Directions of Autism Diagnosis by Electroencephalogram Based brain Computer Interface: A Review

Ebtehal A Alsaggaf[1], MSCS; Sundus S Baaisharah[2]

[1.] Department of Computer Science, Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah, Saudi Arabia.
Email: eaalsaggaf@kau.edu.sa
[2.] Department of Medicine, Faculty of Medicine, King Abdulaziz University, Jeddah, Saudi Arabia
Email: sundus_ba@hotmail.com

Abstract: Autism is a social development disorder that is a difficult task to diagnose by a medical professional with support from physical, occupational and speech therapists. It is being investigated through many different approaches. This paper review the literatures of EEG and BCI that help us to answer some unanswered questions by many psychologists, scholars of education and parents of autistic children about common signs of autism such as problems with social skills, interaction, and communication. This can be seen as the ground work for applying new BCI applications for further development diagnosis of the autism to see how the treatment is working as well in future.
[Alsaggaf E, Baaisharah S. **Directions of Autism Diagnosis by Electroencephalogram Based brain Computer Interface: A Review.** *Life Sci J* 2014;11(6):298-304]. (ISSN:1097-8135). http://www.lifesciencesite.com. 39

Keywords: Autism disorder; Electroencephalography; EEG; BCI.

1. Introduction

Autism is a social development disorder that is marked by a distinct lack of social and language skills. It is a disorder rather than an organic disease and hence is a difficult task to diagnose by a medical professional with support from physical, occupational and speech therapists. In previous years, either a psychologist or psychiatrist experienced with Autistic Spectrum Diagnosis (ASD) can make a diagnosis. Currently doctors use a psychiatric manual, the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV) to diagnose psychiatric disease. Early detection provides the best opportunity for early intervention which results in significantly improved outcomes for children with autism. But, it can be far from accurate as so many mental illnesses are complex disorders with a multitude of symptoms that can ebb and flow and even change over the years.

Therefore, Scientists of AI, including pattern recognition, works for supporting the idea that computer science can be used to help them. Fortunately, with the advancements in technology, researchers have developed innovative solutions to discover and improve the quality of life for those children with the advancement of ECG analysis (Alsaggaf and Gamalel-Din, 2011).

The diagnosis of autism is one of the difficult problems facing researchers and those interested in the field of signal processing and medicine. Therefore, there is a lot of research going on around the world today trying to use neuroscience such as EEG study to identify individuals with Autism (William et al., 2011). Hence, a need for automatic detection of Electroencephalogram (EEG) signals has been sought by many researchers to diagnose autistic people. They reported different findings regarding to discriminate patterns between normal and autism subjects (Fabricius, 2010, Behnam et al., 2007).

In recent years, there has been an increasing interest in applying machine learning methods to the automated detection of autism EEG signals (S. E. Schipul 2010, Bosl, 2011).

EEG signals analysis based on machine learning methods has three main steps: preprocessing, feature extraction, and classification. The developing and understanding classification algorithms for the analysis EEG signals is crucial in the area of ASD which focus on communication and control, the related field. of Neuro Feed Back (NFB) supports feedback training in autism (Varon, 2011, Thompson et al., 2009b, Pfurtscheller et al., 2010). In theory, our review can be covering the need for using neuroscience with computer science to discover autistic subject.

Since there is not a medical test for autism and a diagnosis is based on observed behavior and educational and psychological testing. Thus, the analysis and classification of EEG signals will properly diagnose the patient (Thompson and Thompson, 2010, Fabricius, 2010).

Therefore, the current hypothesis is to make test model more usable and practical in EEG based Brain Computer Interface (BCI). Furthermore, this integration can help us to see how the diagnosis can be done and the treatment are working as well.

Actually, this can help us to see how the diagnosis can be done and the treatment are working as well. Hence it can be improved the behavior via NFB training in future as therapy for ASD (Thompson et al., 2009a, Pineda et al., 2008).

