Blink Rate Variability as a Measure of Computer Vision Syndrome

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Research Article

Keywords: Computer Vision Syndrome (CVS), Electroencephalogram (EEG), Blink rate variability (BRV), Cognitive Task

Posted Date: April 28th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1550893/v1

Abstract

Due to the COVID-19 pandemic and working from home with portable devices, we are spending a longtime on the device screen. Prolonged focus on devices like computer screens, tablets, e-readers, and cellphones – Video Display Terminals (VDTs) has been linked with vision problems which affect over 60 million people globally. The computer related ocular problem is collectively called Computer Vision Syndrome (CVS) [1]. CVS is multidirectional as it affects people differently and with varying associated symptoms. The goal of this research is to analyze Electroencephalograph (EEG) signals and affirm that our hypothesis that if eye Blink rate variability (BRV) is a good indicator of human attentiveness then human attention can be directly correlated to CVS. Two EEG signals were analyzed with one recorded from participant while engaged in a cognitive demanding task and compared with a control data set when participant was in a less attentive. A significant decrease in eye blink rate from 20 to 16 was observed in the signals collected from the participants engaged in cognitive task.

1. Introduction

In the technology driven world we live in today the use of Digital Electronic Screens or Visual Display Terminals (VDT) [2] is almost impossible to do without. The reliance on television, computers, mobile phones, e-readers and tablets amongst others for information, entertainment, communication and education has never been stronger. The shift from printed hard-copy materials and other alternative substitutes to these electronic devices has been partly due to their now relatively low cost of purchase and maintenance than it used to be in the past, ready availability, ease of use and portability. The discovery and commercialization of the internet which operate on the electronic platforms has also contributed immensely to the popularity of the devices with the US Department of Commerce reporting that 96% of American workers use internet as a means of communication daily while 62% use it as an important part of their jobs [12].

However, with the electronic devices several comfort and ergonomic merits, the prolonged use of the electronic devices has some accompanying negative effects on the health of the users. Users start to experience ocular and visual symptoms after prolonged use. These ocular and visual symptoms are collectively termed Computer Vision Syndrome (CVS)[3] or Digital Eye Strain (DES) [2] with the latter preferred by some since the public may not consider all VDTs computers[23]. CVS has different associated symptoms and is multidirectional as its effect varies with age, sex, and existing visual problem(s). The common associated symptoms include pain in and around the eye, headache, blurred near and distant vision, dry eyes, sore/irritated eyes, red eyes, excessive tearing double vision and twitching of the eyelids [13][20][21][22]. With studies in 2013 estimating that an average adult living in the USA spends about 9.7 hours on VDTs (which includes personal computers, mobile phones, e-readers, tablets, television) daily [12]. It is quickly becoming rather a source of concern to optometrists[24][25].

Amongst the different symptoms of CVS dry eye had previously been reported to be the major contributor. For instance [14], it is reported that 10.1% in male and 21.5% in female reports of dry eyes symptoms

were reported in Japanese office workers. And [15] reported that long use of computers by workers also caused significant reports of dry eyes in the workers. With the prevailing symptom of dry eye, it was observed that eye blink reduction was directly correlated to it. Several investigations have confirmed this claim [16], [17], [18], [19]. Electroencephalograph (EEG) which is the electrical signals generated in the head can be recorded via electrodes caps/headsets sensor worn over the head has proven to be an accurate way of recording these signals [4]. The signals produced in the frontal lobes of the head been to clearly show the occurrence of Eye Blinks (EB). EB is defined as the opening and closing of the eyelids and it is different from winks. EBs could be voluntary or involuntary. Therefore, this research is aimed at using these signals carrying EB information to detect EBs. Hence, our objective is to develop an eye blink extraction algorithm to extract blinks from EEG signals [5][6], Pre-process and analyze the eye blink signals. Additionally, do a comprehensive review of Computer Vision syndrome symptoms and how eye blink rate is an indicator and analyze two sets of EEG signals to provide demonstrate how attention affects eye blinks.

2. Literature Review

2.1 Role of Eye blinks in CVS

Blinking, best described as the predominantly involuntary rapid closure of the eyelids is one of many physiological functions of humans that have been described. In addition to its safety function, of protecting the eye from potentially dangerous external interferences and desiccation, it has also been discovered to play a vital role in cognitive high-order functioning [32]. The eye blink is said to be primarily under the control of the Central Nervous System (CNS), especially the Globus pallidus area, with dopamine being the main transmitter involved [31] [6]. In terms of higher order functioning, blinking and its frequency have been linked with attention, intelligence, and overall day-to-day functioning [31] [33]. In a clinical research study carried out in Holland by Chermahini and Hommel, Eye Blink Rate (EBR) was found to be negatively associated with convergent thinking (‘Remote Association Task”) which had a positive relationship with intelligence. Whereas they found out that divergent thinking (“alternative uses” task) was mainly associated with average EBR [31]. Several studies have also found a relationship between higher EBR, fatigue and sleepiness especially in the context of automobile crashes [35] [36]. The average blink rate is 12-20 per minute with each blink lasting between 0.1 to 0.4 seconds [33] [34]. As this rate and duration increase, the likelihood of automobile crashes has been said to increase significantly. While the importance of EB and its variability has been extensively studied with regards to automobiles, the relationship between EB variability and CVS has continued to gain more attention especially with the increasing use of digital electric screens and or visual display terminals.

2.2 Symptoms of CVS

CVS is a constellation of signs and symptoms associated with the use of computers and or digital devices. These include; eye strain (Asthenopia), diplopia, dry eyes, red eyes and blurred vision among

others and it is usually due to computer/screen glare, poor lightning, inappropriate viewing distances, pre-existing visual abnormalities or a combination of any of these [39] [40]. With symptoms increasing significantly with increased screen usage, especially greater than 4 hours of use, CVS is said to affect about 67.4%-90% of the population [41][42][43] [15]. It is also said to be slightly more commonly reported by females, with eye strain and headache being the most prevalent symptoms [43] [44].

CVS is multidirectional as it affects individual of different age groups and gender differently with different associated symptoms. They have been broadly classified into three categories by ophthalmologists [3]

1. Accommodative or asthenopic symptoms
2. Ocular surface related symptoms
3. Extra Ocular symptoms

They further classified different symptom categories into specific symptoms in Table 1. *Asthenopic symptoms* are those eye accommodation problems that are already present in the individual but does not cause any discomfort to them, however with a prolonged exposure to VDTs they start having such symptoms as eye strain, dry eyes etc.

Ocular Surface related symptoms refer to disorders of the surface of the cornea – the transparent layer that forms the front of the eye examples are dry eye, Meibomian gland dysfunction blepharitis, chemical burns, thermal burns etc.

Extra Ocular Symptoms refers to physical posture of the VDT user when using the devices. It includes angle of view of the computer due to the height of the seat, poor or excessive lighting etc. [3]

Table 1

Computer related ocular symptoms and diagnosis

Symptom Category	Symptoms
Accommodative Symptoms	Eye Strain Tired eyes Sore eyes Dry eyes
Ocular Surface related Symptoms	Watery eyes Eye Irritation Contact Lens Problems
Visual Problems	Blurred Vision Poor focusing change Double vision Presbyopia
Extra Ocular symptoms	Neck pain Back Pain Shoulder pain

2.3 EEG Overview

Electroencephalography (EEG) is a bio signal technique used in recording the electrical potential by the activities of the brain cortex which reflects the state of the brain in real-time [4][26]. EEG belongs to a group of electro biological measurements techniques such as Electrocardiography (ECG) for measurement of heart beat, electromyography (EMG) for measurement of muscular contractions, electro-optigraphy (EOG) for eye dipole field measurement and other imaging techniques based on physical principles such as magnetic resonance imaging (MRI), and computer tomography (CT)[27][28]. Study of EEG is important in brain computer interface design. EEG is defined as alternating type of electrical activity recorded by a conductor or metal electrode from the scalp surface of the head [30]. It is a non-invasive technique and poses virtually no health risk to the patients both in adults and children [29].

EEG involves the summed electrical activities of neutrons. Neutrons are excitable cells with characteristic intrinsic electrical properties and their activity produces electrical and magnetic fields. These fields are recorded by means of electrodes at a short distance from the cortal surface [6]. The brain can be classified into three sections from the anatomical view point: cerebrum, cerebellum and the brain stem. The cerebrum is the principal and the most anterior part of the brain, it consists of the left and right hemisphere and the surface is referred to as the cerebral cortex and here is where the EEG electrodes record the electrical signals from[7] [8]. The cerebrum is an important part of the CNS and sensation, complex analysis, emotion etc. are controlled by this art of the brain. The cerebellum is responsible for maintaining balance and voluntary movement of muscles and the brain stem regulates heartbeat, controls hormone secretion and respiration [29]. A layout of the electrodes on the scalp is shown in figure 1.

