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Wavelet Framework for Improved Target Detection in Oddball Paradigms Using P300 and Gamma Band Analysis

Cota Navin Gupta, Yusuf U Khan, Ramaswamy Palaniappan and Francisco Sepulveda

Department of Computing and Electronic Systems, University of Essex, United Kingdom

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Abstract: *We present an application level framework which makes use of Wavelet Packet Analysis (WPA) for improved target detection in oddball paradigm, which are being researched for a brain biometric system. The novelty lies in the usage of both P300 (delta and theta band) and gamma band features from a wavelet perspective using just forty trials. The features were extracted using WPA analysis for target detection, wherein Daubechies (Db4) and Coiflet (Coif3) wavelets are used respectively to extract the P300 and Gamma band energy features. A comparison on the classification accuracy is also presented when the P300 features are used with and without Gamma band features. This work also discusses a new dynamic backward referencing technique which seems to enhance the features (delta, theta and gamma band) from eight channels. A Radial Basis Function (RBF) classifier is used to classify the obtained features as target and non-target for both the paradigms. Initial results on these lines from four subjects show motivating results for further time frequency research.*

Keywords *Authentication system, Brain biometrics, Electroencephalography, Gamma band, Oddball paradigm, Wavelet analysis.*

1. Introduction

Authentication methods to establish a person's identity have numerous everyday applications. Existing modalities are good for normal daily applications. However these current biometric technologies can be easily tampered or cracked, at-least for high security applications. From time immemorial brain electrical activity has been used for brain related studies, however recently there has been a great spurt of activity in brain biometrics [1-5] which could be attributed to the fact that the recorded brain response cannot be duplicated by anyone, and is hence unlikely to be forged or stolen. Our recent work [6] on a novel paradigm using 'Inblock stimulus' which seems better suited for the biometric system being developed forms the application on which the current developed framework is tested. The online Brain Computer Interface (BCI) authentication system being built is envisaged to be used in a multimodal biometric scenario, along-with say fingerprint or face recognition. The only disadvantage of the system lies in the cumbersome setup procedure, but improvements in data collection methods (such as dry electrodes, instead of wet) will reduce the unwieldiness. With the advancement in technology and increase in processing power of computers, we definitely foresee this technology as promising and commercially viable in the future.

The gamma band activities seem to be evoked and coupled with the P300 components in an oddball paradigm [7-10]. Evoked potential is a type of electroencephalogram (EEG) that is evoked in response to a visual, auditory or somatosensory stimulus. Visual evoked potential (VEP) is the evoked response to visual stimulus and P300 is a component in VEP that has been used in many brain related studies. The P300 component is obtained in an oddball paradigm wherein two stimuli are presented with different probabilities in a random order. The subject usually discriminates the infrequently occurring target stimulus from the frequently occurring standard stimulus by either keeping a mental count or by pressing the button [11]. Under these conditions the infrequent target stimulus elicits an evoked potential characterised by the P300 component [12] and has a peak latency of about 400-600 ms for visual stimuli.

The study in [8] seems to show that oscillatory activity in the gamma frequency range (30-48Hz) might be related to the selection of target items, which is just the case for the brain biometric system under development. Rapid serial visual presentation (RSVP) paradigms address cognitive functions such as visual attention, and are currently being combined with electrical brain activity for enhanced analysis. Also recently gamma band waves have received considerable amount of attention, because

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Brain Computer Interface (BCI) Labs, University of Essex
Wivenhoe Park, Colchester-CO4 3SQ, United Kingdom
Ph: +44-120687-2773, +44-7724025949
Email: cnavin_gupta@ieee.org

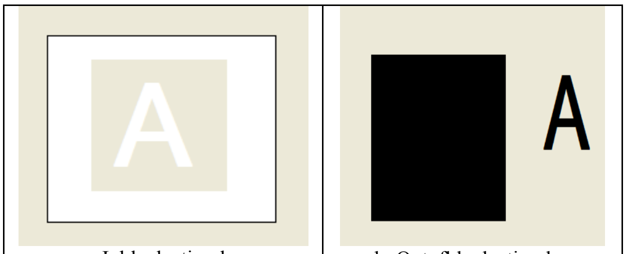
it correlates with higher brain functions and might be a neural correlate of consciousness [13,14].