In this paper, the following needed fields are mandated for improving the diagnosing and therapy performance for the autism using EEG patterns (see Figure 1). We start with autism therapy and EEG based BCI and then give a description of interpretations of brain activity EEG in Autistic disorder. Finally, EEG Signal processing and Machine learning algorithms, that can be used for people with autism, is described in, and a conclusion is given in last section.

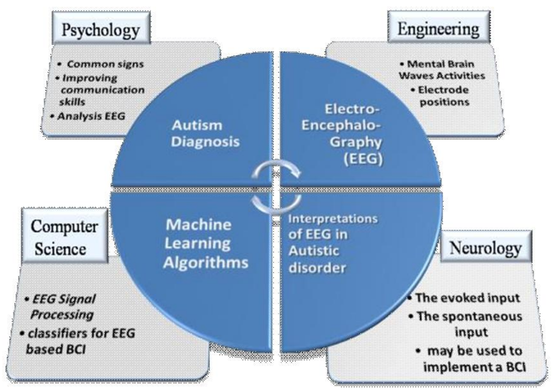

Figure 1. The fields for the Autism Diagnosis and Therapy using EEG patterns.

2. Autism Therapy and EEG based BCI

The principal goal of therapy for autism is to improve useful communication skills where no treatment method has been found for all individuals who have autism(NIDCD, 2011). On the other hand, over 80% of BCI publications describe BCIs that rely on the EEG to measure brain activity where the principal goal of BCI research is to develop systems that allow disabled users to communicate with other persons, to control artificial limbs, or to control their environment. Similarly, BCIs have recently been validated as advanced NFB tools for autism and other disorders, in which the goal of the BCI is not communication but rehabilitation (Allison et al., 2007, Allison et al., 2010). To achieve both goals, the integration of BCIs with other interfaces will be needed(Allison et al., 2007), to improve the diagnosing and therapy performance for the autism. Thus, we focused on research literatures of EEG areas including the evaluation of accuracy for the employed classifiers to discriminate between normal and autism subjects in EEG Signal processing and Machine learning algorithms section.

Furthermore, the main goals of treatment of ASD are to lessen associated deficits and family distress, and to increase quality of life and functional independence. No single treatment is best, and treatment is typically tailored to the child's needs. Available approaches include applied behavior analysis, developmental models, structured teaching, speech and language therapy, social skills therapy, and occupational therapy(Lord and Bishop, 2010, Yaozhang, 2009).

2.1 Autism Diagnosis

The diagnosis of ASDs is based on the DSM-IV criteria. This criteria includes three main impairments that must be fulfilled for the diagnosis:

a) Impairment in social interaction;
b) Impairments in communication;
c) Restricted repetitive and stereotyped patterns.

Early diagnosis of ASDs is crucial and enables early intervention. However, diagnosis before the age of three is very challenging . The DSM-IV criteria is very difficult to be applied on young children especially those under three. The diagnosis depends on clinical judgments which may not meet this criteria (Raymaekers et al., 2009, Thompson and Thompson, 2010). An increasing number of occupational and physical therapists are looking for answers beyond what their training has given them and are seeking to gain a deeper understanding of how best to help these children(Amanor-Wilks, 2009).

Typically, medical professionals are not trained extensively in diagnosing and evaluating autism and related disabilities. Doctors will usually rule out other possibilities(CARD, 2008a) where the diagnosis includes the following:

1. Physical examination (may include neurological examination)
2. Medical history (includes family history, birth history, and early development)
3. Medical tests (to rule out other conditions)(Stanley J. Swierzewski, 2007)

There is no specific medical test or procedure can confirm a diagnosis of autism(CARD, 2008b). Hence, there arises a need for analysis and classification of EEG signals to diagnose the *autism*. In the research literature on autistic spectrum disorders, "five areas of the brain are repeatedly found to differ when compared to people with normal development. Most of these areas are connected to what is called the mirror-neuron system (MNS). Mirror neurons are groups of neurons that fire when a person is watching and mentally mirroring the actions of another person. In children with autism, this MNS is not functioning normally. The great interest is that the lack of normal functioning in these critical areas of the brain can be easily seen using EEG. Later it can be analyzed and one can see what differs in that child's patterns in terms of over-activation (or lack of activation) at various sites on the scalp"(Thompson and Thompson, 2010).

