ON THE ANALYSIS OF VARIOUS TECHNIQUES FOR A NOVEL BRAIN BIOMETRIC SYSTEM

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ABSTRACT

We present various techniques to detect a target in an oddball paradigm. These techniques are presented with reference to two P300 paradigms being studied to build a biometric system using electroencephalogram (EEG) signals. The novel Inblock paradigm presented in this paper proposes a possible variant to the known oddball paradigm and analyses the effect of spatial location of the target block with respect to the non-target block. It brings out a new approach in the oddball paradigm wherein location of the target might help evoke a higher P300 potential. A comparison of the various analysis techniques studied for both the paradigms is also presented. Initial results from four subjects show that energy analysis gave improved results than the traditional amplitude analysis techniques for target detection in the studied oddball paradigms. The results were comparable for all subjects except for one subject where energy analysis provided better target detection suggesting that energy based methods could be further explored. This proposed novel paradigm is a step towards the online brain biometric system which is being built for authentication in high security scenarios.

1. Introduction

Traditional and commonly used authentication methods to establish a person's identity are textual password and usage of personal identification number (PIN). These schemes are motivated by the facts of popularity due to low cost and user familiarity. However they have some obvious shortcomings in the form of dictionary attack, shoulder surfing and people picking up obvious known words. Dictionary attacks can be prevented by using human in loop verifications [1] and Encrypted Key Exchange methods [2] but operating system vulnerabilities and access control failures may lead to disclosure of password databases. Even the recently proposed graphical password which is motivated

by the fact that people have a remarkable memory for pictures seem to share similar problems along with the shortcomings of guessing attacks [3] and reduced effective password space. The ubiquitous presence of mobile phone cameras, digital cameras, and wireless video cams brings in a new threat in the form of 'recorded shoulder surfing' for high security applications.

Hence biometric technology based on measurable physiological and/or behavioral characteristics (e.g. fingerprints [4], the iris [5], and voice recognition [6]) is often considered to surpass conventional automatic identity measures like passwords and personal identification number (PIN) by offering positive human identification. However these current biometric technologies can be easily tampered or cracked, atleast for high security applications (like defense). It is a known fact that no biometric is expected to effectively meet the requirements for all applications and the choice completely depends on the application. Brain electrical activity is the defacto standard for brain related studies, however recently there has been a great flurry of activity in brain biometrics [7,8,9,10,11] 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.

2. P300: History and Paradigms

Evoked potential is a type of electroencephalogram signal (EEG) that is evoked in response to a stimulus, which could be visual, auditory or somatosensory. 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 target stimulus (which occurs infrequently) from the standard stimulus (which occurs more frequently) by either keeping a mental count or by pressing the button [12]. Under these conditions the infrequent target stimulus elicits an evoked potential characterised by the P300 component [13] and has a peak latency of about 300-600 ms for visual stimuli. This potential reflects the attentional resource allocation when working memory is engaged and has provided great deal of information about cognitive operations. This principle has been used in numerous applications (communication, providing control or rehabilitation)

for paralyzed people suffering from neuromuscular disorders [14, 15]. An introduction to the various P300 paradigms along with a comprehensive study on the factors that affect the evoking of the P300 components was presented in [16]. Various factors (stimulus information content, sequence probability structure, task relevance/difficulty) have found to affect the P300 parameters and numerous studies have been performed [17,18,19,20,21].

It is proposed to use this idea for brain biometrics wherein every user will have their own sequence of say (alphabets or images) as a passcode. Considering alphabets alone the objective here is to form an alphabet coded pass code generated by thought alone, which could be used to authenticate the identity of a person. For example, a passcode could be alphabet 'A', alphabet 'C' and alphabet 'Z' (sequence is important as it determines the passcode). The subject focuses on say alphabet 'A' that he wishes to communicate for a predetermined number of trials and keeps a count of the target which evokes a P300 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 alphabets on screen rather than the individuals. It is expected to be stable as P300 is mainly used to differentiate the alphabets and not specific individuals.

For this biometric application, the remembrance of password may be considered as a recall from episodic memory, which is a subset of declarative memory because it is related to storage of facts and can be discussed or declared. However none of the previous studies have taken into consideration the spatial location of the target with respect to the non-target block which this work addresses. Here, we also discuss the possibility of using various P300 features (energy, Shannon energy, amplitude) for target detection.