Recently wavelets have been used in numerous applications for a variety of purposes in various fields. It is a logical way to represent and analyze a non-stationary signal with variable sized region windows and provides local information. In Fourier Transform (FT) the time information is lost and in Short Term Fourier Transform (STFT) there is limited time frequency resolution. A wavelet is a limited duration waveform whose average is zero. Even though basic filters can be used for decomposition of the desired bands, ideal filters are never realized in practice which results in aliasing effects. However wavelet analysis enables perfect decomposition of the desired bands which help us to obtain better features. A detailed study on the application of wavelets to evoked potentials in [15] highlights the advantages of wavelets over digital filtering. It also provides a brief theoretical background on wavelets alongwith the basic background of multiresolution decomposition of the signal. Continuous and Discrete Wavelet Transforms (CWT and DWT) are two ways of obtaining time frequency resolution depending on the application need. A richer and wider range of signal analysis is made possible by Wavelet Packet Analysis (WPA). In WPA analysis details as well as approximations are split and the best decomposition is chosen on an entropy based criterion. Also WPA can be designed to match the time frequency properties of the input signal [16]. Numerous bio-signal applications have used wavelets for a variety of purposes. Wavelet filtering of P300 components was achieved using Daubechies as the mother wavelet in [17]. Wavelet packet best basis decomposition (WPBBD) was used for the purpose of extracting features of electroencephalogram signals produced during motor imagery tasks in BCI's [18]. In [19] wavelet packet transform was used for feature extraction of EEG during mental tasks. Daubechies-2 wavelet (Db2) detail coefficients at the second decomposition level were used in [20] to classify three types of heart sounds. Pattern recognition is the scientific discipline aimed at classifying the patterns (objects) into a number of classes. Various classification techniques, both linear and non-linear are used in different applications. Radial Basis Function (RBF) neural network is one such non-linear classifier commonly used for function approximation and classification purposes. We use RBF in this work for the classification of target and non-target feature vectors in the EEG.

To avoid grand-averaging [6] for target detection we propose the wavelet packet based neural network methodology which seems to offer a better and richer way for target detection.

2. Paradigms under Investigation and Experimental setup

The proposed methodology was tested for the following paradigms that were presented in [6]. The subjects were asked to concentrate on the target block letter 'A' in both the cases. This may be used effectively for a biometric system wherein the target could be presented visually within a block as in Figure 1.a. We compared the Inblock stimulus case with the Outofblock stimulus case (based on Donchin's paradigm [11]) as depicted in Figure 1.b.



a. Inblock stimulus | b. Outofblock stimulus

Figure 1. VEP brain biometric Paradigm used for testing the proposed methodology.

The subjects were shown the two stimuli paradigms as in Figure 1 on a standard computer screen. Visual Basic (VB) software was used to develop the front-end visual interface which was integrated with the ActiView software (Biosemi) to record the EEG data. The flashes were intensified for 100 ms, with an inter-stimulus interval (ISI) of 750 ms during which there were no intensifications. The ISI is defined as the time between the end of one intensification to the start of the next intensification. The period of 750 ms was chosen after some preliminary simulations. The letter 'A' was flashed 30% of the time while the square block was flashed for the rest 70% of the time.

It is proposed to use the Inblock stimulus case for brain biometrics, wherein every user will have their own sequence of say (alphabets or images) as a passcode. For example, a passcode could be letter 'A', letter 'C' and letter 'Z' (sequence is important as it determines the passcode). The subject focuses on say letter 'A' that he wishes to communicate for a predetermined number of trials and keeps a count of the target, which evokes a P300/Gamma component each time the target, is flashed. The computer then detects the alphabet focused by the user using intelligent signal processing algorithms. So at any time, the system's focus for the biometric application is to differentiate the letters (alphabets) on screen rather than the individuals. It is expected to be stable as P300/Gamma is mainly used to differentiate the alphabets and not specific individuals. Also the Inblock stimulus case does suffer from gaze effect, which makes it perfectly suitable for high security applications.

3. Subjects and Data collection

A total of four young subjects (three males and one female) all from University of Essex, without any known neurological and visual imparity served as subjects. A basic understanding of the P300 paradigm and the purpose of the experiments were explained to the subjects, for motivated involvement during the experiments. The subjects were also asked to refrain, from blinking as much as possible during the experiment, which was performed in a room well shielded from electromagnetic interference and a break was given between the two paradigms.

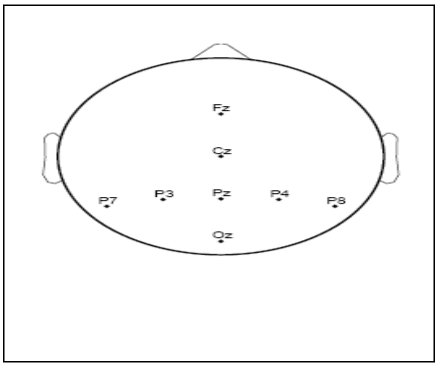


Figure 2. Used electrode configuration [21].