There are two internationally recognized nomenclatures to describe the different scalp locations of electrodes.

- **The 10-20 naming system**: This is an internationally recognized nomenclature; the 10-20 name was derived from the spacing of electrodes from one another with either 10% to 20% front to back electrode spacing or 10% to 20% left to right electrode spacing. Each electrode location is denoted by an alphabet and a number. F stands for frontal; T stands for Temporal; C stands for central (it has no real purpose asides just for identification); P stands for Parietal and O for occipital and odds numbers (1,3,5,7) stands for positions on the left hemisphere of the head and even numbers (2,4,6,8) stands for positions on the right hemisphere of the head.

- **The Modified Combinatorial Nomenclature**: The need for this aroused when it was required to add more electrodes to more accurate recordings. This system uses the intermediate points between the different electrode locations in 10-20 naming system. AF stands for the intermediate location between Fp and F electrodes; FC stands for the intermediate location between F and C; FT stands for the intermediate location between F and T; TP stands for the intermediate location between T and P; CP stands for the intermediate location between C and P; PO stands for the intermediate location between P and O; T7, T8, P7, P8 on the modified combinatorial nomenclature stands for T3, T4, T5, T6 respectively on the 10-20 system.

EEG is one of the hardest bio signals to read because of its low amplitude which normally ranges between 0.5 μV to 100μV [8]. However, it has great advantage of speed as complex brain patterns can be recorded in real-time. EEG waves are an aggregation of multiple potential of different neutrons and it has been classified into different bands of frequency shown in table 2 and pictorially in figure 2. These different band of frequency represents human activities. The beta waves characterized with high frequencies with lower amplitude than the gamma waves indicate wakefulness, high alert, anxiety. Alpha wave has amplitudes lower than that of the beta waves and indicates awake, relaxed, learning. Theta waves indicates rapid eye movement (REM) sleep, meditation, day-dreaming and delta waves are the slowest and they have the highest amplitude and indicates non-rapid eye movement (NREM) sleep and gamma waves occur during sensory processing of sound and light.

Table 2

Frequency bands of EEG signals [9]

EEG bands	Frequency
Gamma (γ)	(30 - 100) Hz
Beta (β)	(12 - 30) Hz
Alpha (α)	(8 -12) Hz
Theta (θ)	(4 - 7) Hz
Delta (δ)	(0.5 - 4) Hz

3. Methodology

This section is divided into two sub-sections with two primary objectives. In the first objective, two EEG signals are analyzed to ascertain that the blink rate variability is a reliable means of assessing human attention. The second is to extract blink rate data from EEG data sets. The research was approved by the institutional review board of Texas A&M University-Kingsville in accordance with handling of human subject data in research.

3.1. Study of human attention level in relation to blink rate variability

Studies have found that eye blink can also be used to measure human attentiveness [37][38]. It is Observed that EBR reduced when individual perform mental demanding tasks, this which he suggested as to be due to the “prevention in interference between the operational memory and perceptual vision system” [50]. It was also found in an investigation that the relationship between attention bias in human and corresponding eye blink rate using GS task as well as spontaneous BR accurately predicted the magnitude and direction of attention [49]. Task performance has relationship with human attention towards display[45], display types, and his mental workload [46][48]. More recently it was investigated the BRV in individual in rest state and in a reading session, which involved a total of 50 participants whom were required to take different test on the computer and take rest at intervals while the EEG signals where been recorded for both the test period and rest period and both were compared, and it was found that EBR reduced when the participants were undertaking the tests and increased significantly in the rest period [51]. To further certify this finding using a different method of EB extraction this research analyzed EEG signals, extracted blink artefacts from them. Two different data sets were used in this research, one was recorded when the participant was undertaking in a cognitive demanding task which required a high level of attentiveness and the other recorded when the subject was involved in a less-attention demanding activity.

3.2. Extraction of Blink Rate from EEG Data Set

Since the focus of this research is to analyze just blinks from EEG, the readings from the frontal electrodes we are focused on, because they capture the muscle movements responsible for blinks due to their proximity to the eye. The same algorithm was used in the pre-processing and extraction of both signals [10] [11]. The blink detection algorithm is divided into two parts, the first part which is the pre-processing of the signals which involves the cutting off extreme amplitudes which are generally due to the sudden movements of the EEG headset during the recording, band pass filtered the signals with the high pass set to 0.5Hz and low pass to 50Hz these were to correct DC drift and signals to more likely to be populated by muscle movements respectively and then notch filtered to remove the 60Hz line noise. Figure 3 and Fig. 4 show the EEG data signals after they have been preprocessed. The second part is where the blinks are detected. Independent Component Analysis (ICA) was used followed by extraction of independent components epochs and icablinkmetrics plugin to average all epoched components and count the number of EBs. All processing was done in the MATLAB environment using EEGLAB toolbox. The ICA is based on Blind Source separation (BSS) field in Signal Processing. It separates neural activities from muscle related artefacts.

3.2 Independent Component Analysis

Independent Component Analysis (ICA) is used to separate artifacts embedded in recorded data from mixed signals from several sensors. It is a way of decomposing the mixed unknown source signals and the resulting signals remain statistically independent of one another. It finds a linear transformation from one space to another space such that the new individual features are mutually independent of one another. It is directional and could distort the phase and time differences between channels. It is a useful method of solving Blind Source Separation problem.
To illustrate ICA with an example we consider a cocktail party scenario where S1, S2 and S3 are people talking simultaneously, and microphone-detectors D1, D2 and D3 are located at different positions in the room capturing all mixed voice signals it gets. ICA un-mixes these individual voices. A figure illustrating this concept is shown in Fig. 5. In this research RUNICA infomax ICA algorithm was used.

4. Simulation Results And Discussion

4.1. Analysis of blink rate

The ERP components were extracted was from the data after running ICA. These are shown in rectangular form in Fig. 6 and Fig. 7 for both data 2 and data 1. This shows the independent components with the components of eye blinks in the first. The eye blinks were extracted using the ica blinkmetrics plugin it

The eye artifact was characterized with a smooth decreasing spectrum and scalp map showing a strong far-frontal projection as shown in Fig. 8 and Fig. 9 for data 2 and data 1.

Eye blinks count was done also in EEGLAB to visualize the number of EBs of the averaged artifact components. The EB consist of the amplitude of the averaged artifact. The amplitude ranges from 0.5 μV and 130 μV. The EBs are shown in Fig. 10 and Fig. 11 for data 2 and data 1.

Figure 12 and Fig. 13 shows the five largest IC components contribution to alpha band which is characterized with cognitive processes.

4.2. Computational Analysis

The measure of the neural signal was done using the Spectral coherence linear correlation because it can be quantified in the frequency domain by means of cross spectrum. This measure is done to see the relationship between the time-series signals frequency structures over a period of time.

$$C_{xy}(\omega) = E\left[F_x(\omega)F_y^*(\omega)\right]$$

Where, E[a] is the Estimation of function |a|; F_x (ω) is the Fourier transform of x; |ω| is the discrete frequency and * is the complex conjugate. The measure of coherence for two different signals X and Y is a statistical measure of shared periodic signals mixtures.

$$\Gamma_{xy}(\omega) = \frac{\left|C_{xy}(\omega)\right|^2}{\left|C_{xx}(\omega)\right|\left|C_{yy}(\omega)\right|}$$

Where C_{xy} is the cross spectral density between signal X and Y; C_{xx} is the autocorrelation of signal X and C_{yy} is the autocorrelation of signal Y. Figure 14 shows the cross-coherence plot between the two data sets after ICA decomposition. Cross coherence has values between O and 1 with 0 indicating a constant phase difference and 1 indicating random phase difference. A higher coherence indicates that two brain sites are working more closely together but at a specific frequency.

Conclusion

From the EB count of the two datasets, we clearly observed the reduction from 20 blinks in data set 1 when engaged in a less attentive task to 16 blinks in the more attention engaging task. On the power spectral density figures in Figs. 8 and Figs. 9 it can also be observed that power is most prominent in the alpha frequency region and steady decreases as the frequency gets higher. Eye blinks artifacts were observed to have a localized spectral component, high frequency and are strong frontal projection in the scalp maps. The spectral analysis using the cross coherence further shows there is in fact no correlation between the two epoched data. As studied and investigated by [14], [15], [16], [17], [18] and [19] that, eye strain caused by a reduction in EBR which is the primary contributory factor to CVS.

From our results there is a significant reduction in EB in human attentiveness compared with less attentiveness tasks and studies that found that a reduction in EBR caused eye strain. Therefore, it can be

inferred from the two results that when performing an attentive task on VDTs EBR reduces which will catalyze eyestrain- a major CVS symptom. Hence, high attention in VDT use is directly correlated to CVS.