3. Novel Stimulus Paradigm: Present Study

In this preliminary study, we investigated the effects of presenting the oddball stimulus in 'Inblock' and 'Outofblock' fashion (as illustrated in Figure 1). Most of the studies have been based on the traditional Donchin's paradigm [12, 14] which is similar to the Outofblock stimulus case but however our investigations show that the location of

the target with respect to the non-target could improve the P300 response amplitudes. The target (alphabet 'A') is made to appear and disappear for the Inblock case unlike in the Outofblock case where it flashes 'ON' and 'OFF' and hence the alphabet 'A' is depicted in white in Figure 1.a. The subjects were asked to concentrate on the target block letter 'A' in both the cases. In this study EEG data was recorded when the subject perceived alphabet 'A' as the target and square block acted as the non-target.

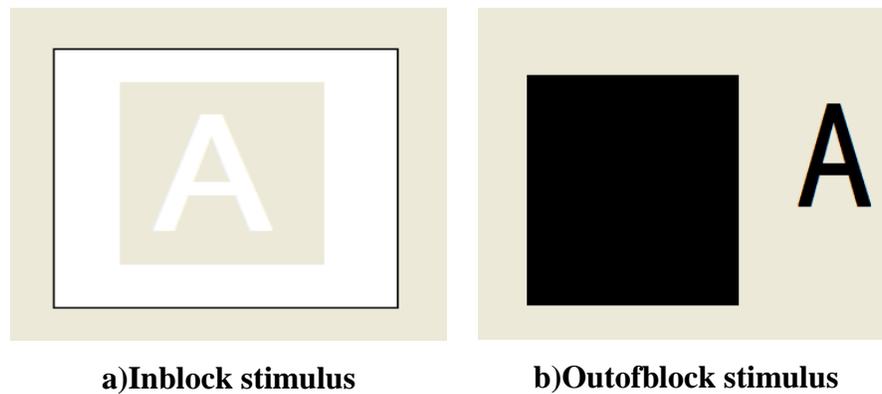**a)Inblock stimulus**   **b)Outofblock stimulus**

Figure 1: Novel stimulus paradigm for VEP based brain biometric.

This may be used effectively for a biometric system wherein the target (say: character or picture which forms the passcode) could be presented visually in the Inbock fashion as in Figure 1.a. The Inblock stimulus paradigm suits perfectly for the current biometric application because it will not have the gaze effect which could be prevalent in the Outofblock stimulus case.

3.1. Subjects

A total of four young subjects (three males and one female), all students from University of Essex served as subjects. None of them had any known neurological as well as visual imparity and had provided written consent. 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.

3.2 Experimental setup and stimuli

The subjects were shown the two stimuli paradigms on a standard computer screen. Visual Basic 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 the ISI, there would be no intensifications. The ISI is defined as the end of the 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 assumed that the infrequent stimuli (i.e. when the subject concentrates on the alphabet 'A') will evoke a P300 component. 60 trials of target (alphabet 'A') and 140 trials of non-target (square block) were recorded.

3.3 Recording conditions

Electroencephalographic (EEG) activity was recorded at the eight electrodes along with the mastoid electrodes as in [22], which reported the optimal locations for P300 based systems. The 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. We chose only eight electrodes as the fewer the electrodes, lesser is the time required to setup. Also it is foreseen that having a lesser number of electrodes will help move this system towards practicality and will make it more user friendly. EEG data was recorded from 8 channels using Bio-semi system with a sampling frequency of 256 Hz. EEG data was recorded for every flash of the 'square block' or letter 'A'. Then, averages of left and right mastoid channels were used to re-reference the data. The recordings were made in the noise free environments of the BCI lab and a break was given for every subject between the two paradigms.
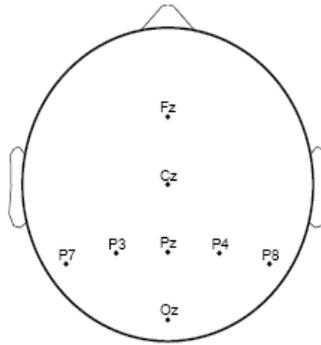
Figure 2: Used electrode configuration [22].

