A Source-Discrimination Approach for Detection of ASD Using EEG Data

Uvais Qidwai and Wafaa khazaal Shams

Abstract—**This paper presents a study which was done in an attempt to discriminate between two motor actions; eyes-open task and eyes-closed task, for two classes; Autism Spectrums Disorders (ASD) and Typical or Normal (TP). Both of these groups were composed of school children with ages between 6 to 9 years. Utilizing the Time Different of Arrival (TDOA) approach applied with raw Electroencephalography (EEG) data for feature extracted in time domain. For each action, specific features were calculated and a Multilayer Perception (MLP) based Neural Network was used to classify the data into the two classes. The classification process was carried out for three scenarios for each group; first, all task for both group were combined together, second, eyes-open were classified for both groups separately, and third, eyes–closed was classified separately. The results show accuracy over 90 % and clearly discriminate for the features.**

Index Terms—**Multilayer perceptron (MLP) classifier, source location, ASD detection, EEG signals, angular displacements, motor actions.**

I. Introduction

Pattern recognition methods are used widely for many applications including the clinical and psychiatric practices. The perspective of discriminating one group of patients from the other or early detection of the abnormalities in human body or behaviour has been a great area of interest for researchers in computing world using different medical tools and advance statics and mathematics approaches. The Electroencephalograph (EEG) is one of the imaging tools that record the spontenuose electric activity of neurons in the cortex of the brain. Therefore EEG is the particular tool to study and understand the nervous system behaviour [1]-[3]. EEG has been utilized for understanding and digonise Autism Spectrum Diorder (ASD) for more than two decades [4]-[6].

ASD is neurodevelopment disorder that causes impairment in social interaction, deficits in communication, restricted and repetitive actions, and other co-occurring deficits such as motor imitations [7]. One of the ways in which ASD can be diagnosed is based on the psychology tests and the symptoms that appear in early age, 6-9 years. For early detection of ASD, EEG has been used as a good procedure since it is noninvasive, easy to be used, safe for infants and not costly. However, the non stationary and non linear nature of EEG makes the classification process very challenging. Furthermore, the signal gets very noisy since it is heavily influenced by the environment such as electronic noise, and un-correlated human mental activities.

In a previous related work [8], new methods for quantified EEG signals were proposed and had significant result for characterizing the EEG signals during simple motor tasks such as ‘eyes-open’ and ‘eyes-closed’ form a number of normal and autistic children. In this previous study, TDOA approach [9] was utilized to extract relative source-temporal features.

However, in this paper, newer and more discriminating features are presented compared to the relative source temporal features. These features are essentially the angles of the projections of the source points in each plane (X-Y), (Y-Z), and (X-Z). Thus, the first goal of the work presented in this paper is to investigate further these new features, and secondly, to understand how ASD and Normal groups of children can be distinguished during rest conditions as well as other motor tasks.

II. Methods

A. Data Collection

Six typical subjects aged (6 to 9 years) from a local primary school and six autistic subjects of the same ages from the National Autistic Society of Malaysia (NASOM) were selected for this study. The ASD group was diagnosed positive by psychiatrists based on the DSM-IV criteria [7]. All the children were asked to wear the EEG probes set on their heads before any data collection was done.

The EEG data were recorded using eight channels based on the EEG International (10-20) Standard System by using BIMEC EEG machine with sampling frequency of 250 Hz. These channels represent C3, C4, F3, F4, T3, T4, P3, and P4 with Cz as reference. Fig. 1 shows such an arrangement of probes. The experiment consisted of two tasks; eyes –open and eyes-closed where the subject was asked to sit in a relaxed position and was asked to open his/her eyes for one minute looking at a black screen. Then the subject was asked to closed his/her eyes for another 1 minute. EEG signals were collected within clear environment and with short time to reduce the artefacts that might be injected from child’s movement. In this study, five seconds are excluded from the beginning and ending of the collected time (1 min). The EEG signals are filtered for the band of interest (i.e., alpha band) in the range of 8-13 Hz using band pass filter.

