for the EEG signal classification.

2.2 Wigner Ville Distribution

Wigner-Ville distribution (WVD) is a bilinear distribution used for representing signals in time-frequency domain. For any signal s(t), the WVD is defined as,

$$WVD_s(t,\upsilon) = \int_{-\infty}^{+\infty} s(t+\tau/2)\,.\,s^*(t-\tau/2)\,.e^{-j2\pi\upsilon\tau}.d\tau \quad (1)$$

Where t corresponds to time, v corresponds to frequency.

The time-marginal property of Wigner Ville Distribution can be used for feature extraction from transient signals [10]. The WVD of a received signal can be used to get an estimate of the instantaneous signal power. So we can make use of this time-marginal property of WVD to calculate the instantaneous signal power, which do not depend on the signal time duration. The time marginal property of WVD is defined as,

$$\int_{-\infty}^{+\infty} W_s(t,\nu)\,d\nu = |s(t)|^2 \tag{2}$$

The equation shows that, the instantaneous signal power of a signal s(t) can obtained by integrating its WVD over the frequency axis. And the resultant quantity $|s(t)|^2$ does not depend on the time duration of the signal. It only represents the amplitude of the analysis signal. So the instantaneous signal power calculated from the WVD of the signal is the parameter used for feature extraction from EEG signals.

2.3 Power Spectral Density (PSD) and Mean Power

A plot of the frequency components on the x-axis and Power in that frequency on the y-axis is called the Power Spectrum of the signal. The Power Spectrum is also referred to as the Power Spectral Density. The two terms refer to the same thing. The Power spectrum does not directly give us the total or average power in the signal, but gives only the power in a particular spectral component. To obtain the total power in the signal, we must integrate the Power Spectrum over the range of frequencies of interest. The total power can be defined as the integral of the Power Spectral Density as,

$$Px = \frac{2}{2\pi}\int_{0}^{+\infty} S_s(\omega)\,d\omega \tag{2}$$

Where S_x is the two-sided spectral density.

In this research, power spectral density (PSD) is calculated and the average power is estimated for the different trials of each brain signal. Then the mean value of power is calculated among the different trials of the same task. A data sample size of 2000 is taken for computing the PSD with a sampling frequency of 200 Hz.

2.4 Interface with Mobile Phones

The address book dialing of a smart phone using brain-machine interface (BMI) requires the identified features to be unique for different people. A specific feature may be identified that has unique set of values when the test subject is trying to remember about some of his/her known person; for example his mother. This states that, this value of the particular feature can be used as a decision maker to initiate a call to the particular person. A suitable classification algorithm can make the decision on this. In the real life, the physically disabled person or the subject can be trained to learn the features corresponding to different known people, so that the algorithm can remember the decision thresholds. And during the test phase, any unknown signal can be compared with respect to these remembered features in order to make the decision.

3. RESULTS AND DISCUSSION

The names ‘Face-1’ and ‘Face-2’ used in the explanations and figures in this section do not mean the same for all the test subjects. These terms just mean that 2 different face images are remembered by a specific subject and are different in case of different subjects.

3.1 Frequency Spectrum Analysis

The frequency spectrum of the EEG signals is studied for the frequency range of 0-20 Hz. A focused plot of the spectrum in the sub-range of 4-15 Hz is also shown in Figs. 1 and 2. The task given to the different test subjects is to recall the face images of known people. 15 test subjects are studied in such way.

In case of subject 1, it was found that the frequency spectrum in this range for EEG signals corresponding to remembering Father’s face (Face-1), crosses the decision threshold lesser number of times than that for Mother’s face (Face-2). The mean value of the number of crossings for ‘Face-1’ is found to be 11.6 whereas that for ‘Face-2’ is 12.4. A similar analysis for subject 2 also gave a similar result. For ‘Face-1’ the mean number of spectral crossings is found to be 3 whereas for ‘Face-2’ it was 4.3. Additionally the frequency range of 0-5 Hz also shows higher number of crossings for the decision thresholds of 1.5, 0.3 and 3.5 in case of ‘Face-2’ than ‘Face-1’. The number of spectral crossings for the subject 3 was also showing a higher mean value of 9.7 for 'Face-2' than that of 'Face-1' which was found as just 0.4.

To conclude about the results, it is found in all the trials of the same task that, the EEG signals corresponding to Face-2 (as in Fig. 2) is giving a different range of values for the number of spectral crossings, in comparison with that of Face-1 (as in Fig. 3).