4. Data Analysis and Results

Single trials of 1000 ms were extracted from the data i.e. from the start of intensification which is considered as the stimulus onset. The recorded data was pre-preprocessed in the following way. The average signal from the two mastoids was used for referencing. To extract the features, each EEG signal was low pass filtered with a 10-12 Hz transition band and then high pass filtered with a 1-2 Hz using fourth order Elliptic Infinite Impulse Response filters (with forward and reverse filtering to avoid phase distortion). The trials were then normalised to zero mean and standard deviation of one. The cut-off frequencies for both the filters were chosen after some preliminary experimentation.

We analysed the extracted features from the eight optimum channels as reported in [22] for detection of target for both the above discussed paradigms. We reported the use of grand-averaging of the same eight channels in our previous work [23] to highlight the fact that the Inblock paradigm helped in evoking a better P300 component during a visual task and had a better threshold of difference between target and non-target trials than the Outofblock paradigm. The recorded 60 trials of target and 140 trials of non-target were averaged to obtain an averaged trial of 1 second for the target and non-target cases. The performance of below features from eight channels was studied in detecting the target independently.

      a) Using P300 amplitudes in the 300-600 ms range from the averaged trials

      b) Using energy of the 1 second averaged trials

c) Using Shannon energy [24] of the 1 second averaged trials

The above features were extracted from the eight channels for target and non-target case for each subject and a simple rule based strategy was used. If for a given selected feature (say: energy), if the energy from the averaged target trial was greater than that of the energy from the averaged non-target trial in more than four channels, then it is considered as correct detection of the target. A comparison of the performance of the features (P300 amplitudes, Energy, Shannon Energy) for target detection in four subjects is shown in Table 1 and Table 2 for Inblock and Outofblock cases respectively. CD means correct target detection and ICD means incorrect target detection

Table 1: Target Detection for four subjects using various features from

8 channels (Inblock Paradigm)

Inblock Paradigm			
Subject	P300 Amplitudes	Energy	Shannon Energy
1	8(CD)	7(CD)	7(CD)
2	8(CD)	8(CD)	7(CD)
3	8(CD)	8(CD)	8(CD)
4	2(ICD)	8(CD)	6(CD)

Table 2: Target Detection for four subjects using various features from

8 channels (Outofblock Paradigm)

Outofblock Paradigm			
Subject	P300 Amplitudes	Energy	Shannon Energy
1	6(CD)	5(CD)	6(CD)
2	1(ICD)	5(CD)	6(CD)
3	5(CD)	7(CD)	7(CD)
4	6(CD)	8(CD)	7(CD)

It can be easily inferred from Table 1 and Table 2 that Inblock paradigm is better than the Outofblock paradigm [23] for all subjects and for almost all three cases of features. A closer introspection of the table shows that energy as a feature seems to detect the target for subject 4 (Inblock case) and subject 2 (Outofblock case) than P300 amplitudes and Shannon energy as a feature. Though the performance of all three features is comparable, the usage of energy for target detection could prove an attractive alternative in oddball paradigms.

Conclusion

A novel paradigm which enhances the evoked response of the P300 component for an oddball scenario is presented. This work analyses the spatial effect of the target with respect to the non-target block. Initial results from four subjects suggest that the novel Inblock paradigm might better enhance the evoked response of the P300 component during the visual task. The better evoking of the P300 component could be attributed to the fact that the target (alphabet 'A') disappears for the Inblock case thereby increasing the surprising factor unlike in the Outofblock case where it flashes 'ON' and 'OFF'. Also comparison between the various possible features which could be used to detect the target in the oddball paradigm is outlined wherein the energy feature might be a better parameter to detect the target. This presented novel paradigm is envisaged to be a module of an online authentication system, which is being built using the BCI technology for high security scenarios.

Acknowledgements

References

[1] B. Pinkas and T. Sander, Securing Passwords against Dictionary Attacks, *In 9th ACM Conference on Computer and Communications Security*, ACM Press, 2002, 161-170.

[2] S. Bellovin and M. Merritt, Encrypted Key Exchange: Password-Based Protocols Secure Against Dictionary Attacks, *In IEEE Computer Society Symposium on Research in Security and Privacy,* 1992, 72-84.