2.2 Electroencephalogram (EEG)

EEG is a procedure that measures the electrical impulses in the brain. An EEG is done by placing small sensors (electrodes) on a person's scalp to detect the electrical impulses moving through the brain. Recent advances in computer hardware and signal processing have made possible the use of EEG signals or "brain waves" for communication between humans and computers.

EEG is becoming increasingly important measurements of brain activity and they have great potential for the diagnosis and treatment of mental and brain diseases and abnormalities. It is recorded between electrodes placed in standard positions on the scalp and has typical amplitude of 2-100 microvolts and a frequency spectrum from 0.1 to 60 Hz. Most activity occurs within the frequency bands (Sanei and Chambers, 2007) describe in following table .

Furthermore, Electrodes are cup-shaped to hold electrolytic paste or gel depending on how they are affixed to the scalp. The electrolytic paste and gel aid the conductivity of the electrodes and help prevent motion artifact.

.The international 10–20 system of electrode placement and the electrode position names consist of a letter followed by a number. The letter indicates the structural lobe below the electrode: Frontal, Central, Parietal, Occipital, and Temporal. Numbers indicate if the electrode is left, right, or on the midline. Odd numbers indicate left, even numbers indicate right, and 'z' for 0 indicates on the midline (Graimann et al., 2011)(See Figures 2 and 4)

Table 1. Mental Brain Waves Activities

Type	Frequency	Location	Use
(delta, δ)	0.5 - 4 Hz	everywhere	occur during sleep, coma
(theta, θ)	4-8 Hz	temporal and parietal	correlated with emotional stress (frustration & disappointment)
(alpha, α)	8-13 Hz	occipital and parietal	reduce amplitude with sensory stimulation or mental imagery
(beta, β)	13-30 Hz	parietal and frontal	can increase amplitude during intense mental activity
(gamma, γ)	30-40 Hz	Somatosensory cortex	related to subjective awareness
(Mu, μ)	8-13 Hz	frontal (motor cortex) It is detected on the central electrode sites (over the sensorimotor cortex)	diminishes with movement or intention of movement Sensory motor rhythms

A difficulty faced by EEG researchers is the fact that electrical activity generated by these separate assemblies becomes mixed and via across the scalp. That is, each EEG electrode records a mixture of signals arising from multiple cognitive processes and from on-going "background" oscillatory activity. Furthermore, scalp electrodes also record activity from non-brain sources including muscle (e.g., eye-movements) and in some cases from non-physiological electrical sources (e.g., line-noise). Filtering and artifact rejection reduce the influence of some of these unwanted contributions to EEG which is difficult to observe and measure on a trial-by-trial basis(Milne, 2011).

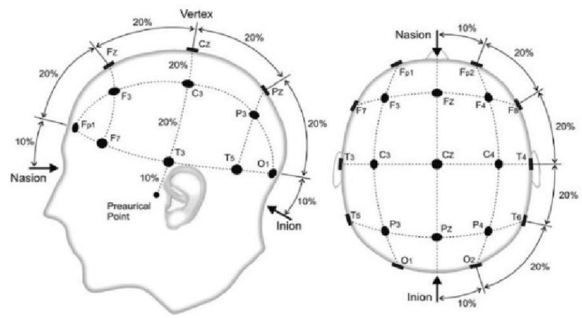

Figure 2 *The international 10–20 system: the left image shows the left side of the head, and the right side presents the view from above the head. The nasion is the intersection of the frontal and nasal bones at the bridge of the nose. The inion is a small bulge on the back of the skull just above the neck*