3.2 Wigner Ville Distribution

Instantaneous power based on Wigner Ville Distribution (WVD) is calculated and analyzed. The time marginal of the EEG signals for all the 10 trials of each task using Pseudo- Wigner Ville Distribution (PWVD) is drawn in Figs. 4 to 7.

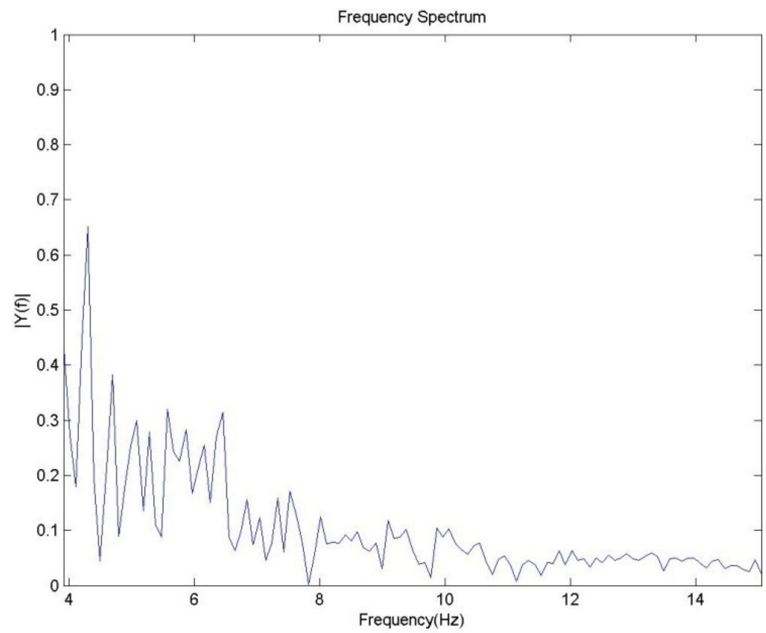

Fig. 2. Spectrum – remember face-1 by subject 2

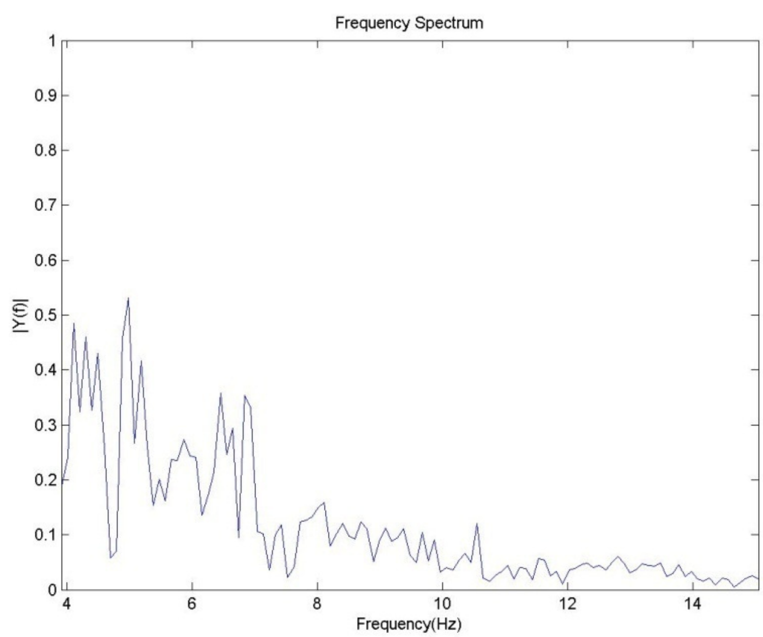

Fig. 3. Spectrum – remember face-2 by subject 2

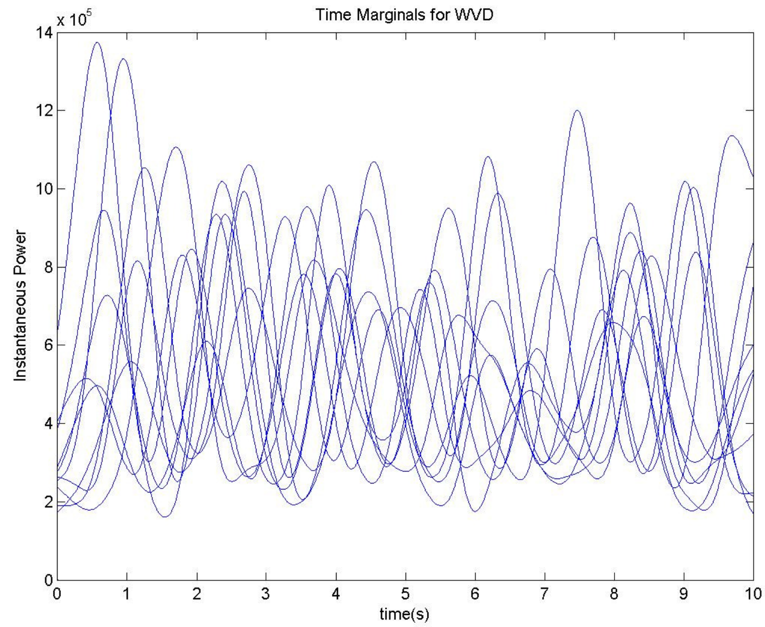

Fig. 4. Instantaneous power - remember face-1 by subject 2

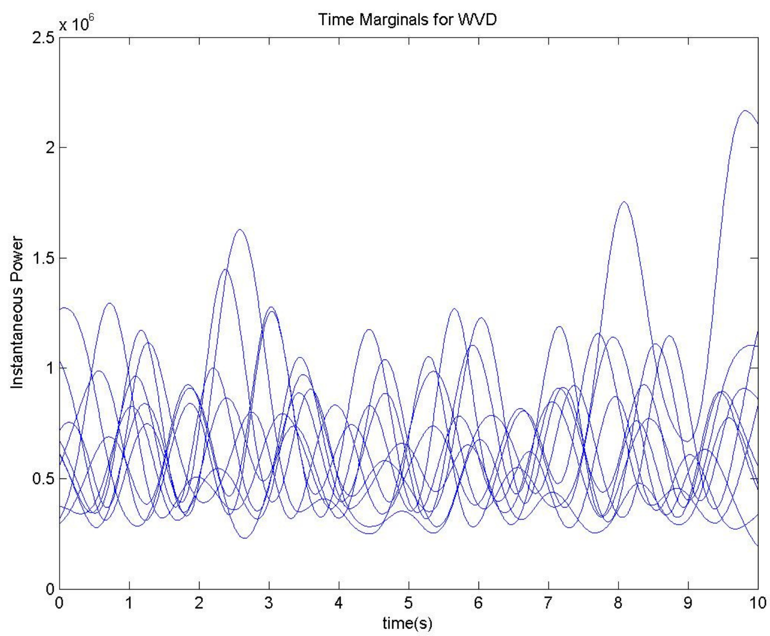

Fig. 5. Instantaneous power - remember face-2 by subject 2

Pseudo-Wigner Ville Distribution (PWVD) is a smoothed version of WVD which has reduced number of cross-terms in comparison with basic WVD. As can be seen in the figures, the average value of the instantaneous power peaks show a big difference among the EEG signals corresponding to mother and father. Note that the peaks are concentrated approximately between the values $8x10^5$ to $11x10^5$ for father's face in subject 2 whereas for mother's face it is concentrated approximately between the values $10x10^5$ to $15x10^5$. This is shown in Figs. 4 and 5.

Similarly for subject 3 as seen in Figs. 6 and 7, the peaks of instantaneous power are seen in the range of $2x10^5$ to $3x10^5$ for father's face whereas for mother's face in the range of $0.5x10^6$ to $1x10^6$ giving a good classification results if we take suitable threshold values. This is an indication for the feature to be used as a parameter for classification of brain signals, in order to identify the face images. In the Fig. 6, one of the trials show a very high peak in comparison with others, so this is omitted in the analysis. Since the instantaneous power is not found to be used in the past researches for EEG feature extraction using similar protocols, the result of this analysis could not be compared with the past results.