[3] J. Thorpe and P.C. Van Oorschot, Graphical Dictionaries and the Memorable Space of Graphical Passwords, *In 13th USENIX Security Symposium*, 2004.

[4] A. R. Roddy and J. D. Stosz, Fingerprint Features - Statistical Analysis and System Performance Estimates, *Proceedings of the IEEE*, *85*, 9, 1996, 1390-1421.

[5] J. Daugman, How Iris Recognition Works, *IEEE Transactions on Circuits and Systems for Video Technology*, *14*, 1, 2004, 21-30.

[6] F. Monrose, M. K. Reiter, Q. Li, and S. Wetzel, Cryptographic Key Generation From Voice, *In IEEE Conference on Security and Privacy*, 2001, 202-213.

[7] R.Palaniappan and D.P.Mandic, Biometrics from Brain Electrical Activity: A Machine Learning Approach, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *29*, 4, April 2007, 738-742.

[8] S.Marcel and J.Millan, Person Authentication Using Brainwaves (EEG) and Maximum A Posteriori Model Adaptation, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *29*, 4, April 2007, 743-752.

[9] R. Palaniappan and K.V.R. Ravi, Improving visual evoked potential feature classification for person recognition using PCA and normalization, *Pattern Recognition Letters*, *27*, 7, 2006, 726-733.

[10] R. Palaniappan and P. Raveendran, Individual identification technique using visual evoked potential signals, *Electronics Letters*,*138*,25, 2002, 1634-1635.

[11] R.B. Paranjape, J. Mahovsky, L. Benedicenti, and Z. Koles, The Electroencephalogram as a Biometrics, *Proc. Canadian Conf. Electrical and Computer Eng*, *2*, 2001, 1363-1366.

[12]   L.A.Farwell and E.Donchin, Taking off the top of your head: Toward a mental prosthesis utilizing event-related potentials, *Electroencephalogr. Clin. Neurophysiol*, *70*, 1988, 510-523.

[13]   S.Sutton, M.Braren, J.Zubin and E.R.John. Information delivery and the sensory evoked potential. *Science*, *155*, 3768,1967,1436-1439.

[14]   E.Donchin, K.M.Spencer and R.Wijesinghe, The mental prosthesis: Assessing the speed of a P300-based brain-computer interface, *IEEE Trans. Neural Systems and Rehab. Eng., 8*, 2, June 2000, 174-179.

[15]   H. Serby, E.Y.Tov and G.F.Inbar, An improved P300 brain computer interface, *IEEE Trans. Neural Systems and Rehab. Eng.*, *13*, 1, 2005, 89-98.

[16]   J.Polich. and J.R.Criado, Neuropsychology and neuropharmacology of p3a and p3b, *International Journal of Psychophysiology*, *60*, 2, 2006, 172-185.

[17]   R.Johnson, The amplitude of the P300 component of the event-related potentials: review and synthesis, In: Ackles, P., Jennings, J., Coles, M.(Eds.), *Advances in Psychophysiology*,*2*. JAI Press, Inc., Greenwich,CT, 1988, 69-137.

[18]   B.Oken, Endogenous event-related potentials. In:Chiappa.K., Evoked Potentials in Clinical Medicine, Lippincott-Raven Publishers, New York, 1997,529-563.

[19]   E.Donchin and M.Coles., Is the P300 component a manifestation of context updating?, *Brain Behav. Sci, 11*, 1988, 357-374.

[20]   W.Sommer, H.Leuthold and J.Matt, The expectancies that govern P300 are mostly automatic and unconscious, *Behav.Brain.Sci., 21*,1998,149-150.

[21]   R.Verleger, Event-related potentials and cognition: a critique of the context updating hypothesis and an alternative interpretation of P3, *Behav.Brain Sci.*, *11*,1988,343-356.

[22]   U.Hoffmann, J.M.Vesin, T.Ebrahimi and K.Diserens, An efficient P300-based brain-computer interface for disabled subjects, *J Neurosci Methods*, *167*,1, 2007,115-125.

[23]   C.N. Gupta, R. Palaniappan, and S. Swaminathan, Novel P300 Paradigm-Moving Towards Brain Biometric Systems, Book of Abstracts, International Symposium of Global trends in BioMedical Informatics Research, Education and Commercialization, Chennai, India, 2008, pg.38.