3. Interpretations of EEG in Autistic disorder

The brain wave patterns of other disorders differ broadly. Generally brain wave patterns in patients with brain disease, mental retardation, and brain injury show overall slowing. Several types of childhood autism have characteristic differ EEG patterns that lead to a specific diagnosis and treatment. Interpretations of EEG signals visually often require expert medical or technical professionals. To overcome this problem and to automate EEG analysis, spectral analyses of EEG signals have been used. On other hand, BCI is a direct connection between computer(s) and the human brain. It is the ultimate in development of Human-Computer Interfaces (HCI). Mostly it is used for disabled or autism persons. Recently, efforts have been made on the development of EEG-based real-time applications in multimedia communication, rehabilitation games, interaction in virtual environments, etc. (Sourina et al., 2011).

The literatures of EEG and BCI help us to answer some of the questions that unanswered by many psychologists, scholars of education and parents of autistic children about common signs of autism such as problems with social skills, interaction, and communication. Several kinds of mental which can be divided into two main groups according to how they are generated; using evoked input (e.g. Steady State visual evoked potentials and P300) and spontaneous input (e.g. sensorimotor rhythms) and might be used to implement a BCI system. In the following subsections, these neurophysiological phenomena were used to answer their questions . These answers are based on a lot of pattern recognition methods such as signal processing, feature extraction and pattern classification algorithms.

3.1 P300 Evoked Potential

The P300 (P3) wave is an Event Related Potential (ERP) elicited by infrequent, task-relevant stimuli. It is considered to be an endogenous potential as its occurrence links not to the physical attributes of a stimulus but to a person's reaction to the stimulus.

More specifically, one study was reported a decrease P300 components in autistic individuals, indicating that this population presents abnormalities on central aspects of auditory processing(Magliaro et al., 2010). Because individuals with autism may exhibit perceptual, attention and memory impairments, they might sometimes be misdiagnosed as hearing impaired. Therefore, it is necessary to identify alterations in the central auditory system through objective tests in order to provide an accurate diagnosis and a more effective intervention, which will determine a smaller reduction in quality of life of these individuals.

The other literature was reported focusing on bottom-up and top-down attention in HF-ASD using the P300. Their results suggested that bottom-up involuntary attention is unaffected in high-functioning autism spectrum disorder (HF-ASD), while lower level and top-down visual information processing are impaired in the condition(Maekawa et al., 2010). This explains why the individuals with HF-ASD often show superior performance in simple visual tasks, despite difficulties in the perception of socially important information such as facial expression. The neural basis of visual perception abnormalities associated with HF-ASD is currently unclear.

These literatures analysis of simultaneous EEG by applying preprocessing techniques and using statistical methods such as ANOVA1 or effective machine learning algorithms such SVM classifier to automatically detect seizures onset.

3.2 Steady State Visual Evoked Potential

SSVEP is signals that are natural responses to visual stimulation at specific frequencies. When the retina is excited by a visual stimulus ranging from 3.5 Hz to 75 Hz, the brain generates electrical activity at the same (or multiples of) frequency of the visual stimulus. This technique is used widely with EEG research regarding vision. Rather, SSVEPs recorded from the occipital scalp are used as the input of our BCI system. SSVEP-based BCI is essentially EEG-based vision-tracking system which can be useful to measure the autistic ability to control eye movements.

Abnormal attention in autism shown by SSVEP and they found that lack of hemispherically independent modulation in autism may reflect the operation of a non-specific mechanism of sensory gating . EEG analysis was applied using statistical methods (Belmonte, 2000).

Another study aimed to objectively evaluate the neural substrates of the atypical visual performance observed in ASD, their results indicated that color-processing abnormalities are also involved in high-functioning ASD. Offline data analysis was applied using Fast Fourier Transform(FFT) and the mean number of viable trials between the two groups was analyzed using t-tests (Fujita et al., 2010).

The interpretation from those literatures is in accord with findings showing in previous Section where the individuals with ASD often show superior performance in processing fine detail, but impaired performance in processing global structure and motion information.