Declarations

• Funding :

we declare that this work has not been funded from any funding sources.

• Conflict of interest :

we declare no conflict of interest.

• Competing interests statement :

This research is a version of MS thesis of the first author Mukhtar bello worked under the supervision of Dr.Gahangir Hossain at the Texas A&M University-Kingsville, TX.

• Authors' contributions :

All authors deserves equal contribution for this paper.

References

1. Computer vision syndrome [Online] Available: http://www.aoa.org/patients-and-public/caring-for-your-vision/protecting-your-vision/computer-vision-syndrome?sso=y [Accessed March 6, 2017]
2. D.W. Thomson, "Eye Problems and visual display terminals-the facts and the fallacies" Ophthal Physiol Opt. pp. 111-119, 1998.
3. S. Wimalasundera, "Computer Vision Syndrome" Galle Medical Journal Vol. 11: No. 1, pp. 25-29 September 2009.E. H. Miller, "A note on reflector arrays (Periodical style—Accepted for publication)," *IEEE Trans. Antennas Propagat.*, to be published.
4. P.L Nunez and R. Srinivasan, "Electric Fields of the Brain", 2nd edition: Oxford University Press, 2006.
5. F. Lopes Da Silva and S. Van Leeuwen, "The cortical source of the alpha rhythm" Neurosciences Letter Vol. 6 237-41. 1977
6. F. Lopes Da Silva, "EEG: Origin and measurement" Centre for Neurosciences, Swammerdam institute for life sciences, University of Amsterdam
7. F. Sharbrough, G.E. Chatrian, R.P. Lesser, H. Luders, M. Nuwer and T.W. Picton, "American Electroencephalographic society guidelines for standard electrode position nomenclature" Journal of Clinical Neurophysiology, Vol. 8, no. 2, pp. 200-202, 1991.

8. David Ibañez, “Artifacts Contaminating Your EEG Recordings”, [Online] Available: http://blog.neuroelectrics.com/author/david-ibanez/. December 18, 2014. Last accessed: February 23, 2017.
9. “5 Types of Brain Waves Frequencies: Gamma, Beta, Alpha, Theta, Delta, Mental Health Daily”, http://mentalhealthdaily.com/2014/04/15/5-types-of-brain-waves-frequencies-gamma-beta-alpha-theta-delta/. Last accessed: Month day, 2017.
10. P. L. Nunez., “Neocortical Dynamics and Human EEG Rhythms”, Neurology, vol. 45 no. 9, 1793-1793-a. September 1995.
11. J.R. Hayes, J.E Sheedy, J.A. Stelmack. C.A. Heaney, “Computer use, symptoms, and quality of life. Optom Vis Sci. 84(8). Pp. 738-744, 2007.
12. http://2010-2014.commerce.gov/news/fact-sheets/2011/05/13/fact-sheet-digital-literacy.html#_edn4 last accessed: February 22, 2017.
13. Ranasinghe, P. et al. “Computer Vision Syndrome among Computer Office Workers in a Developing Country: An Evaluation of Prevalence and Risk Factors.” BMC Research Notes 9 (2016): 150. PMC. Web. 23 Feb. 2017.
14. M. Uchino, D. A. Schaumberg, M. Dogru, Y. Uchino, K. Fukagawa, S. Shimmura, T. Satoh, T. Takebayashi, K. Tsubota. “Prevalence of dry eye disease among Japanese visual display terminal users” Ophthalmology. 2008 Nov; 115(11): 1982–1988. Published online 2008 Aug 16. doi: 10.1016/j.ophtha.2008.06.022
15. A.M. Rossignol, E.P. Summers and L.D. Pagnotto, “Visual display terminal use and reported health symptoms among Massachusetts clerical workers” Journal of Occupational Medicine and Toxicology, Vol. 29 pp. 112-118, 1987.
16. Bagley J., Manelis L., “Effect of awareness on an indicator of cognitive load”. Perceptual and Motor Skills, 49, 591–594. 1979
17. M.K. Holland and G. Tarlow, “Blinking and mental load”. Psychological Reports, 31, 119–127. 1972.
18. M.K. Holland and G. Tarlow, “Blinking and thinking”. Psychological Reports, 41, 403–406. 1975.
19. H.G. Wallbott and K.R. Scherer, “Stress specificities: Differential effects of coping style, gender, and type of stressor on autonomic arousal, facial expression, and subjective feeling”. Journal of Personality and Social Psychology, 61, 147–156. 1991.
20. Montés-Micó, Robert. "Role of the tear film in the optical quality of the human eye." Journal of Cataract & Refractive Surgery 33, no. 9 (2007): 1631-635. doi:10.1016/j.jcrs.2007.06.019.
21. A.R. Bentivoglio, S.B. Bressman, E. Cassetta, D. Caretta, P. Tonali and A. Albanese, “Analysis of blink rate pattern in normal subjects” Movement Disorder Vol. 12, Issue 6, pp. 1028-1034, Nov. 1997. doi:10.1002/mds.870120629.
22. Timothy Root, "Chapter 2: Eye Anatomy." December 13, 2007. Accessed February 27, 2017. https://timroot.com/anatomy/.

23. "The Ocular Surface and Tear Film - URMC - University of ..." Accessed February 27, 2017. https://www.urmc.rochester.edu/medialibraries/urmcmedia/eye-institute/patient-services-information/documents/tear-film-white-paper_020310.pdf.
24. M. Rosenfield, “Computer vision syndrome (a.k.a. digital eye strain)” Optometry in practice. Vol. 17 Issue 1 pp. 1-10 2016.
25. S.G. Mason, A. Bashashati, M. Fatourechi, K.F. Navarro and G.E. Birch, “A comprehensive survey of brain interface technology designs.” Annals of Biomedical Engineering, 35, 2 pp. 137-169. 2007.
26. B.Z. Allison, E.W. Wolpaw, J.R. Wolpaw, “Brain computer interface systems: Progress and opportunities.” In Poll, E. ed. British Review of Medical Devices, In Review
27. P. Shyamkumar, S. Oh, N. Banerjee, V. K. Varadan, "A Wearable Remote Brain Machine Interface Using Smartphones and the Mobile Network", Advances in Science and Technology, Vol. 85, pp. 11-16, 2013
28. R.D. Bickford, “Electroencephalography. In: Adelman G. ed.” Encyclopedia of Neuroscience Birkhauser Cambridge (USA) pp. 371-373. 1987.
29. M. Teplan, “Fundamentals of EEG Measurement” Measurement Science Review Vol. 2 Section 2, 2002.
30. E. Niedermeyer, F.H Lopes da Silva, “Electroencephalography: Basic principles, clinical applications and related fields” 3rd edition, Lippincott, Williams & Wilkins. Philadelphia. 1993.
31. S.A. Chermahini and B. Hommel, “The (b)link between creativity and dopamine: spontaneous eye blink rates predict and dissociate divergent and convergent thinking.” Cognition, 115(3), pp. 458-465. 2010.
32. C.W. McMonnies, “Incomplete blinking: exposure keratopathy, lid wiper epitheliopathy, dry eye, refractive surgery, and dry contact lenses.” Cont. Lens Anterior Eye, 30(1) pp. 37-51. 2007. Doi:10.1016/j.clae.2006.12.002.
33. T. Nakano, M. Kato, Y. Morito, S. Itoi and S. Kitazawa, “Blink-related momentary activation of the default mode network while viewing videos.” Proceedings of the National Academy of sciences of the United States of America, 110(2), pp. 702-706. 2013. Doi:10.1073/pnas.121480410.
34. H.R. Schiffman, “Sensation and perception: An integral approach” John Wiley & Sons. 1990.
35. R. Schleicher, N. Galley, S. Briest and L. Galley, “Blinks and saccades as indicators of fatigue in sleepiness warnings: looking tired?” Ergonomics, 51(7), pp. 982-1010. 2008. Doi: 10.1080/0014013070181817062
36. W. Zhang, B. Cheng and Y. Lin, “Driver drowsiness recognition based on computer vision technology.” Tsinghua Science and Technology, 17(3), pp. 354-362. 2012.
37. E.J. Sirevaag, A.F. Kramer, C.D. Wickens Mark Reisweber, D.L. Strayer and J.F. Grenell,”Assessment of pilot performance and mental workload in rotary wing aircraft” Ergonomics Vol. 36, Iss. 9, pp. 1121-1140. Sep. 1993.