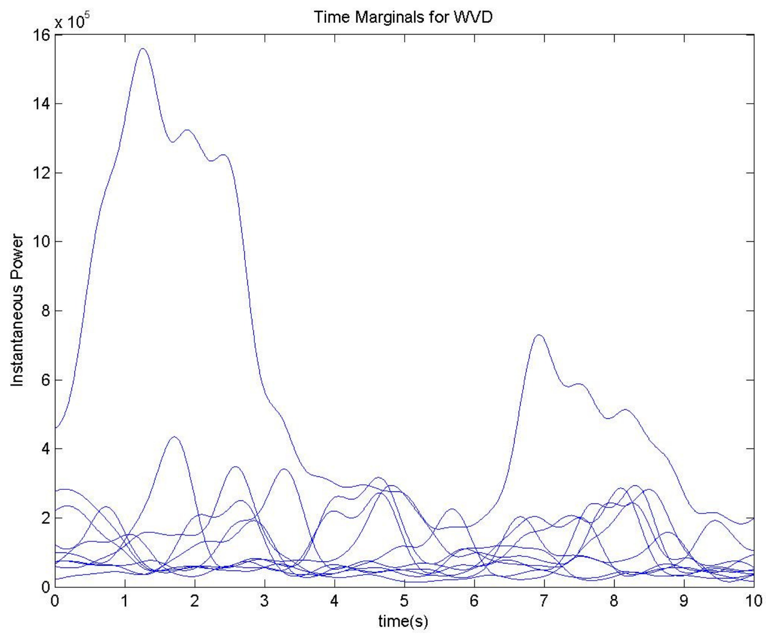

Fig. 6. Instantaneous power – remember face-1 by subject 3

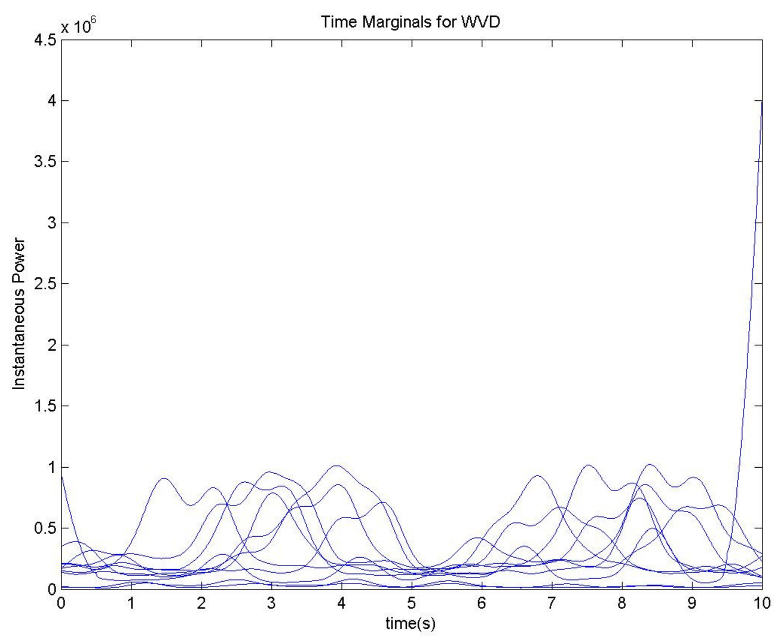

Fig. 7. Instantaneous power - remember face-2 by subject 3

3.3 Power Spectral Density (PSD)

Single sided power spectral density of the brain signals are drawn as in Figs. 8 to 11. PSD analysis for most of the subjects in the frequency range of 0-20 Hz showed a higher average value in case of remembering Face 2 than in Face-1, as can be seen in the figures.

Looking carefully at the PSD values in dB between 0 Hz and 20 Hz, it can be noticed that, there is a slight shift in the upward direction for the cases of Face 2 in comparison with Face 1.

A similar study for the Subject 3 is also shown in Figs. 10 and 11. A difference in the PSD values in the same frequency range can be noticed here also.