The filter was designed in MATLAB using the Filter Design & Analysis Tool (fdatool) for the alpha band. The resulting filter response is shown in Fig. 2, and the actual filter coefficients are shown further below.

Manuscript received February 29, 2013; revised May 17, 2013.
Uvais Qidwai is with Computer Science and Engineering Department, Qatar University, Qatar (e-mail: uqidwai@qu.edu.qa).

Wafaa khazaal Shams is with Computer Science Department, International Islamic University, Malaysia (e-mail: wafaa_dth@yahoo.com, abdulwahab@iium.edu.my).

DOI: 10.7763/IJBBB.2013.V3.262

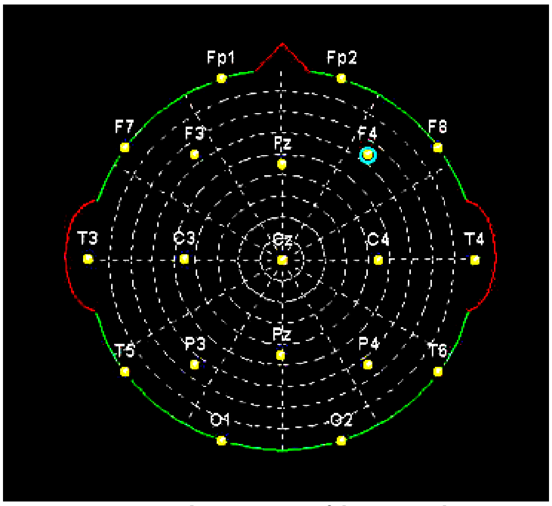

Fig. 1. Typical arrangement of the EEG probes.

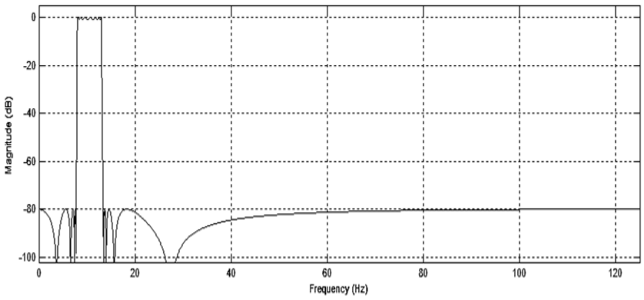

Fig. 2. The alpha band filter response.

The filter ($f(z)$) was realized using Ten 2nd order Elliptic filter blocks with basic structure of

$$f(z) = \sum_{n=1}^{10} g_n \left(\frac{b_0+b_1z^{-1}+b_2z^{-2}}{a_0+a_1z^{-1}+a_2z^{-2}}\right) \quad (1)$$

where g_n represents the gain of the n^{th} 2nd order stage, and coefficients [b_0 b_1 b_2 a_0 a_1 a_2] represents the n^{th} row in the design matrix. Both the gain and coefficient matrices are shown below:

Gains = [0.0015 1 1 1 1 1 1 1 1 1 255.8362]

Coefficients = [

1.0176	-2.0000	1.0176	1.0000	-1.9495	0.9926
1.0654	-2.0000	1.0654	1.0000	-1.8909	0.9890
0.4038	-0.8042	0.4038	1.0000	-1.9187	0.9763
0.0052	-0.0081	0.0052	1.0000	-1.9012	0.9736
1.0195	-2.0000	1.0195	1.0000	-1.9589	0.9992
1.0590	-2.0000	1.0590	1.0000	-1.8929	0.9986
1.0139	-2.0000	1.0139	1.0000	-1.9372	0.9852
0.0996	-0.1838	0.0996	1.0000	-1.8926	0.9801
1.0190	-2.0000	1.0190	1.0000	-1.9558	0.9969
1.0605	-2.0000	1.0605	1.0000	-1.8916	0.9951]

B. *Time Difference of Arrival (TDOA) Approach*

In a previous work, a new method was proposed to quantify EEG signal to relative source-temporal features by applying TDOA features [8]. TDOA approach is very well-known in disciplines like communications, seismology, tomography, etc… The principle of TDOA is to estimate the location of the emitter/source under consideration by computing time delays of the travelling signal between a source and two or more synchronized receivers, which can be represented as hyperboloids. The intersection of these hyperboloids is the estimated source location. In its very simple form, with only two receivers, the technique can be thought of similar to the 'triangulation' technique used in the navigation.