3.3 µ–rhythm BCI (Motor imagery)

µ–rhythm is the idle-rhythm of the motor cortex. It changes as people perform or imagine movement. If you imagine moving, you can reduce the amount of mu activity. The beta component of the µ wave arises from the motor cortex and is most active under the CZ, C3, and C4 electrodes.

Several studies have suggested that individuals with autism suffer from impairments in imitation, which is thought to be critical for early affective, social and communicative, this is due to a dysfunctional MNS which may explain the pathology observed in ASD. Because EEG oscillations, in the mu frequency over sensorimotor cortex, are thought to reflect mirror neuron activity. Some results supported the hypothesis of a dysfunctional mirror neuron system in individuals with ASD. In most of these studies, Raw EEG data was filtered and re-referenced off-line to the digital average of the two mastoids. Eye movements were corrected using an Independent Component Analysis (ICA) procedure. For each such segment, the power spectra were computed using a FFT to classify the power spectra features. Then the classifications were applied by statistical analysis, such as three-way MANOVA, t-test and one-sample t-tests and the correlation analyses (Raymaekers et al., 2009, Thompson and Thompson, 2010, Oberman et al., 2005, Pineda et al., 2008, Thompson et al., 2009a).

On other hand, there are many ways to design a BCI system for mu . This dictates many of the choices, such as the use of spatial and spectral filtering options(McFarland et al., 2006). In addition, the adaptive processes in the Wadsworth mu-based BCI are summarized in Table 2.

Table 2. Wadsworth mu-based BCI

Parameter	Dependency	Method of adaptation	Algorithm
Signal mean	EEG data	Feedforward	Signal statistic
Proportion of signal mean	Pattern of targets hit	Feedback	LMS
Standard deviation	EEG data	Feedforward	Signal statistic
Gain for standard deviation	Pattern of targets hit	Feedback	LMS
Weighted features	Difference between target position and cursor position	Feedback	LMS

3.4 *γ –rhythm BCI (Gamma)*

The Gamma -band has received significant attention in recent years because of its long postulated association with perceptual binding and connectivity, related concepts as dysfunctional in autism(Rojas et al., 2008). Autism seen as a signal-processing problem, several studies have shown a significant decrease in the coherence and increased activity in the Gamma band in the autistic brain(Thompson and Thompson, 2010, Fabricius, 2010). Signal statistic is achieved to discriminate between normal and Autism subjects. This explains why they often show superior performance in simple visual tasks.

Overall, both Gamma and Mu rhythms different from the P300 and the VEP- brain computer interfaces because they are not evoked potentials. Moreover, the P300 and the VEP are mainly tested on adults and Teens. They also are displayed even when a person is not processing sensory motor inputs or motor outputs. For that reasons, we interest to study the Mu or Gamma frequency that appear in BCI task.

4. EEG Signal processing and Machine learning algorithms

Machine Learning is generally taken to encompass automatic computing procedures based on logical or binary operations, which learn a task from a series of examples. Here we are just concerned with classification. As known, in machine learning and pattern recognition, classification refers to an algorithmic procedure for assigning a given piece of input data into one of a given number of categories. The construction of a classification procedure from a set of data for which the true classes are known has also been variously termed pattern recognition, discrimination, or supervised learning (in order to distinguish it from unsupervised learning or clustering in which the classes are inferred from the data) (Michie et al., 1994).

Several different machine learning algorithms were combined with the EEG to distinguish between individuals with autism and neurotypical controls with an accuracy based on brain imaging data concerning structure, activation, and synchronization(S. E. Schipul 2010, Bosl, 2011). These classifiers were able to distinguish between individuals with autism and neurotypical controls with high percent accuracy. Taking into account that signal processing and machine learning algorithms are part of typical BCI algorithms which consist of different stages summarized in Figure 3.