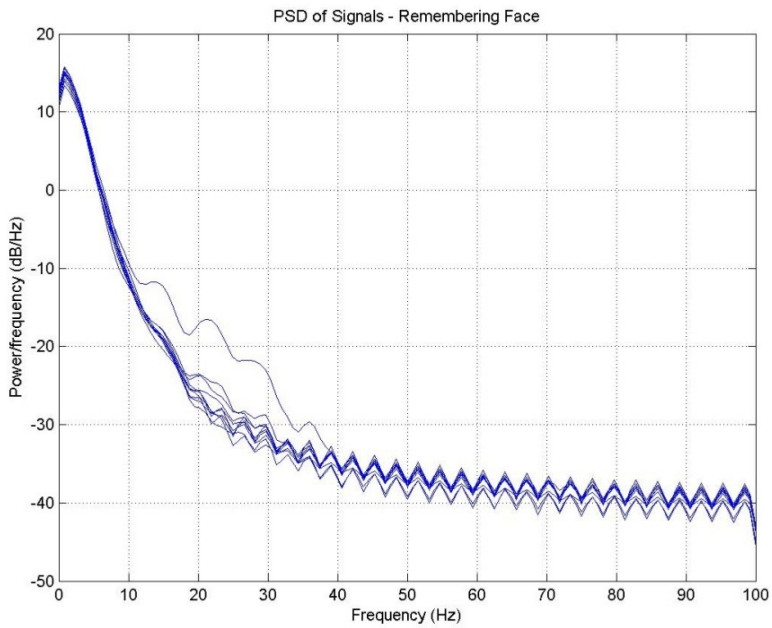

Fig. 8. PSD –remember face-1 by subject 1

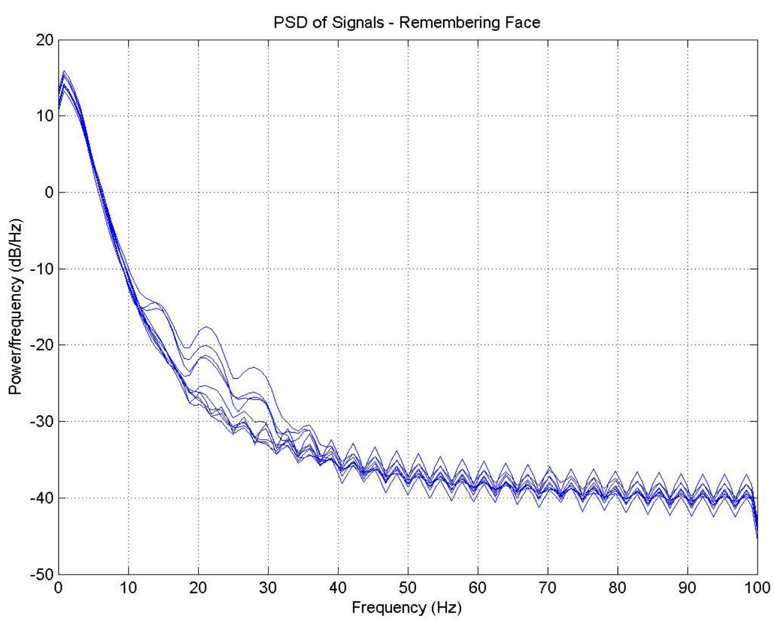

Fig. 9. PSD - remember face-2 by subject 1

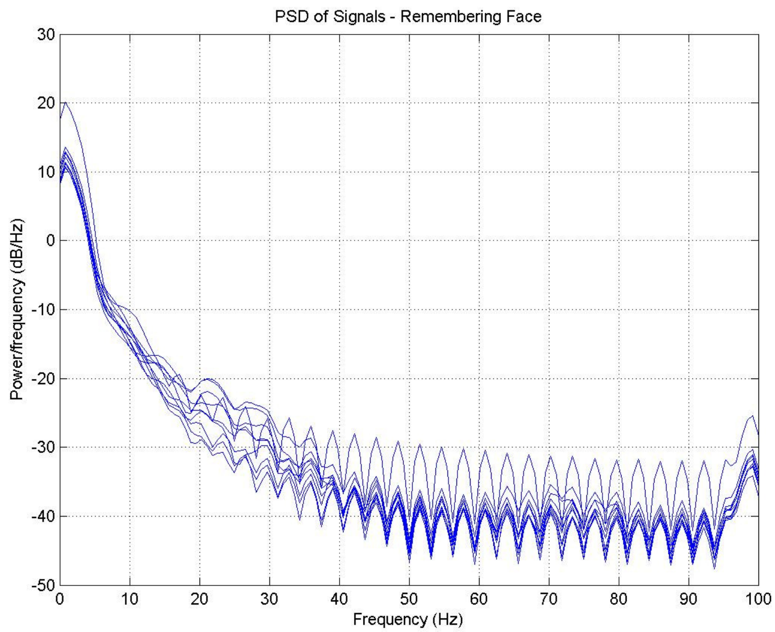

Fig. 10. PSD - remember face-1 by subject 3

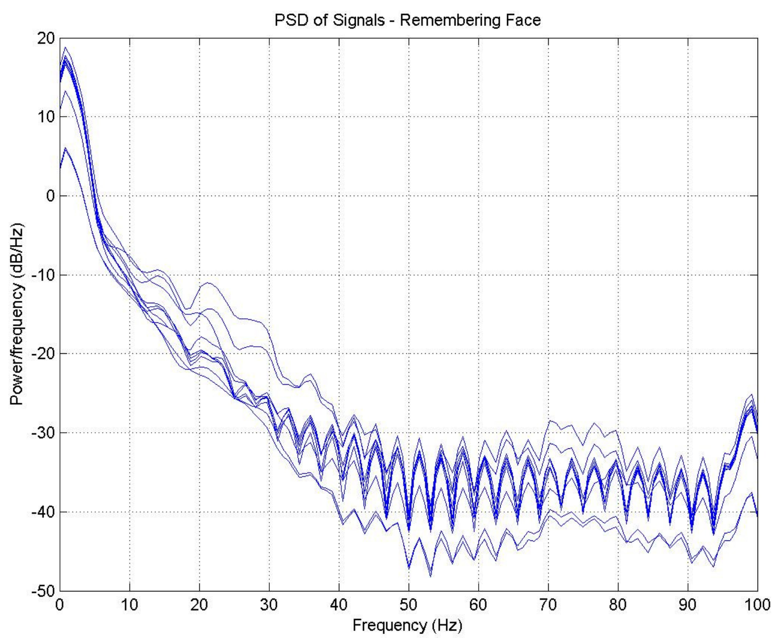

Fig. 11. PSD - remember face-2 by subject 3

3.4 Mean Power

When the signal power is calculated from PSD for different trials, it is noticed that the signal power is significantly different in cases of father and mother. For example, in case of subject 1, while remembering father's face, most of the values are found above value 85 and in mother's case most values are below 85 as can be seen in Figs. 12 and 13. The mean value of signal power is calculated as 86.14 in case of father and 81.35 for mother. A threshold mean power value of 86 when used for classification in this case, gives almost 70% of correct classification.

A similar analysis for subject 2 gave a mean power value of 235 in case of father's face whereas for mother's face it was 283.8 as described in the Figs. 14 and 15. The mother's face gave a higher mean value in almost all the trials in comparison with the face image of father. A threshold value of 270, when used here for classification gives 90% of correct classification.