[24]   S. Choi and Z.Jiang, Comparison of envelope extraction algorithms for cardiac sound signal segmentation, *International Journal Expert Systems with Applications, 34*, 2, 2008, 1056-1069.

Author biographies

Cota Navin Gupta received his first degree in Electronics and Communications Engineering (ECE) in 2001 from University of Madras, India. He then had a stint with Matrixview Inc working on imaging techniques before embarking for his M.S degree in Biomedical Engineering in 2003. During his M.S. degree, he worked on algorithm development for heart sounds as part of the Biomedical Engineering Research Centre, University of Washington (BMERC-SUWA) Alliance's Telemedicine Project at Nanyang Technological University, Singapore. After graduating in 2005 he worked as a Research Engineer at National University of Singapore (NUS) on array signal processing techniques.

He is currently pursuing his doctorate at University of Essex, UK on Overseas Research Scholarship Award (ORSAS) and University of Essex doctoral studentship. His research interests include biological signal processing, brain-computer interfaces, heart signal analysis, artificial neural networks, genetic algorithms, and biometrics. He is a student member of the Institute of Electrical and Electronics Engineers (IEEE), Institution of Engineering and Technology (IET), and Japanese Neuroscience Society (JNS).

Ramaswamy Palaniappan received his first degree and MEngSc degree in electrical engineering and Phd degree in microelectronics/biomedical engineering in 1997, 1999 and 2002, respectively from University of Malaya, Kuala Lumpur, Malaysia. He is currently a lecturer with the Dept. of Computing and Electronic Systems (formerly known as Computer Science), University of Essex, United Kingdom, where he is the coordinator of Biosignal Analysis Group. Prior to this, he was the Associate Dean and Senior Lecturer at Multimedia University, Malaysia and Research Fellow in the Biomedical Engineering Research Centre-University of Washington Alliance, Nanyang Technological University, Singapore. He has been a referee to the Industry Grant Scheme managed by Ministry of Science, Technology & Environment, Malaysia. He helped to set-up the Biomedical Engineering Department in University Malaya, Malaysia and founded and chaired the Bioinformatics division in Centre for Bioinformatics and Biometrics in Multimedia University, Malaysia. His current research interests include biological signal processing, brain-computer interfaces, biometrics, artificial neural networks, genetic algorithms, and image processing. To date, he has published over 130 papers in peer-reviewed journals, book chapters, and conference proceedings.

Dr. Palaniappan is a senior member of the Institute of Electrical and Electronics Engineers and IEEE Engineering in Medicine and Biology Society, member in Institution of Engineering and Technology, and Biomedical Engineering Society. He also serves as

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Sundaram Swaminathan has been a senior faculty member at the School of Electrical and Electronic Engineering, Nanyang Technological University for the last 17 years. Having had a First Class educational career throughout the period of his studies at the University of Calcutta, Dr Swaminathan was awarded the prestigious Commonwealth Scholarship to pursue his PhD programme at the University of Warwick, U.K. in 1981, in the area of III-V semiconductor Devices and characterization. He started his career at the Indian Institute of Technology, Roorkee, India, where he worked in the rank of Associate Professor until 1990, and after a brief spell at the University of Warwick as a Visiting Fellow, he joined the Nanyang Technological University, Singapore in 1991. His professional; recognitions include Best Teacher of the Year nomination for two years, Invited and Plenary Speaker at International Conferences, etc. He has been actively involved in collaborating with a number of research initiatives that include one with the Singapore- University of Washington Alliance (SUWA) where novel SPR imaging techniques and fluorescence methods are being developed for the detection of immuno assays. Another key project where he is actively involved is in the area of optical MEMS where methods to accurately describe the optical properties of a living cell using a single optical chip is underway. He has successfully supervised a number of Master's and PhD students on topics related to III-V semiconductor material characterization, high resolution x-ray diffraction, device modeling, Ion-Sensitive Field Effect Transistor (ISFET) Characterization, Fluorescence based Immunoassay sensor system development, etc. He has authored a number of peer reviewed publications in this area in international journals and international conference proceedings. He is a senior member in IEEE since 1992.