38. J.A. Veltman and A.W.K. Gaillard, “Physiological workload reactions to increasing levels of task difficulty” Ergonomics Vol. 4, Iss. 5, pp. 656-669. May 1998.
39. “The effects of computer use on eye health and vision” American Optometric Association. 1997. [Online available- 02 August 2011] http://www. aoa. org/documents/EffectsComputerUse. pdf [Accessed on March 6, 2017]
40. K. Loh and S. Redd, “Understanding and preventing computer vision syndrome.” Malays Fam Physician, 3(3), pp. 128-130. 2008.
41. M. Logaraj, V. Madhupriya and S.K. Hegde, “Computer Vision Syndrome and Associated Factors Among Medical and Engineering Students in Chennai”. Annals of Medical and Health Sciences Research, 4(2), pp. 179-185. 2014. doi:10.4103/2141-9248.129028
42. P. Ranasinghe, W.S. Wathurapatha, Y.S. Perera, D.A. Lamabadusuriya, S. Kulatunga, N. Jayawardana and P. Katulanda, “Computer vision syndrome among computer office workers in a developing country: an evaluation of prevalence and risk factors.” BMC Research Notes, 9, 150. 2016. doi:10.1186/s13104-016-1962-1
43. S.C. Reddy, C.K. Low, Y.P. Lim, L.L. Low, F. Mardina and M.P. Nursaleha, “Computer vision syndrome: a study of knowledge and practices in university students.” Nepal Journal of Ophthalmol, 5(2), pp. 161-168. 2013 doi:10.3126/nepjoph.v5i2.8707
44. M. Rosenfield, “Computer vision syndrome: a review of ocular causes and potential treatments.” Ophthalmic and Physiological Optics, 31(5), pp. 502-515. 2011. doi:10.1111/j.1475-1313.2011.00834.x
45. S.J. Dain, A.K. McCarthy and T. Chan-Ling, “Symptoms in VDU operators.” American Journal of Optometry and Physiological Optics, 65(3), pp. 162-167. 1988.
46. J.E. Sheedy, I.L. Bailey, D. Fong, M. Ostermeier and S. Stanton “Task performance and contrast polarity on hard copy and video displays.” 1990
47. G.D Brown, S. Yamada, T.J. Sejnowski, “Indepenednt compoenent analysis at the neural cocktail party” Trends in Neurosciences volume 24, Issue 1, pp. 54-63 Jan. 2001.
48. [Online Available] www2.hu-berlin.de/eyetracking-eeg/testdata.html#exampledata.html. Last accessed March 23, 2017.
49. H.A Slayter, R.J. Davidson and R. Tomer, “Eye blink rate predicts individual differences in pseudoneglect”
50. E. Ponder and W.P. Kennedy, “On the act of blinking”. Quarterly Journal of Experimental Physiology 18, pp 89-110. 1927. doi:10.1113/expphysiol.1927.sp000433
51. A. Lenskiy, R. Paprocki, “Blink rate variability during resting and reading sessions” IEEE conference on Norbert Wiener in the 21st century (21CW). Australia, pp. 90-95, July, 2016.

Figures

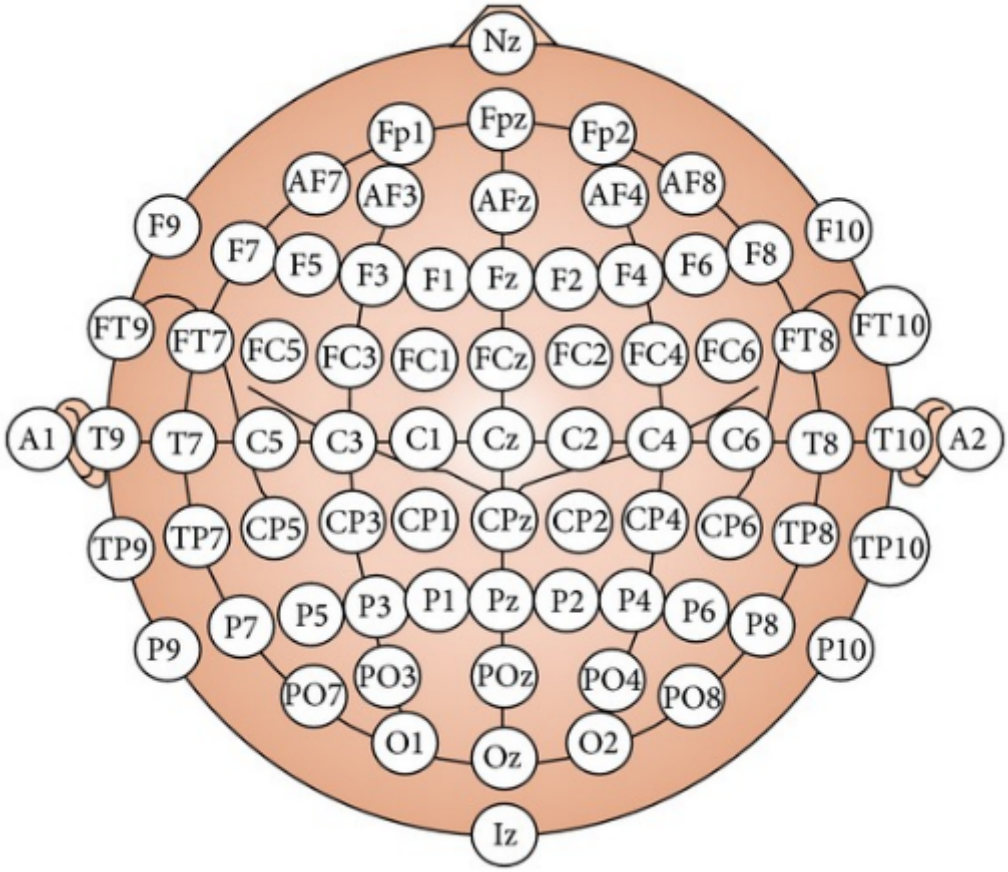

Figure 1

The 10-20 system of electrode placement [8].

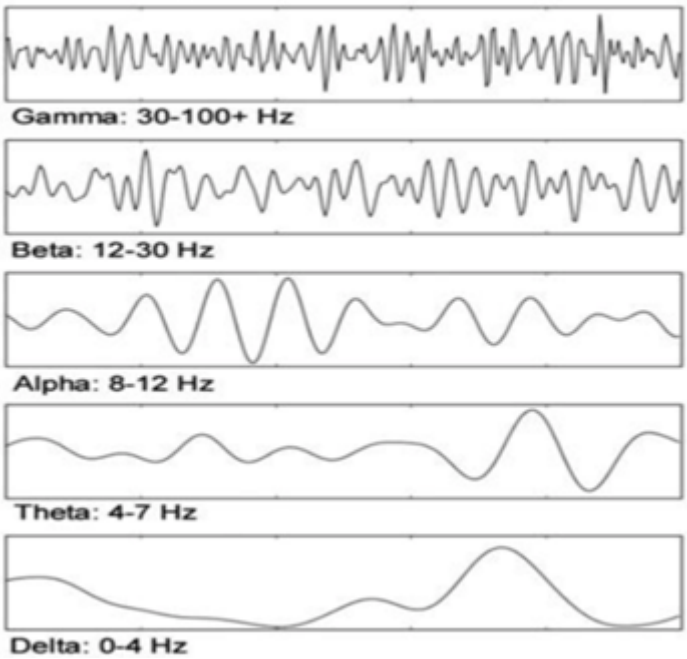

Figure 2

Frequency bands of EEG signals [10]