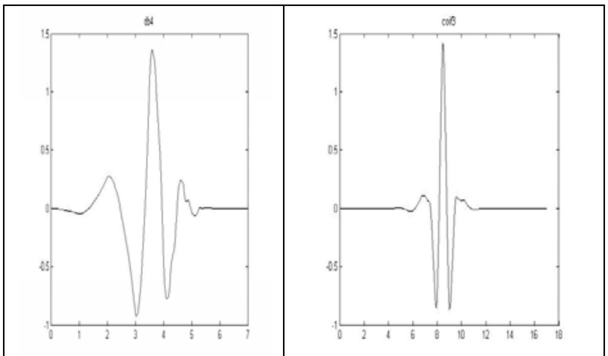
Eight electrodes used (Fz, Cz, Pz, Oz, P3, P4, P8, P7) were placed at the standard positions using the extension of the 10-20 electrode system and are depicted in Figure 2. The work [21] discusses the classification rates achieved using various electrode configurations, for disabled as well as healthy subjects. The study highlights a good tradeoff between the classification accuracy and practical applicability of a BCI system, wherein using more than eight electrodes yielded similar or small increases in performance. Also it is foreseen that having a lesser number of electrodes will help move this system towards practicality requiring less setup time, thereby making it more user friendly. EEG data was recorded from the eight channels using Bio-semi system with a sampling frequency of 256 Hz. The sampling frequency was at-least twice the highest frequency required for analysis (here it is the Gamma band activity upto 48 Hz).

4. Method

The developed methodology consists of two stages. The first stage consists of the feature extraction, which is followed by neural network classification.

4.1 Feature extraction using Wavelet Packet Analysis (WPA)

This work involves a comparison on the classification accuracy in an oddball paradigm, when P300 features are used with and without Gamma band features. To extract the P300 and Gamma band energy features using WPA, Daubechies (Db4) [17] and Coiflet (Coif3) were used as the mother wavelets respectively. The mother wavelets shown in Figure 3 were chosen because of its similarity to the signal feature to be analyzed.



a. Db4 wavelet for P300 components

b. Coif3 Wavelet for Gamma band

Figure 3. Mother wavelets used.

Consider an averaged epoch of EEG of 1 sec (256 samples) from forty trials. If ‘s’ corresponds to the 300-600 ms interval of the epoch, where the oddball activity due to P300 and Gamma components seem to be pronounced. The wavelet coefficients corresponding to δ (< 4 Hz), θ (4-8Hz) and γ (32-48Hz) bands are extracted for the averaged signal. The energy in each band is calculated as ($\sum_{i=300ms}^{600ms} s_i^2$) for the two P300 bands along-with the Gamma band to form a 3-dimension feature vector as below:

$$\lfloor \delta_p \quad \theta_p \quad \gamma_p \rfloor \tag{1}$$

We introduce a dynamic backward referencing technique in this work which seems to enhance the already obtained features. The energy of the epoch corresponding to 650 ms to 1 sec is calculated for each feature resulting in:

$$[\delta_n \quad \theta_n \quad \gamma_n] \tag{2}$$

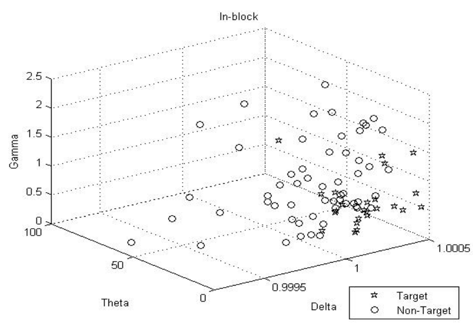


Figure 4. Target and non-target features for Inblock paradigm (Subject 1).

The normalized band energy for each of the three features is calculated as in (3). The ratio of features in equation (1) and (2) gives the final feature vector set for the epoch of EEG.

$$\delta_f = \frac{\delta_p}{\delta_n}$$

$$\theta_f = \frac{\theta_p}{\theta_n}$$

$$\gamma_f = \frac{\gamma_p}{\gamma_n} \qquad (3)$$

The obtained wavelet features (delta, theta and gamma band) for target and non-target cases are shown in Figure 4 and Figure 5 for the Inblock stimulus and Outblock stimulus cases for subject 1. Similar distribution was observed in other subjects and is not being shown to avoid repeatability. On close introspection of the features in a three dimensional view, we find a better and clear clustering of the target features (i.e. the crosses) in Figure 4 for the Inblock case than in Figure 5 for the Outofblock case.