In this paper, the presented model, the EEG channels are assumed to be the receivers and the source of the active region in brain as emitter. Spherical head model is used and the speed of alpha wave (v) is computed from the dielectric properties of head tissue as explained in subsequent sections.

Let (x, y, z) represent the location of the source, while (x_i, y_i , z_i) represent the location of electrodes where i=1…..n; and n is the number of the receivers (electrodes). The procedure to compute RST features is explained by the following steps:

- Initial electrode location and their x, y and z coordinates is taken from Kayser and Tenke [10] for the four site electrodes.
- Compute the time delay among the channels using Cross-Correlation [11]. One second movement window is used with 125 sample movement. Thus the time delays are computed for each one second samples within 50 seconds.
- Apply TDOA principle as explained in [8] and using Chan method [12] to find the location, three linear equations are produced which can be solved using Gaussian elimination method [13] to get x, y and z variables. The first of these equations would look like the following:

$$R = Ax + By + Cz \quad (2)$$

where

$$R = vt_{13} - vt_{12} + \left(\frac{x_1^2+y_1^2+z_1^2}{t_{13}} - \frac{x_3^2+y_3^2+z_3^2}{t_{13}}\right) - \left(\frac{x_1^2+y_1^2+z_1^2}{t_{12}} - \frac{x_2^2+y_2^2+z_2^2}{t_{12}}\right) \quad (3)$$

$$A = 2\left[\frac{(x_2-x_1)}{vt_{12}} - \frac{(x_3-x_1)}{vt_{13}}\right] \quad (4)$$

$$B = 2\left[\frac{(y_2-y_1)}{vt_{12}} - \frac{(y_3-y_1)}{vt_{13}}\right] \quad (5)$$

$$C = 2\left[\frac{(z_2-z)}{vt_{12}} - \frac{(z_3-z_1)}{vt_{13}}\right] \quad (6)$$

where x_1, y_1, z_1 are the coordinates of the electrode in locations 1. x_2, y_2, z_2 and x_3, y_3, z_3 are the coordinates of the electrodes in locations 2 and 3 respectively, t_{12} and t_{13} are the time delays between EEG signals at locations 1, 2 and 1, 3, respectively. The other two equations can be computed in a similar manner using location 2-3, 2-1, 4-1, and 4-2.

Another set of 4 different electrodes' site locations are chosen next and the previous procedures are repeated. This procedure is repeated 20 times more with different electrodes sites. At the end, 20 features with time samples are computed for three variables x, y and z that are called in this work as the virtual sources for the alpha wave activities.

C. Compute Alpha Speed

EEG alpha wave speed can be estimated from the permeability and the permittivity of tissues inside the head using this equation [14]

$$v = 1/(\mu\epsilon)^{1/2} \tag{7}$$

where μ is the permeability and ε is the permittivity of the brain tissues which are given by :

$$\mu = \mu_0 \mu_r \tag{8}$$

$$\epsilon = \epsilon_0 \epsilon_r \tag{9}$$

μ_0 and ε_0 are the permeability and permittivity in free space and μ_r, and ε_r are the relative permeability and permittivity respectively. However , in this study the permeability of tissues are assumed to be equal to that of air (μ=1) [15] and the permittivity of different head tissues are derived from Gabriel curves [16]; as shown in Table I. The results obtained in this work using these values are very similar to the estimation has been done in [17] and [18].