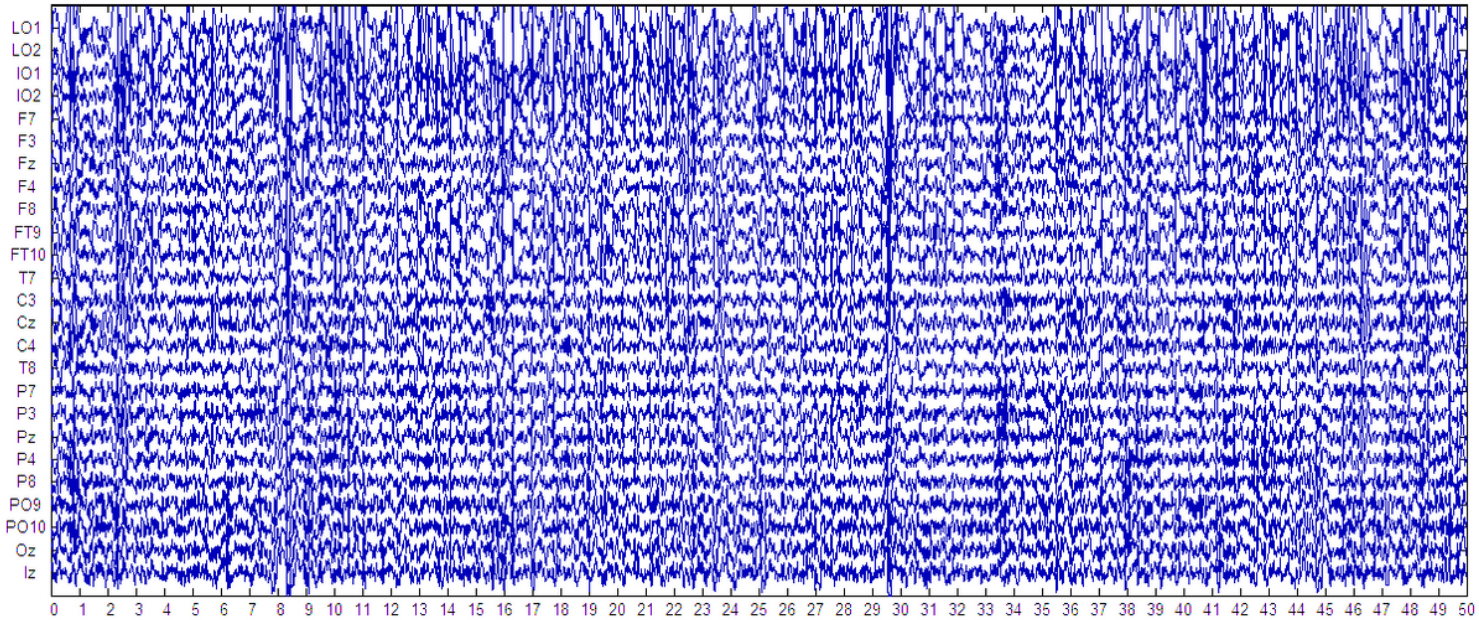

Figure 3

Time-series plot of Data 2

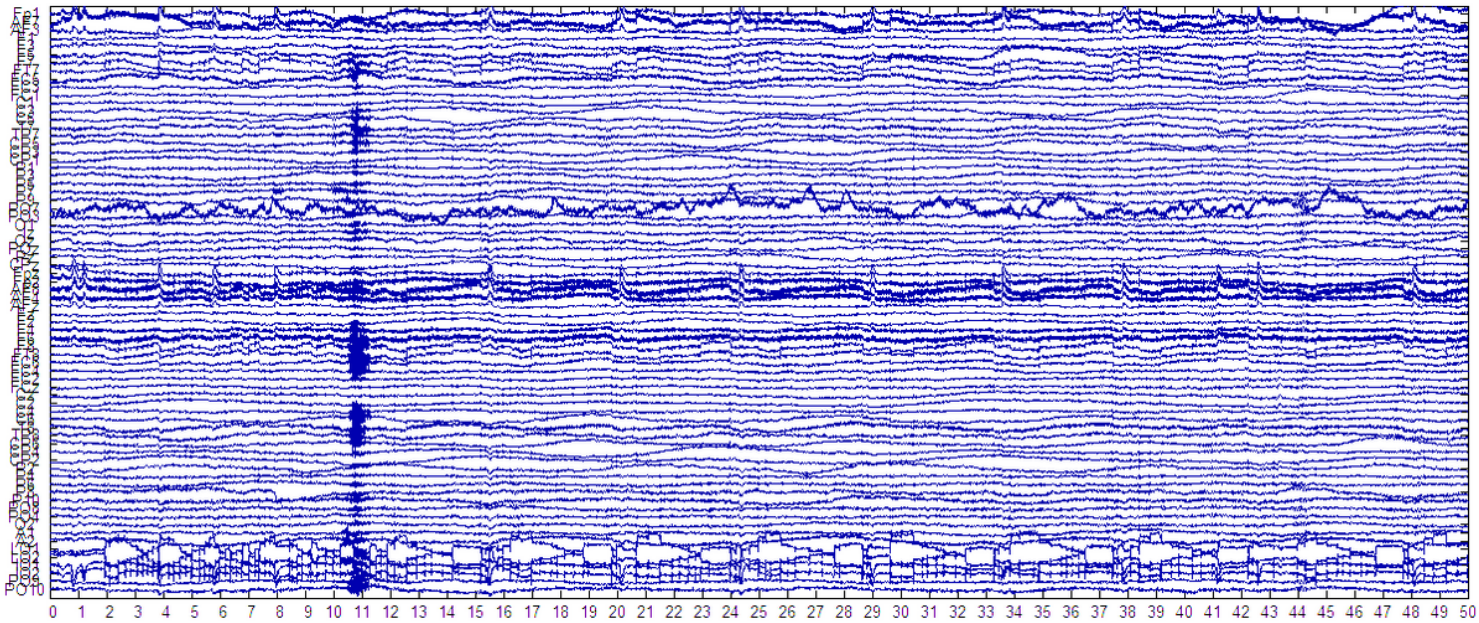

Figure 4

Time-series plot of Data 1

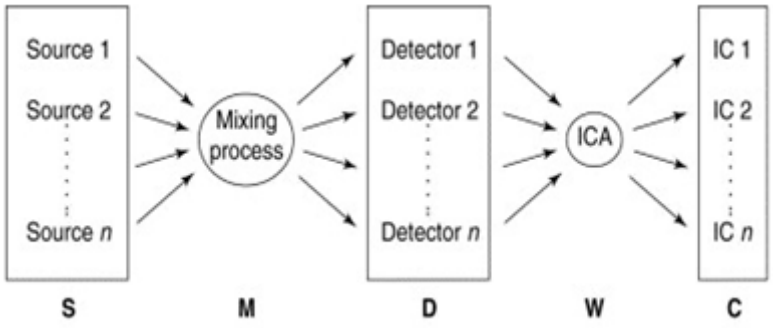

Figure 5

BSS using ICA illustration [47]