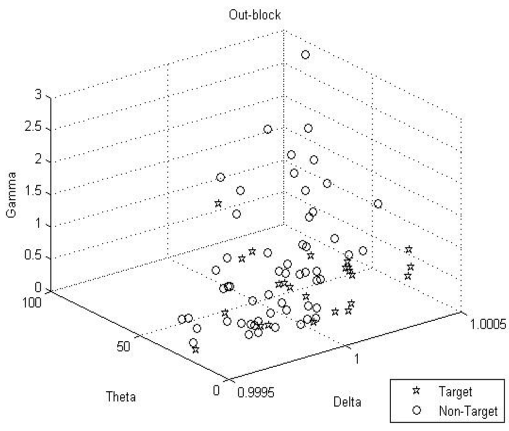


Figure 5. Target and Non-Target features for Outofblock stimulus (Subject 1).

4.2 Classification

Radial basis networks can be designed with ease; however they require more neurons than a standard feed-forward backpropagation network. We used a generalized regression neural network (GRNN) depicted in Figure 6 to perform classification.

The first hidden layer in the GRNN contains the radial units. A second hidden layer contains units that help to estimate the weighted average. Each output has a special unit assigned in this layer that forms the weighted sum for the corresponding output [23]. To get the weighted average from the weighted sum, the weighted sum must be divided through by the sum of the weighting factors. A single special unit in the second layer calculates the latter value and the output layer then performs the actual divisions (using special division units) [23]. Spread which is the distance an input vector must be from a neuron's weight vector was chosen as 0.4 in this work.

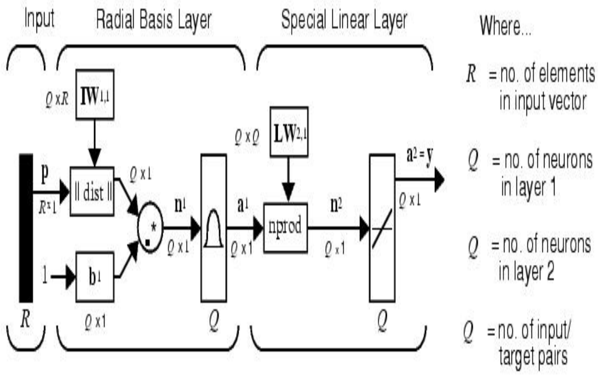


Figure 6. Network architecture of RBF classifier [22].

The features to be used for classification are comprised of vectors, whose elements are the band energies for the projected signal. Each subject recording had 200 trials of EEG data of which 140 were for non-target and 60 for target events. On these trials, a 40 trial window was used for averaging and a window shift by one trial was done for next computation. The EEG resulting from the averaging represented a single epoch of 1 sec duration (256 samples). Features were formed using the methodology described above.

The RBF classifier used a three fold cross-validation. The data set was divided into three disjoint sets of equal size. The classifier was then trained on two of these sets and the third set was used as a test set. This strategy gives three generalization performances, the mean of which provides the true performance of the classifier. The overall accuracy for Inblock recordings was 78% when only delta and theta bands were used as feature vectors. This accuracy increased to 85% when gamma band energy was added as an additional feature to the vector. Figure 7 illustrates the mean classification rates observed in the 4 subjects recorded. Similar results were observed for Outofblock recordings where delta, theta band combined gave an accuracy of 72% while the accuracy increased to 77% when gamma band feature was added. Figure 8 shows the results for Outofblock recordings for the same subjects. On comparison between the Inblock and Outofblock results, Inblock had a better recognition in all subjects as shown in our previous studies [6]. Table 1 gives the obtained average results for both the paradigms. The results indicate improved performance in all the subjects when gamma band energy was added as a feature in the feature

Table 1: The recognition rates (%, rounded) for 4 subjects for In-block and Out-block recordings with and without Gamma band feature set

	Inblock		Outofblock	
Subject	Without Gamma	With Gamma	Without Gamma	With Gamma
1	77 (6)	86 (5)	68 (1)	75 (6)
2	79 (2)	87 (6)	70 (2)	72 (6)
3	79 (2)	82 (3)	72 (7)	77 (3)
4	78 (1)	83 (1)	77 (1)	85 (3)

vector.