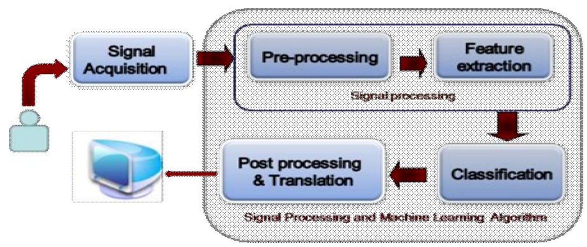

Figure 3. Schematic of a typical BCI system

However, all these researches will help us to design new detection model for discriminate of autisms that statistical methods and effective machine learning algorithms (e.g, as feature extraction and classification) are utilized in EEG signal processing for automatic seizures detection.

5. Conclusion

In this paper the background of EEG and Autistic disorder was review. All utilized electrical activities of the brain for BCI (e,g, Mu rhythms, P300 and SSVEP), are showed the relationship between EEG pattern and Autistic disorder and how this relationship based on a lot of pattern recognition methods such as signal processing, feature extraction and pattern classification algorithms. Two factors that can classify the exact type of the seizure are the pattern of EEG and location of these waves.The classification algorithm is the main part for autism diagnosis which supervised learning algorithms are used to learn and model the input relationship of the BCI applications.

This review can be seen as the ground work for applying new BCI applications for further development diagnosis of the autism. For more, this way solves the problem of autism diagnosis which is baffled all scholars in various fields such as Psychologists, Engineering, Neurologists and Computer Science scholars. This will aid more efficient and highly useful diagnosis for both patients and doctors than the traditional diagnosis method which previously had some constrains for efficient treatment.

Acknowledgements:

This article was funded by the Deanship of Scientific Research (DSR), King Abdulaziz University, Jeddah. The authors, therefore ,acknowledge with thanks DSR technical and financial support.

Corresponding Author:
Mrs. Ebtehal A Alsaggaf
Department of Computer Science, Faculty of Computing and Information Technology, King Abdulaziz University,
Jeddah, Saudi Arabia.
Email: eaalsaggaf@kau.edu.sa

References

1. Alsaggaf E, Gamalel-Din S. Exploration of Autistic Children using Case Based Reasoning system with Cognitive Map. In: WASET; 2011; Dubai, UAE. 2011. p.1114-4.
2. William B, Adrienne T, Charles N. EEG complexity as a biomarker for autism spectrum disorder risk. BMC Medicine. 2011;9.
3. Fabricius T. The Savant Hypothesis: Is autism a signal-processing problem? Medical Hypotheses. Science Direct. 2010.
4. Behnam H, Sheikhani A, Mohammadi M.R, Noroozian M, Golabi P. Analyses of EEG background activity in Autism disorders with fast Fourier transform and short time Fourier measure. In: International Conference on Intelligent and Advanced Systems. IEEE; 2007. p.1240-4.
5. Schipul S.E, Just M.A. Applying Machine Learning Techniques to Brain Imaging Characteristics to Distinguish Between Individuals with Autism and Neurotypical Controls. INSAR. 2010.
6. Bosl C.A.N. Using EEGs to Diagnose Autism Spectrum Disorders in Infants: Machine-Learning System Finds Differences in Brain Connectivity. ScienceDaily. 2011.
7. Varon D.A.V. Practical Brain Computer Interfacing. Dr.Hut; 2001.
8. Pfurtscheller G, Leeb R, Faller J, Neuper C. Brain-Computer Interface Systems used for Virtual Reality Control. Virtual Reality. 2010.
9. Thompson L, Thompson M. Notes on Autism Quantitative Electroencephalogram (QEEG) Findings & Neurofeedback Training ADD Centre. Biofeedback Institute of Toronto. 2010.
10. Thompson L, Thompson M. and Reid A. Neurofeedback Outcomes in Clients with Asperger's Syndrome. Applied Psychophysiology and Biofeedback. 2009;35:63-18.
11. Pineda J.A, Brang D, Hecht E, Edwards L, Carey S, Bacon M, Futagaki C, Suk D, Tom J, Birnbaum C. Positive behavioral and electrophysiological changes following neurofeedback training in children with autism. Research in Autism Spectrum Disorders. Science Direct. 2008; 2:557-24.
12. NIDCD. Communication Problems in Children with Autism. MD USA. 2011.
13. Allison B, Graimann B, Garser A. Why use a BCI if you are healthy. In: Proceedings of BRAINPLAY 2007. Playing with your brain. 2007 . p. 7-4.
14. Allison B, Luth T, Valbuena D, Teymourian A, Volosyak I, Graser A. BCI Demographics: How many (and what kinds of) people can use an SSVEP BCI?. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2010;18:107-9.
15. Lord C, Bishop S.L. Autism spectrum disorders. Social Policy Report. 2010;24.
16. Yaozhang P. Brain signal processing and neurological therapy. NATIONAL UNIVERSITY OF SINGAPORE. 2009.
17. Raymaekers R, Wiersema J.R, Roeyers H. EEG study of the mirror neuron system in children with high functioning autism. Brain Research. Science Direct. 2009;1304:113-8.
18. Amanor-Wilks S. Stimulating the Autistic Brain with Motor Patterning and Childhood Reflexes. 2009.
19. CARD. Diagnosing & evaluating autism: part 1. CARD fact sheet. Gainesville Fla. Center for Autism and Related Disabilities. University of Florida. 2008.
20. Stanley J, Swierzewski I, M.D. Autism Diagnosis [Internet]. [updated 2007; cited 2013 Dec 1]; available from: http:// www.Healthcommunitie.com
21. CARD. Diagnosing & evaluating autism: part 2. CARD fact sheets. Gainesville Fla. Center for Autism and Related Disabilities. University of Florida. 2008.
22. Sanei S, Chambers J. EEG signal processing. Wiley-Interscience. 2007.
23. Graimann B, Allison B, Psurtscheller G. Brain-Computer Interfaces: Revolutionizing Human-Computer Interaction. Springer Verlag. 2011
24. Milne E. Increased Intra-Participant Variability in Children with Autistic Spectrum Disorders: Evidence from Single-Trial Analysis of Evoked EEG. Frontiers in Psychology. 2011;2.