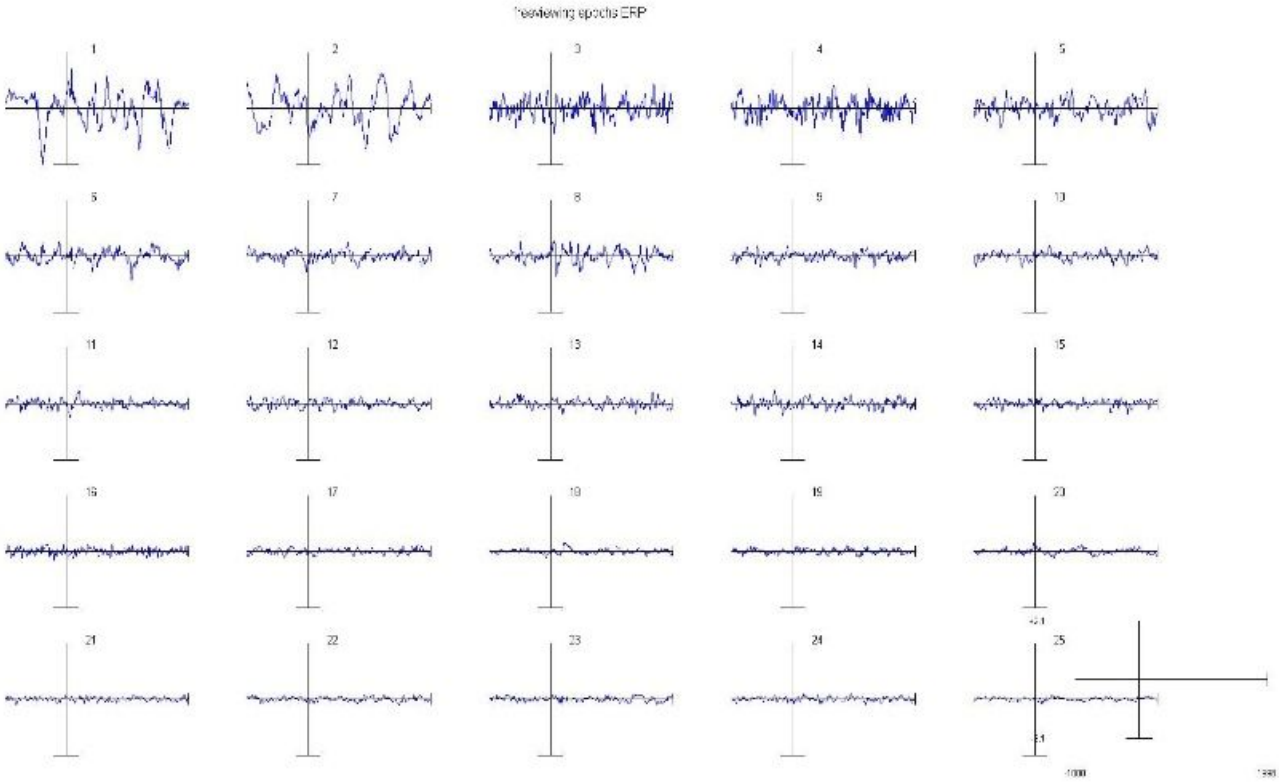

Figure 6

Independent components array in rectangular array for data 2

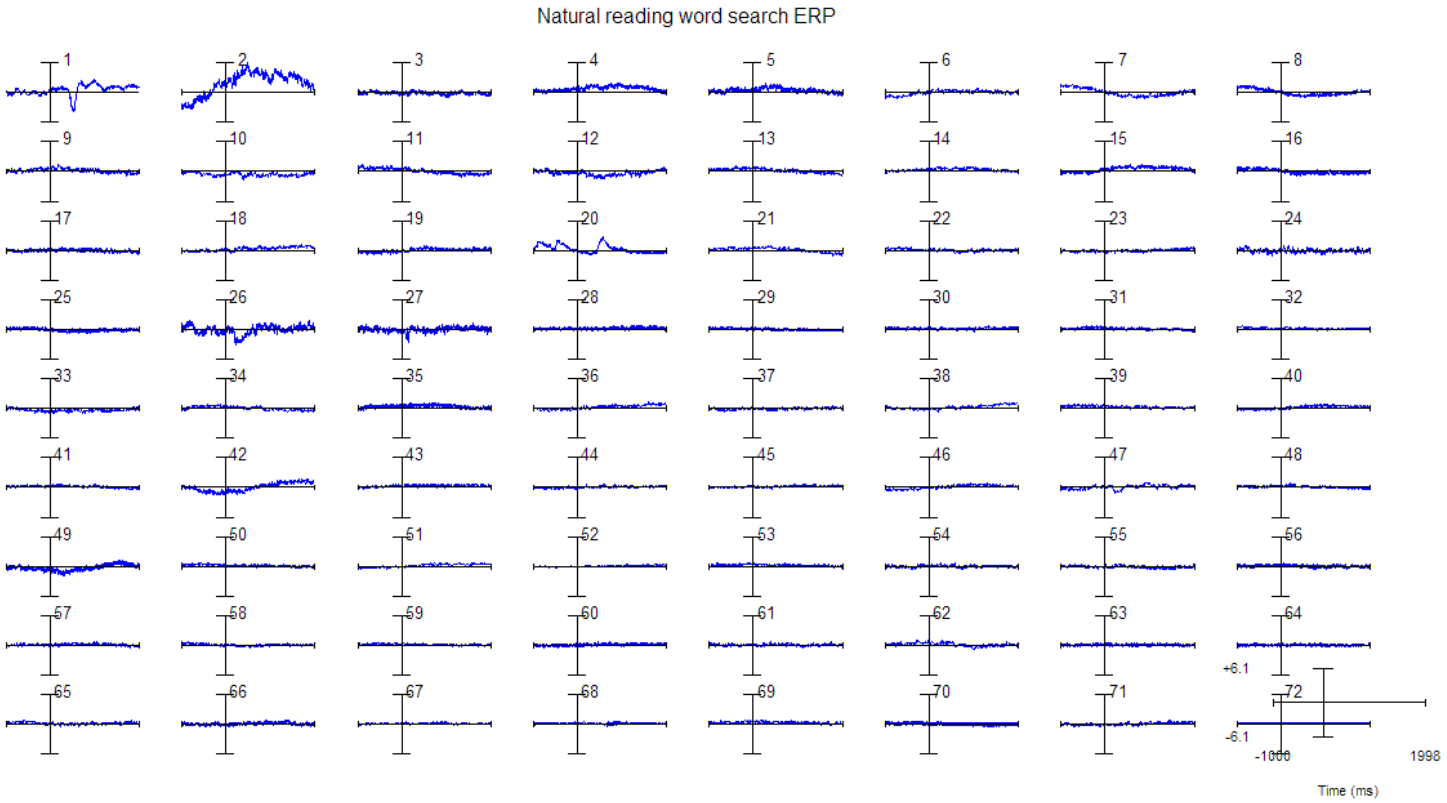

Figure 7

Independent components array in rectangular array for data 1

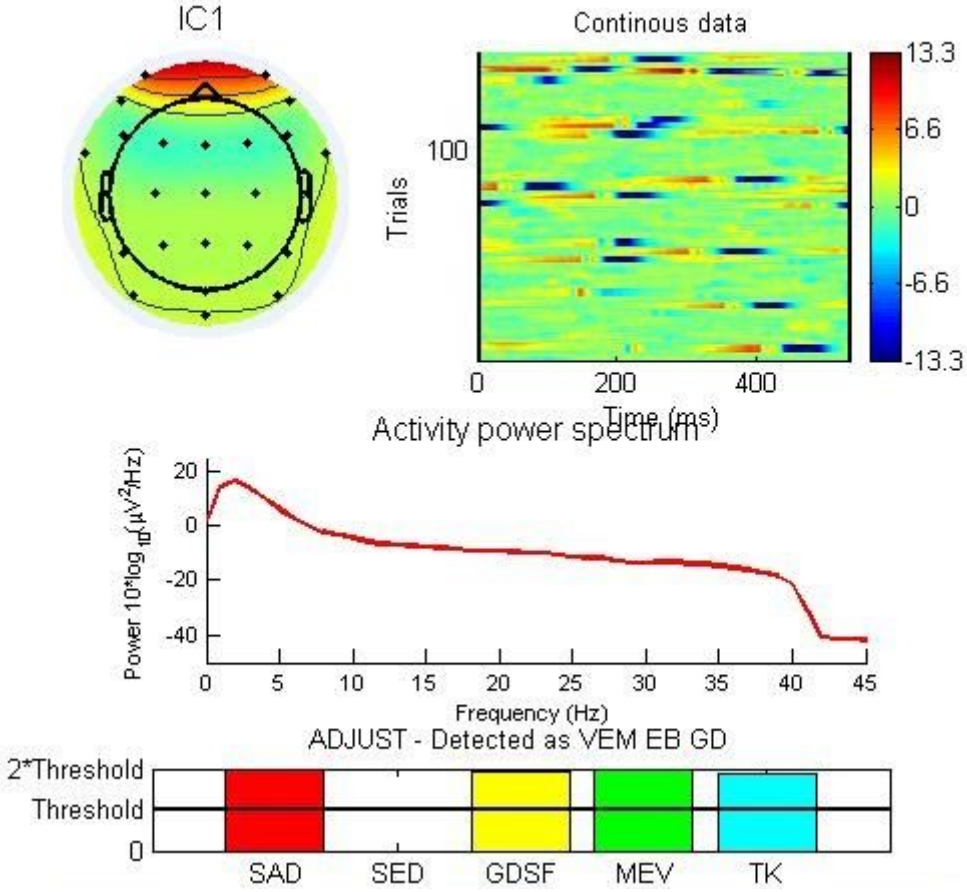

Figure 8

Image showing scalp projection and power spectral density plot of Data 2