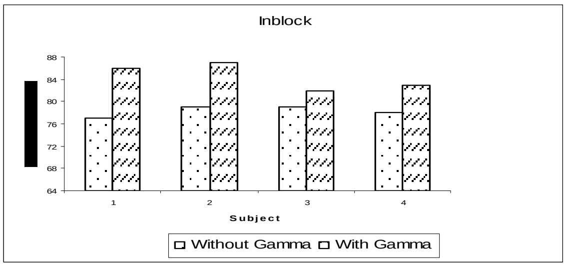


Figure 7. The mean recognition rate of subjects for Inblock recordings without and with Gamma band based feature vector.

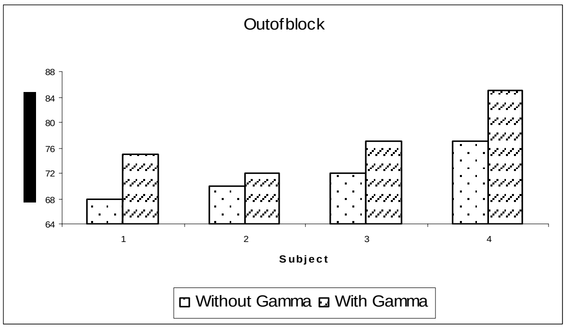


Figure 8. The mean recognition rate of subjects for Outofblock recordings without and with Gamma band based feature vector.

5. Discussion and Conclusion

This work discusses the link between P300 components and Gamma band in an oddball scenario from a wavelet and neural viewpoint. We have presented an analysis framework using wavelet packet analysis (WPA) and RBF neural network for the oddball paradigms using just forty trials. The overall accuracy for Inblock stimulus case was 78% when the P300 components (delta and theta bands) were used as feature vectors. This accuracy increased to 85% when gamma band energy was added as an additional feature. Similar results were observed for Outofblock stimulus recordings where delta, theta band features together gave an accuracy of 72% while the accuracy increased to 77% when gamma band feature was added. The results obtained seem to justify the initial results [6] that the novel Inblock paradigm might enhance the evoked responses during the visual task. This presented novel paradigm along with the analysis framework is foreseen to be a module of an online authentication system for high security scenarios.

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Cota Navin Gupta
Cota Navin Gupta received his first degree in Electronics and Communications Engineering from University of Madras, India and then had a short stint with Matrixview Inc where he worked on imaging projects. During his M.S he worked on heart sounds as part of Singapore-University of Washington(SUWA) alliance’s Telemedicine project at Nanyang Technological University and then worked as a Research Engineer at National University of Singapore on array signal-processing techniques. He is currently pursuing his Doctorate on Overseas Research Scholarship Award (ORSAS) and University of Essex doctoral studentship. His research interests include bio-signal analysis, biometrics, image processing and artificial neural networks.

Yusuf Uzzaman Khan received the M.E. in Electrical Engineering with university medal from University of Roorkee in 1993. He received the D. Phil. degree in Signal Processing from University of Oxford in 1997. He was lately a Commonwealth Fellow at the Brain Computer Interface research group in Essex University. He is a Reader at the Department of Electrical engineering, Aligarh University. He is a Fellow of IETE, India, Life Member of System Society of India and Member of IEEE, USA. His research interests are in biomedical signal processing with special emphasis on electrical brain activity analysis, automated seizure classification systems and brain computer communication systems.

Ramaswamy Palaniappan is currently a Lecturer with the Department of Computing and Electronic Systems, University of Essex, UK where he coordinates the Biosignal Analysis Group. His research interests include biological-signal processing, brain-computer interfaces, biometrics, artificial neural-networks and genetic algorithms. To date, he has published over 130 papers in peer-reviewed journals, book chapters and conference proceedings. He is a Senior Member of the Institute of Electrical and Electronics Engineers, member of Institution of Engineering and Technology and Biomedical Engineering Society. He serves as editorial board member for several international journals. His pioneering work on brain signal biometrics has received international recognition.

Francisco Sepulveda

Dr. Francisco Sepulveda is a Reader and Coordinator of the Brain-Computer Interfaces research group in the Department of Computing and Electronic Systems at the University of Essex, where has been since 2002.He has previously held academic posts at Aalborg University, Denmark, and at the State University of Campinas (Unicamp), in Brazil. He received his PhD summa cum laude in Biomedical Engineering from Unicamp (with a fellowship in the Bioengineering Unit at the University of Strathclyde, UK), in 1996, an MSc in Bioengineering from Clemson University, USA, in 1990, and a BSc in Nuclear Engineering (with the award of 'Outstanding Graduating Senior' in the then Dept. of Chemical and Nuclear Engineering) at the University of California, Sta. Barbara, in 1988. His research interests are in neural engineering, biomedical signals, machine learning, electrophysiology, neuroscience, psychophysics and affective computing.