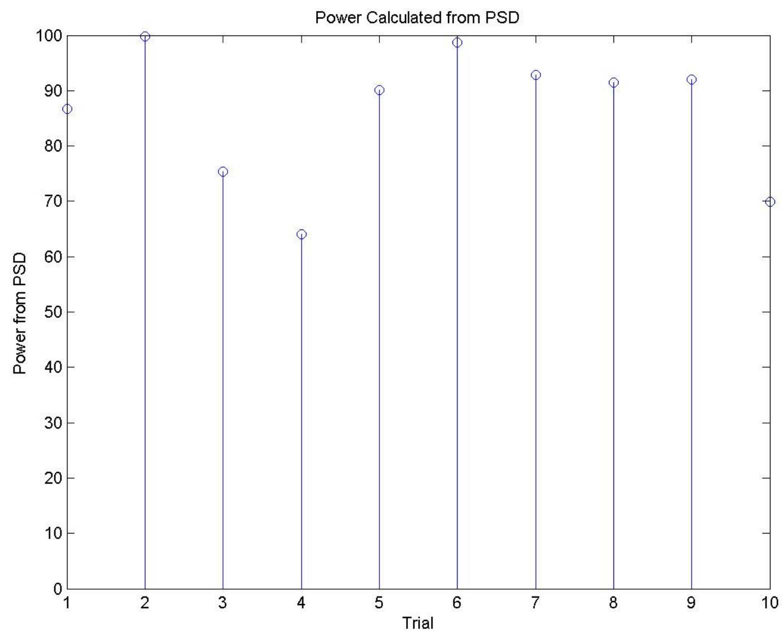

Fig. 12. Signal power - remember face-1 by subject 1

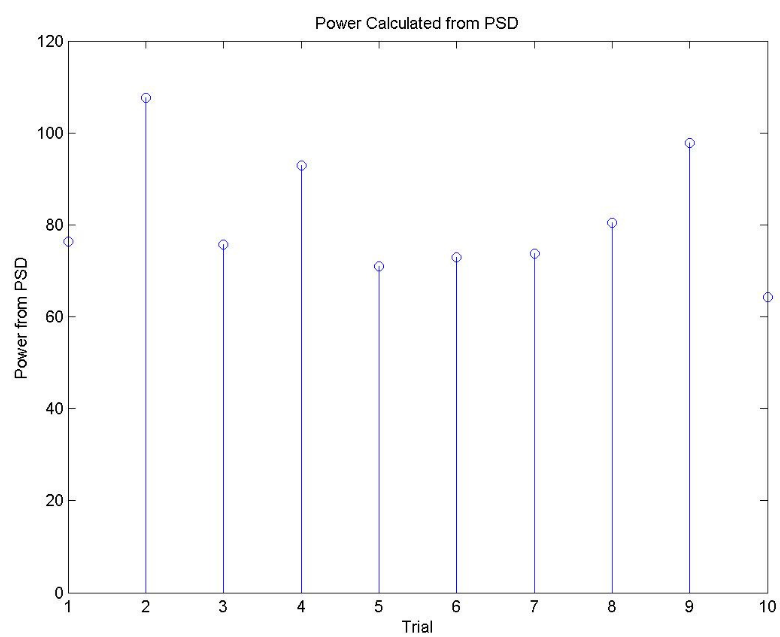

Fig. 13. Signal power - remember face-2 by subject 1

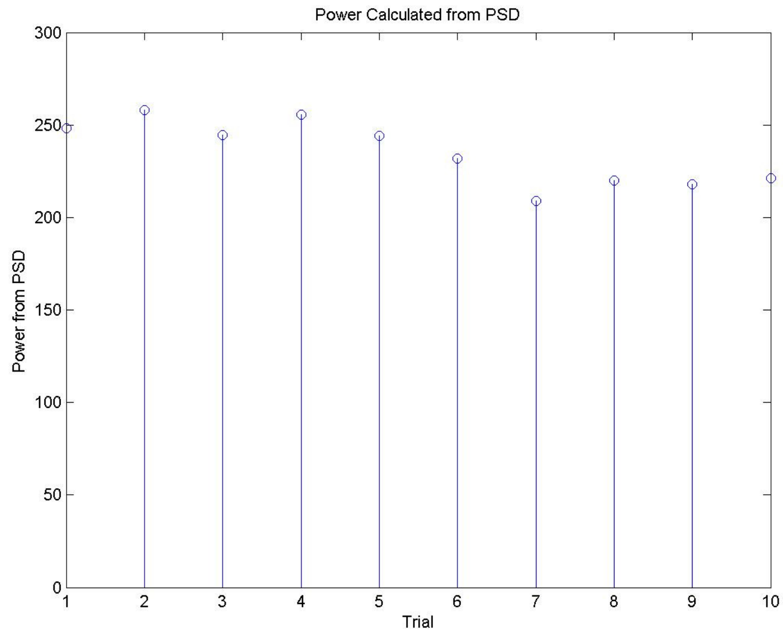

Fig. 14. Signal power - remember face-1 by subject 2

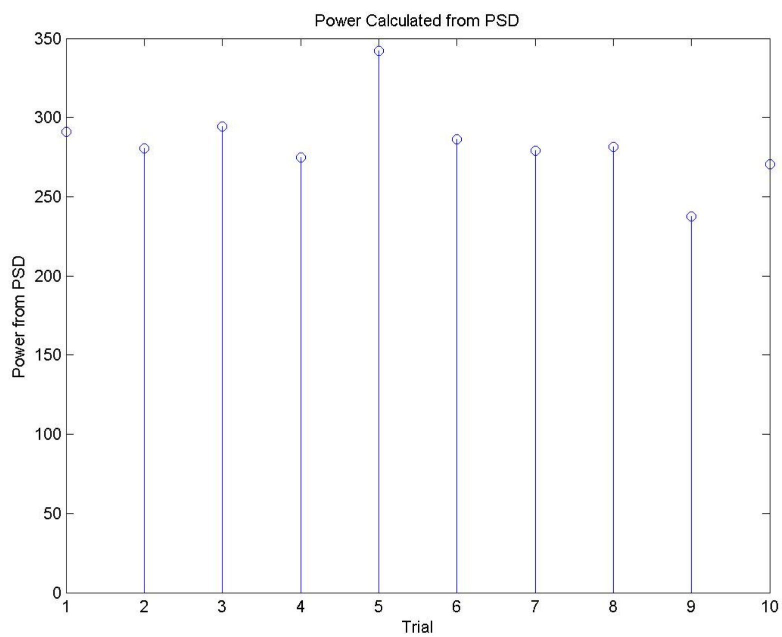

Fig. 15. Signal power - remember face-2 by subject 2

As another example, for the case of subject 3,while remembering father's face gave a mean power value of 39 after omitting the unexpected trial number 1 (and a value of 59.6 without omitting this trial from the calculation). On the other hand, the mother's face gave a mean power value of 109.4. As shown in Figs. 16 and 17 setting a threshold value of 60 here will give 80% of correct classification results. There was no machine learning algorithm used for classification. The whole data set was classified according to the known results. The amplitude of the features were just compared against a threshold value that is strong enough to make a decision as in Table 1.