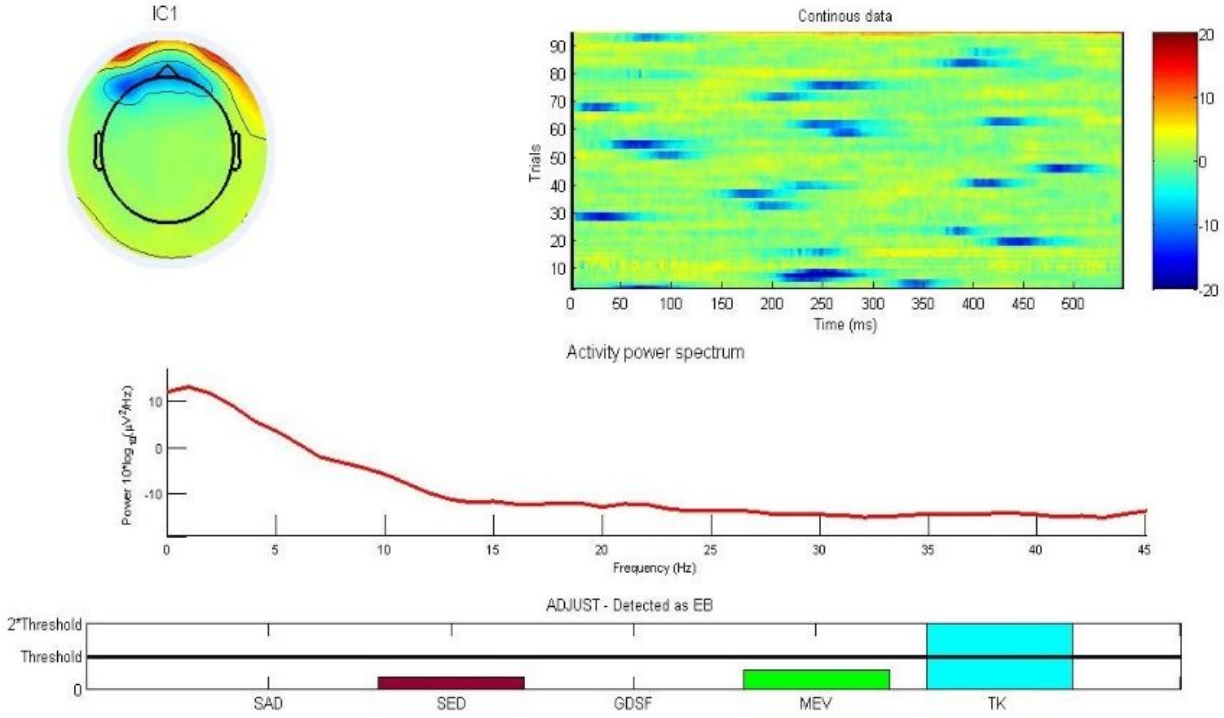

Figure 9

Image showing scalp projection and power spectral density plot of Data 1

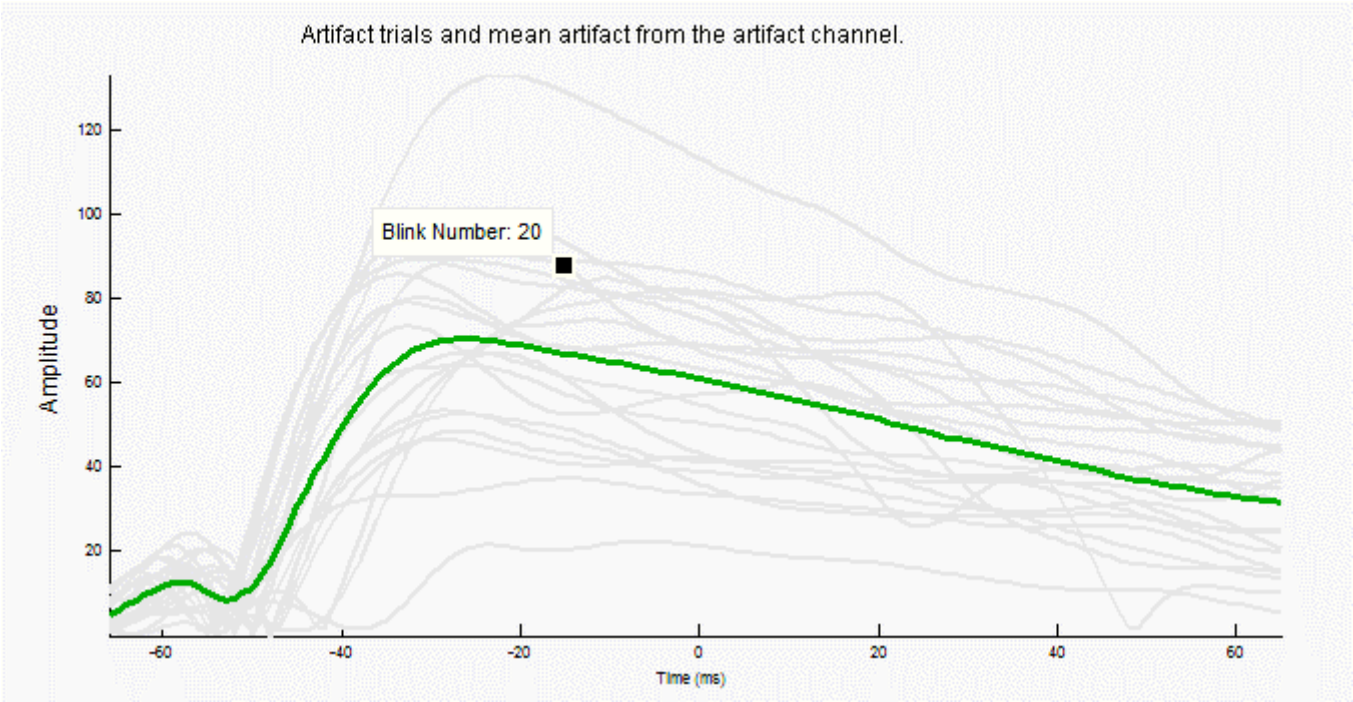

Figure 10

Number of blinks for data 2

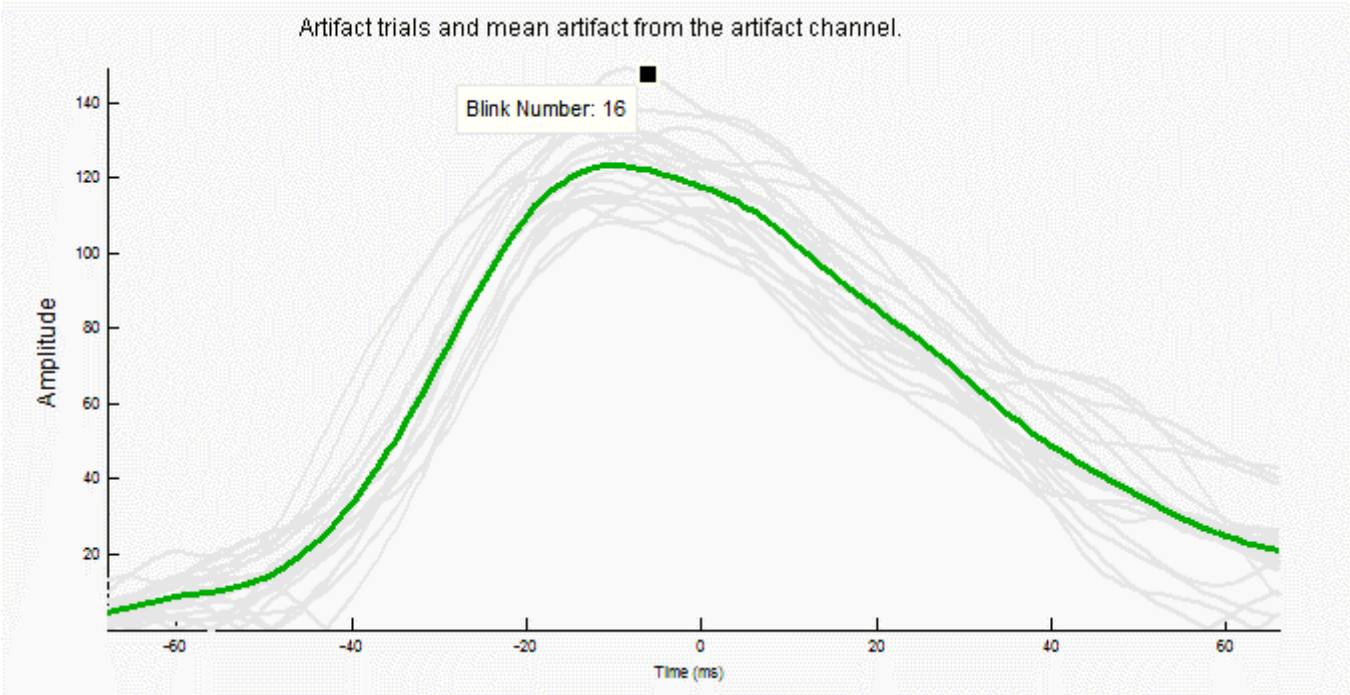

Figure 11

Number of blinks for data 1

