Analysis of EEG background activity in Autism disease patients with Bispectrum and STFT measure

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Abstract—**Electroencephalography (EEG) is an essential tool for the evaluation and treatment of neurophysiologic disorders. Careful analysis of the EEG records can provide insight and improved understanding of the mechanism causing disorders. In this study we have investigated the EEG background activity in patients with Autism disease using frequency analysis methods. We calculated Bispectrum tansform, short time Fourier transform (STFT) and also STFT at bandwidth of total spectrum (we named it STFT-BW) for 21 channel of EEG. Coefficients of the EEG in 10 Autism patients and 7 age control subjects with the same age were measured. These coefficient assessments with variance analysis. We did not find any significant differences between Autism patients and control subjects EEGs with Bispectrum and STFT. On the other hand, Autism patients had significantly difference STFT at bandwidth (STFT-BW). At electrodes FP1, F3 and T5 with ($p<0.01$) and F7, T3 and O1 with ($p<0.05$) had significantly differences. In addition our findings suggested that STFT-BW can discriminate 82.4% between normal and Autism subject with mahalanobis distance.**

Keywords: Bispectrum; STFT; EEG; Autism;

I. INTRODUCTION

AUTISM spectrum disorders (ASDs) are devastating conditions with an onset in early childhood and core symptoms of varying degree involving communication and social and cognitive development, and usually sparing gross motor development. In 1943, Kanner [1] first described the case of an autistic individual who developed epilepsy, and since then, multiple case reports or population series have described an association of abnormal EEG findings within autistic individuals [2-5].

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Autism spectrum disorders affect 1 in 166 births. Although EEG abnormalities and clinical seizures may play a role in ASDs, the exact frequency of EEG abnormalities in an ASD population that has not had clinical seizures or prior abnormal EEGs is unknown [6].

The electroencephalogram (EEG) is a record of a time series of potentials caused by systematic neural activities in brain. The measurements of the human EEG signals are performed through electrodes placed on the scalp, and they are usually recorded on paper against time. The voltage of the EEG signal corresponds to its amplitude. The typical amplitudes of the scalp EEG lie between 10 and $100\,\mu V$, and in adults more commonly 10 and $50\,\mu V$ [7, 8].

EEG signals involve a great amount of information about the function of the brain. But classification and evaluation of these signals are limited. Since there is no definite criterion evaluated by the experts, visual analysis of EEG signals in time domain may be insufficient. Routine clinical diagnosis needs analysis of EEG signals. Therefore, some automation and computer techniques have been used for this aim. Since the early days of automatic EEG processing, representations based on a Fourier transform have been most commonly applied. This approach is based on earlier observations that the EEG spectrum contains some characteristic waveforms that fall primarily within four frequency bands-delta (<4HZ), theta (4-8HZ), alpha (8-13HZ) and beta (13-30HZ).Such methods have proved beneficial for various EEG characterizations [7, 8].

Bispectrum is based on the third-order statistics which can preserve phase information present in a signal. The phase of a signal is particularly critical in analyzing nonlinear systems where sinusoidal components of distinct frequencies could interact nonlinearly to produce one or more sinusoidal components at sum and difference frequencies [9-11]. EEG, being generated by a nonlinear system, would be expected to have many such sinusoidal components produced due to the nonlinearity in the system. The third-order statistics, therefore, can help in identifying these components [11].

Spectral analysis of the EEG signals is performed using the short-time Fourier transform (STFT), in which the signal is divided into small sequential or overlapping data frames and fast Fourier transform (FFT) applied to each one. The output of successive STFTs can provide a time-frequency representation of the signal. To accomplish this, the signal truncated into short data frames by multiplying it by a window so that the edified signal is zero outside the data frame. In order to analyze the whole signal, the window is translated in time and then reapplied to the signal [12].