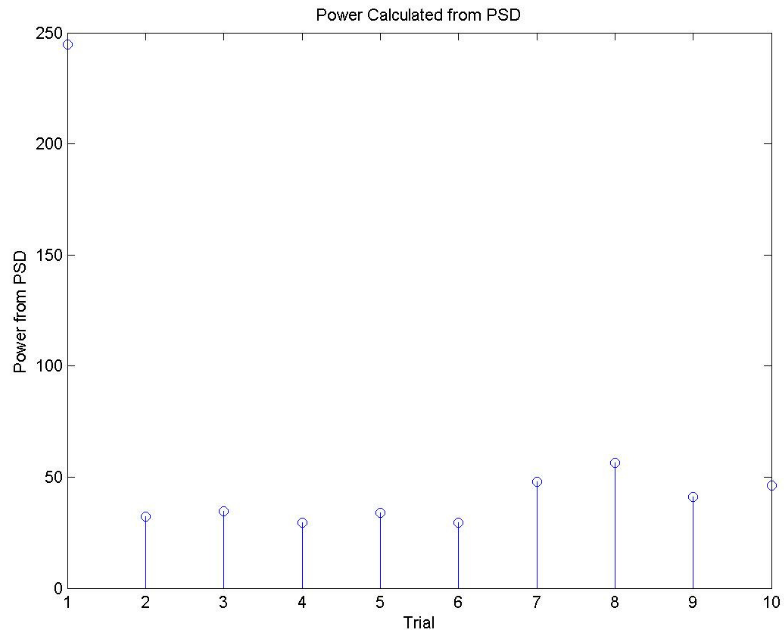

Fig. 16. Signal power - remember face-1 by subject 3

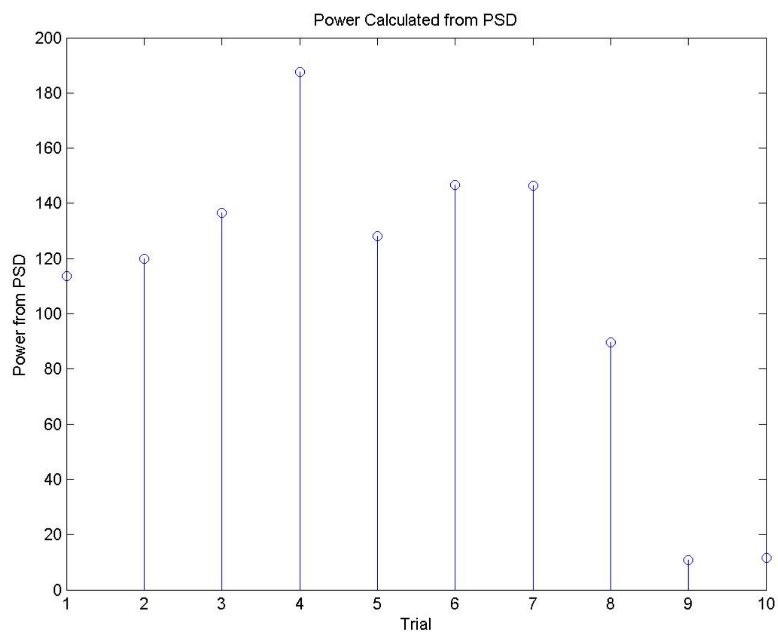

Fig. 17. Signal power - remember face-2 by subject 3

Table 1. Performance of different methods for EEG signal analysis

Methods	Percentage of correct classification (using different thresholds)
Spectral analysis	60-70%
Wigner ville analysis	80-90%
Power spectral density analysis	50-60%
Mean power analysis	70-80%

4. CONCLUSION

From the above experiments and results we conclude that, the EEG signal parameters extracted using advanced signal processing algorithms can be used to identify the face images of people in a better way. The features that can be used as identifiers of individual faces are obtained by analyzing the spectral components and time-frequency parameters. It is noticed that the band of frequencies in the range 0-40 Hz shows higher spectral variations, due to "remembering" or retrieving memories possibly due to the presence of Alpha or Beta waves. It is noticed that there is a considerable difference in the average power and spectral parameters of the same subject when the subject is trying to remember different face images. If a bedridden physically impaired person would like to dial a phone number in his smart phone, this can be done through brain mobile phone interface hardware with the help of a light weight signal processing algorithm. This helps him to interact with the external world in a hands free manner.

The above work can be extended and improved by defining different protocols like remembering the mobile numbers or names of people, so that additional features can be identified to help in a better decision making to interface with smart phones. We have considered just 4 features, which is one of the limitations of the proposed algorithm. Another limitation of our work is the cross-terms in Wigner Ville Distribution that we used for feature extraction. The mathematical cross-terms in WVD can be removed by suitable signal processing methods. The EEG feature extraction algorithms using WVD can be improved by adopting suitable kernel filtering mechanisms for removing the cross-terms in WVD. This will improve the performance of feature identification step in the Brain Machine Interface algorithm.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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