TABLE I: THE DIELECTRIC PROPERTIES OF HEAD TISSUE

Head tissue	Permittivity at 10 Hz (F/m)
Scalp	5e+04
Skull	5.5e+04
CSF	4e+03
Brain tissue	1e+08

Then by using the permittivity in free space which is (ε_0: 8.852 exp^{-12} F/m) and applying equation (7), the estimated speed of alpha wave inside the brain will be: **33.2 m/sec.**

D. Features Computation (Angles)

After computing the relative sources locations, different types of feature can be extracted from the coordinate values. In [8], the coordinates were directly used with the Neural Network classifier. However, from a very theoretical perspective, this approach is quite confusing since a very big solution space can exist with different combinations of *x*, *y*, and *z* coordinated. In this paper, we have extracted the angles which represent the projections of source points in each plan (X, Y, Z). This implies that the angles can be computed as :

Angle 1: the projection of point source in X, Y plane

Angle 2: the projection of point source in Y, Z plane

Angle 3: the projection of point source in X, Z plane

The angular combinations are quite independent entities and do not propose the same type of type-mixing combinations that would have arisen with the simple coordinates.

E. Classification Process

Multi-layer perception (MLP) with back propagation [19] is used in this study for the classification of Normal and the ASD classes with the motor action EEG data. The MLP network consists of three layers: input layer contain neurones with the same number of features, i.e., ***, hidden layers and the output layer. The number of hidden layers and neurons are design based on the optimization process. The configuration of the network is described in Table II.

TABLE II: PARAMETERS FOR MLP

Parameters	**Values**
Number of hidden layers	2
Number of neurones in hidden layers	10
Learning rate	0.1
goal	0.01
epoch	10000000

III. RESULTS AND DISCUSSION

Features are extracted as explain in suction D from both groups ASD and normal during eyes-open and eyes–closed tasks. All features are combined together and fed to MLP classifier with different training sizes which are randomly selected from the whole data set. The proposed labels for the classes are (1, 1) for eyes-closed normal, (1, -1) eyes-open normal, (-1, 1) eyes-closed ASD and (-1, -1) eyes-open ASD. Table III shows the average accuracy for each class using different training sizes repeated 5 times for each try.

TABLE III: THE AVERAGE ACCURACY FOR EACH CLASS

Training size	AC.CE-normal	AC.OE-normal	AC.CE-autistic	AC.OE-autistic
80%	0.939	0.893	0.979	0.961
60%	0.927	0.935	0.931	0.954
50%	0.905	0.88	0.92	0.975
40%	0.933	0.89	0.974	0.903
20%	0.849	0.843	0.822	0.91

The results are in the acceptable range comparing to the recent methods that is reported using quantitative EEG for detect ASD [4], [5]. However, in our model we combined all tasks together. It is noticeable that the accuracy values for Normal subjects under eyes-open task are very closed to the values of the Normal group during eyes-closed and ASD during eyes-open. This is shown in Fig. 3 where the predicated value of each class, using 50% data for training and 50% for testing.

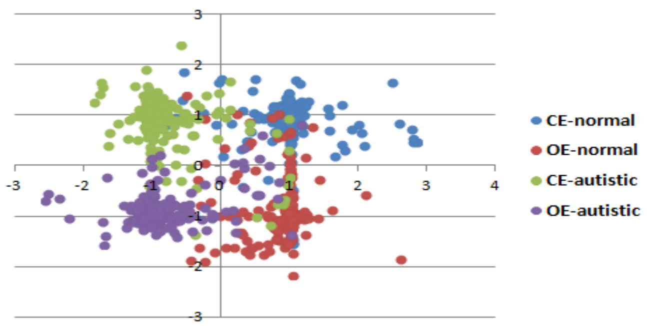

Fig. 3. The predicate values for each class of normal and ASD groups.

Another scenario was tested in order to classify eyes-open and eyes closed within the same group. Table IV and Table V show the accuracy for different training sizes. Fig. 4 and Fig. 5 show the predicate value for each class, the labeled is set as in the first scenario.