25. Sourina O, Wang Q, Liu Y, Nguyen M.K. A real-time fracal-based brain state recognition from EEG and its application. In: Proc of Biosignals; 2011. p.82-9.
26. Magliaro F.C.L., Cheuer C.I, Assumpcojnior F.B, MATAS C.G. Study of auditory evoked potentials in autism. Pr -FonoRevista de Atualizaç o Cientfica. 2010;22:31-5.
27. Maekawa T, Tobimatsu S, Inada N, Oribe N, Onitsuka T, Kanba S, Kamyo Y. Top-down and bottom-up visual information processing of non-social stimuli in high-functioning autism spectrum disorder. Research in Autism Spectrum Disorders. ScienceDirect. 2010.
28. Belmonte M. Abnormal attention in autism shown by steady-state visual evoked potentials. Autism. 2000; 4:269.
29. Fujita T, Yamasaki T, Kamio Y, Hirose S, Tobimatsu S. Parvocellular pathway impairment in autism spectrum disorder: Evidence from visual evoked potentials. Research in Autism Spectrum Disorders. ScienceDirect. 2010.
30. Oberman L.M, Hubbard E.M, Cleery J.P.MC, Altschuler E.L, Ramachandran V.S, Pineda J.A. EEG evidence for mirror neuron dysfunction in autism spectrum disorders. Cognitive Brain Research. ScienceDirect. 2005;24:190-8.
31. MCFarnland D.J, Krusienski D.J, Wolpaw J.R. Brain-computer interface signal processing at the Wadsworth Center: mu and sensorimotor beta rhythms. Progress in brain research. 2006;159:411-8.
32. Rojas D.C, Maharjh K, Teale P, Rogers S.J. Reduced neural synchronization of gamma-band MEG oscillations in first-degree relatives of children with autism BMC psychiatry. 2008;8:66.
33. Michie D, Spiegelhalter D.J, Taylor C.C. Machine learning, neural and statistical classification. 1994.

3/30/2014