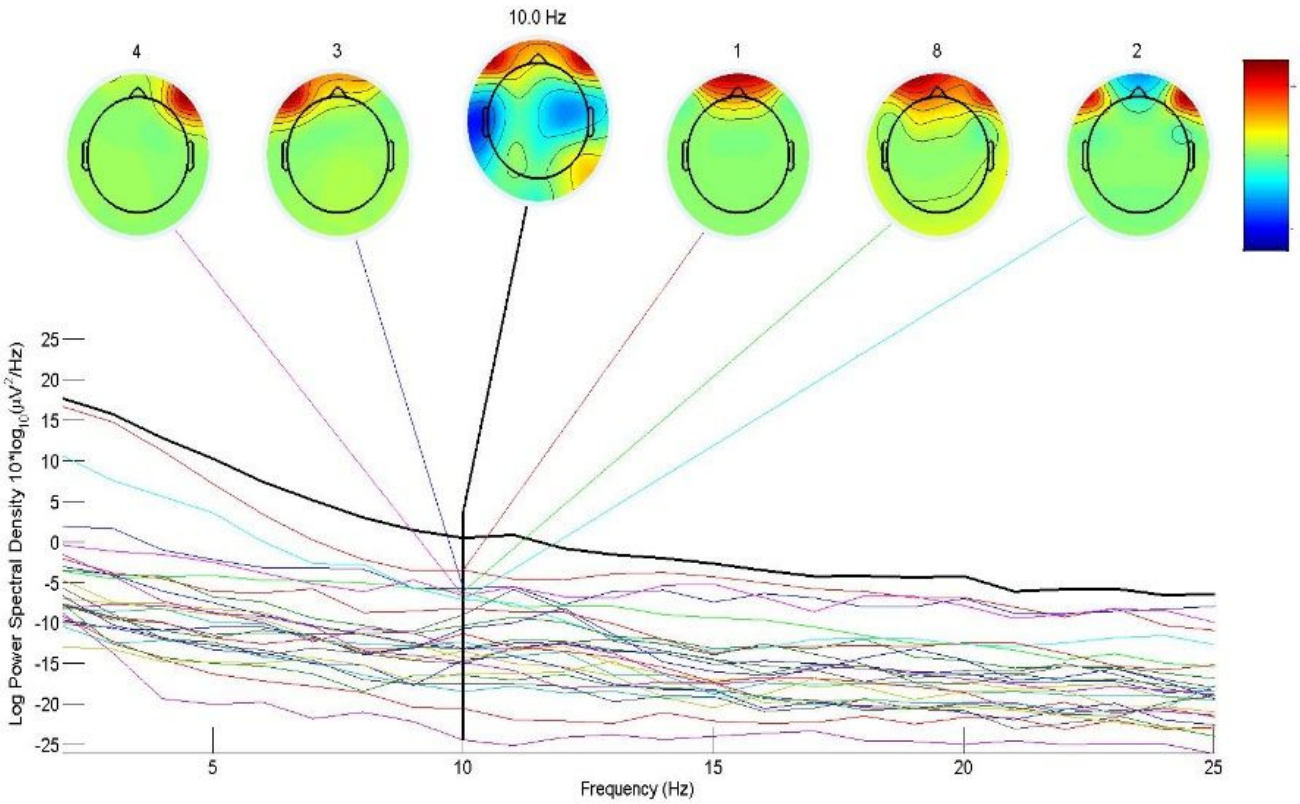

Figure 12

Largest data 2 contributor to the alpha band component

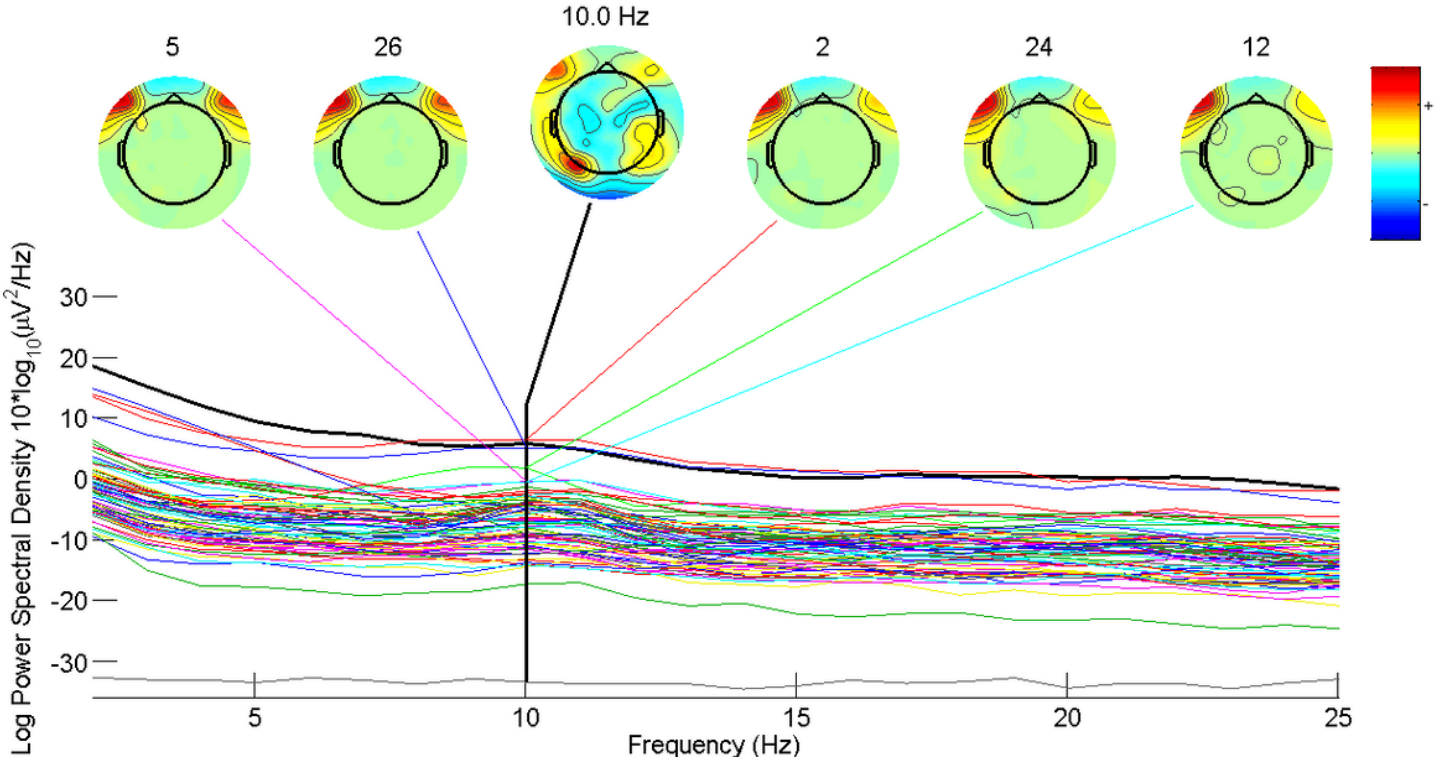

Figure 13

Largest data 1 contributor to the alpha band component

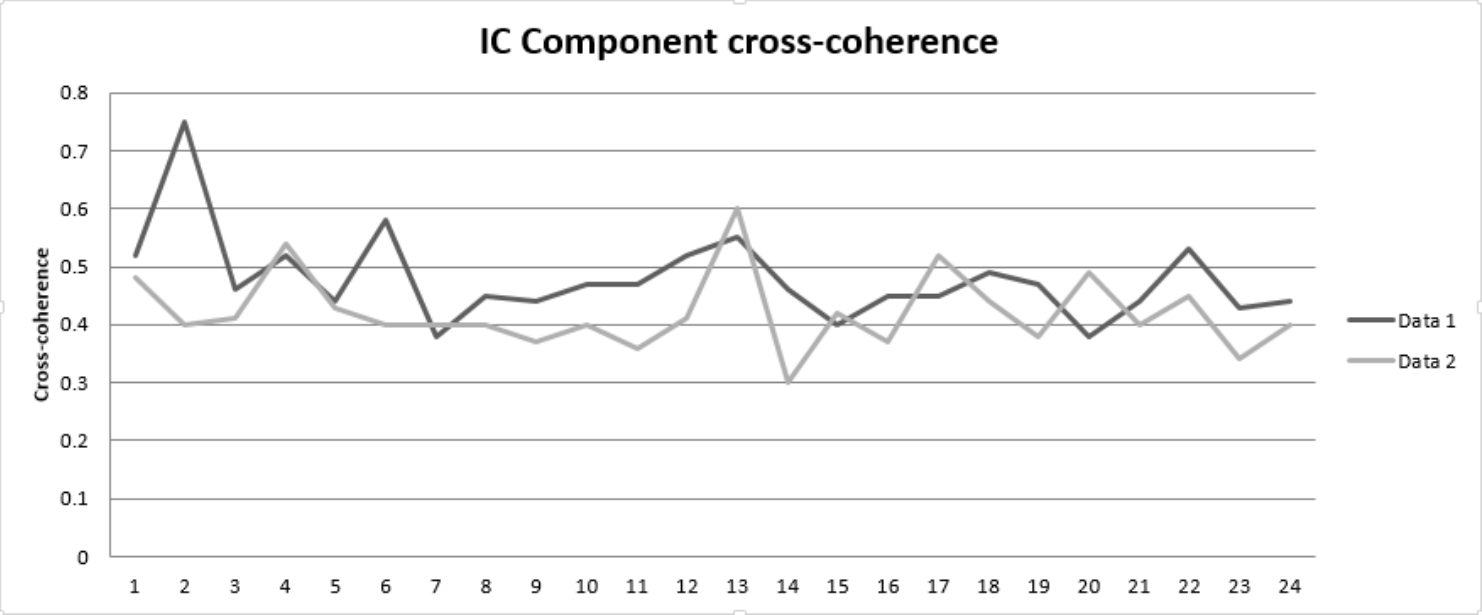

Figure 14

Cross-coherence between the two data sets