It can be noticed from the results that using the source domain to distinguish between eyes-open and eyes–closed for both ASD and Normal subjects appears to be quite efficient. Moreover, the high separation between eyes-open and eyes-closed classes for ASD may indicate the difference of behavior of neurons under each task compared to the normal subjects. More investigation is underway on these lines, but these initial findings put a lot of confidence in the approach and more improved feature set as well as classification procedures can be obtained.

TABLE IV: THE AVERAGE ACCURACY FOR EACH CLASS NORMAL GROUP

Training size	AC.CE-normal	AC.OE-normal
80%	0.99	0.97
60%	0.992	0.961
50%	0.978	0.948
40%	0.95	0.94
20%	0.954	0.935

TABLE V: THE AVERAGE ACCURACY FOR EACH CLASS AUTISTIC GROUP

Training size	AC.CE-autistic	AC.OE-autistic
80%	0.99	0.99
60%	1	0.99
50%	0.96	0.96
40%	0.984	0.966
20%	0.969	0.935

Fig. 4. The predicate values for each class of normal group.

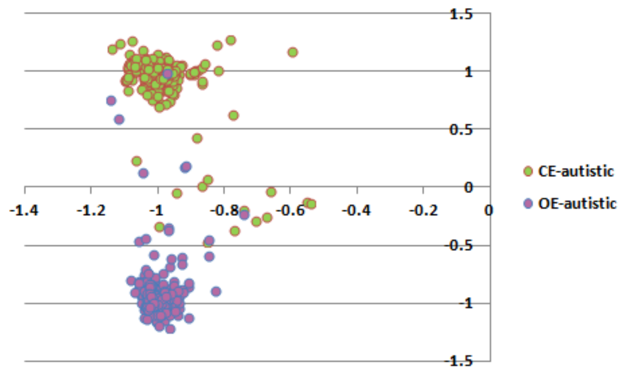

Fig. 5. The predicate values for each class of ASD group.

IV. CONCLUSION

In this study, a new kind of feature set has been used to characterize the information from the EEG signals. These features present the projections of source locations (*x*, *y*, *z*) for estimating the locations of active regions inside the brain in the three orthogonal plan (X, Y), (Y, Z) and (X, Z). The source location gives an indication of the presence of the ASD related signatures that can be very helpful in the diagnostic process. Hence, a very simple non-invasive test can be used for helping the doctors/psychiatrists in making the diagnosis. The results show high discrimination between eyes-open and eyes-closed for both groups. Using TDOA technique for feature extraction has shown significant results.

REFERENCES

[1] D. P. Subha, P. K. Joseph, R. Acharya U, and C. M. Lim, "EEG signal analysis: A survey," *Journal of medical systems*, vol. 34, pp. 195-212, 2010.

[2] S. Sanei and J. A. Chambers, *EEG signal processing*, Wiley-Interscience, pp. 100, 2007.

[3] H. Adeli, S. Ghosh-Dastidar, and N. Dadmehr, "A wavelet-chaos methodology for analysis of EEGs and EEG subbands to detect seizure and epilepsy," *IEEE Transactions on Biomedical Engineering*, vol. 54, pp. 205-211, 2007.

[4] A. Sheikhani, H. Behnam, M. R. Mohammadi, M. Noroozian, and M. Mohammadi, "Detection of abnormalities for diagnosing of children with autism disorders using of quantitative electroencephalography analysis," *Journal of medical systems*, vol. 36, pp. 957-963, 2012.

[5] M. Ahmadlou, H. Adeli, and A. Adeli, "Fractality and a wavelet-chaos-neural network methodology for EEG-based diagnosis of autistic spectrum disorder," *Journal of Clinical Neurophysiology*, vol. 27, pp. 328, 2010.

[6] L. M. Oberman and V. S. Ramachandran, "The simulating social mind: the role of the mirror neuron system and simulation in the social and communicative deficits of autism spectrum disorders," *Psychological bulletin*, vol. 133, pp. 310, 2007.

[7] A. P. Association, *Diagnose and Statistical Manual of Mental Disorder DSM-IV-IR*, Washington DC: American Psychiatric Publishing, Inc, pp. 70, 2000.

[8] W. Shams, A. Wahab, and U. Qidwai, "Detecting Different Tasks Using EEG-Source-Temporal Features," *Neural Information Processing*, pp. 380-387, 2012.

[9] R. O. Schmidt, "A new approach to geometry of range difference location," *IEEE Transactions on Aerospace and Electronic Systems*, pp. 821-835, 1972.

[10] J. Kayser and C. E. Tenke, "Principal components analysis of Laplacian waveforms as a generic method for identifying ERP generator patterns: I. Evaluation with auditory oddball tasks," *Clinical neurophysiology*, vol. 117, pp. 348-368, 2006.

[11] C. Knapp and G. Carter, "The generalized correlation method for estimation of time delay, " *Acoustics, Speech and Signal Processing, IEEE Transactions on*, vol. 24, pp. 320-327, 1976.

[12] Y. Chan and K. Ho, "A simple and efficient estimator for hyperbolic location," *Signal Processing, IEEE Transactions on*, vol. 42, pp. 1905-1915, 1994.

[13] K. E. Atkinson, *An Introduction to Numerical Analysis*, John Wiley & Sons, ch. 8, 1987, pp.435-490.

[14] A. Baden Fuller, *J, Microwaves*, New York: Oxford Pergamon Press, ch. 2, 1979, pp.31-50.

[15] C. Sumi and K. Hayakawa, "Mathematical expressions of reconstructions of conductivity and permittivity from current density," *Int. J. Bioelectromagn*, vol. 9, pp. 103-104, 2007.

[16] C. Gabriel, S. Gabriel, and E. Corthout, "The dielectric properties of biological tissues: I. Literature survey," *Physics in Medicine and Biology*, vol. 41, pp. 2231, 1999.

[17] D. Miklavčič, N. Pavšelj, and F. X. Hart, "Electric properties of tissues," *Wiley Encyclopedia of Biomedical Engineering*, pp. 3578, 2006.

[18] D. Rafiroiu, S. Vlad, L. Cret, and R. Ciupa, "3D Modeling of the Induced Electric Field of Transcranial Magnetic Stimulation," in *Proc. International Conference on Advancements of Medicine and Health Care through Technology*, 2009, pp. 333-338.

[19] D. Rumelhart, G. Hinton, and R. Williams, "Learning Internal Representations by Error Propagation, Parallel Distributed Processing, Explorations in the Microstructure of Cognition," D. E. Rumelhart and J. McClelland. Cambridge, MA: MIT Press, vol. 1, 1986, pp.533-536, 1986.

Uvais Qidwai received his Ph.D(EE) from the University of Massachusetts–Dartmouth USA in 2001, MS(EE) in 1997 from KFUPM Saudi Arabia, and BS(EE) in 1994 from NED University of Engineering & Technology, Karachi, Pakistan.

He taught in the Electrical Engineering and Computer Science Department, Tulane University, in New Orleans as Assistant Professor, and was in-charge of the Robotics lab as well as a research member of Missile Defence Centre, during June 2001 to June 2005. He joined the Computer Science and Engineering Department, Qatar University, in FALL of 2005 where he is currently working as Associate Professor.

Dr. Qidwai's present research interests include Robotics, Signal and Image Processing, Expert Systems design for Industrial Applications, and Intelligent Algorithms for medical informatics. He has participated in several government- and industry-funded projects in the United States, Saudi Arabia, Qatar, UAE, Singapore, Malaysia, and Pakistan, and has published over 95 papers in reputable journals and conference proceedings.

Wafaa Shams received her B.S. degree in physic science from Baghdad University, Baghdad, Iraq, in 1997. In 2000, she received the M.S. degree in image processing and remote sensing from Physics Department, Baghdad University, Baghdad, Iraq. She is a Ph.D. student in brain development group, Computer Science Department, International Islamic University, Kuala Lumpur, Malaysia. Her current research interests include feature extraction, supervised learning, Autism Spectrums Disorder (ASD) diagnosis and cognition.