The paper is organized as follow. In section 2 we explain the selection of patients and control subjets, and the procedure for recording the EEG and selecting artifact-free epochs. Bispectrum, STFT and STFT at bandwidth in total spectrum, and their application used to evaluate the differences between autism patient and control subjects are also introduced in section 2. Section 3 presents our results and compares them in autism patients. Finally in section 4 future works and conclusions will be presented.

II. METHODS

A. Selection of patients and controls

We studied 10 patients (9 boy and 1 girl; age = 9.3 ± 1.8 years, mean $\pm$ standard deviation (S.D.)). Patients were diagnosed as having an ASD by DSM-IV-TR criteria [13]. The patients were recruited from the Autism Patient's Relatives Association of Roozbeh Hospital (Tehran), where the EEG was recorded.

The control group consisted 7 age-matched, elderly control subjects without past or present neurological disorder (4 boys and 3 girls; age 9.2 ± 0.7 years, mean $\pm$ S.D.). All control subjects and all caregivers of the demented patients gave their informed consent for participation in the current study. A EEG was recorded from all patients and controls.

B. EEG recording

The EEGs were recorded from the 21 scalp loci of the international 10 – 20 system (channels FP1, FP2, F7, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, PZ, P4, T6, O1, O2, A2, A1) with both earlobes chosen as common referece electrodes. Recordings were made with the subjects in a relaxed state and under the eyes-closed condition in order to obtain as many artifact-free EEG data as possible. More than 10 min of data were recorded from each subject. Data were first processed with a low-pass hardware filter at 100Hz, and then they were sampled at 256 Hz and digitized by a 12-bit analogue-digital converter.

The recordings were visually inspected by a specialist physician to reject artifacts. Thus, only EEG data free from electrooculographic and movement artifacts and with minimal electromyography (EMG) activity were selected. Afterward, EEGs were organized in 10 s artifact-free epochs (2560 points) that were copied as ASCII files for off-line analysis on a personal computer.

In order to remove the residual EMG activity and the noise owing to the electrical main, all selected epochs were digitally filtered. We used a Hamming window FIR band-pass filter with cut-off frequencies at 0.5 and 48 Hz and another filter at 52 to 80 Hz designed with Matlab.

C. Bispectrum, STFT and STFT-BW measure

Higher-order spectra are multi-dimensional Fourier transforms of higher-order statistics. Thus, the bispectrum is defined in term of third-order cumulate or third-moment sequence. Let $x(n)$ be a stationary, discrete, zero-mean random process and its third-order cumulant sequence $c_3^x(\tau_1,\tau_2)$ will be identical to its third-moment sequene:

$$c_3^x(\tau_1,\tau_2) = E\{X(k)X(k+\tau_1)X(k+\tau_2)\} \quad (1)$$

where $E\{.\}$ denote statistical expectation. The bispectrum $B(\omega_1,\omega_2)$ of $X(n)$ is defined as the two-dimensional (2D) Fourier transform of $c_3^x(\tau_1,\tau_2)$:

$$B(\omega_1,\omega_2) = C_3^x(\omega_1,\omega_2) = \sum_{\tau_1=-\infty}^{\infty}\sum_{\tau_2=-\infty}^{\infty} c_3^x(\tau_1,\tau_2)\exp[-j(\omega_1\tau_1+\omega_2\tau_2)]$$

$$|\omega_1|,|\omega_2| \le \pi, \qquad |\omega_1,\omega_2| \le \pi \quad (2)$$

In general, $B(\omega_1,\omega_2)$ is complex and the sufficient condition for its existence is that $c_3^x(\tau_1,\tau_2)$ is absolutely summable.Also, $B(\omega_1,\omega_2)$ is periodic in ω_1 and ω_2 with period 2π, Thus $B(\omega_1,\omega_2)$ is a symmetric function. For real process, the bispectrum has 12 symmetry regions. The bispectrum in the triangular region, where $(\omega_2 \ge 0, \omega_1 \ge \omega_2, \omega_1+\omega_2 \le \pi)$, can completely describe the whole bispectrum (as shown in fig. 1).

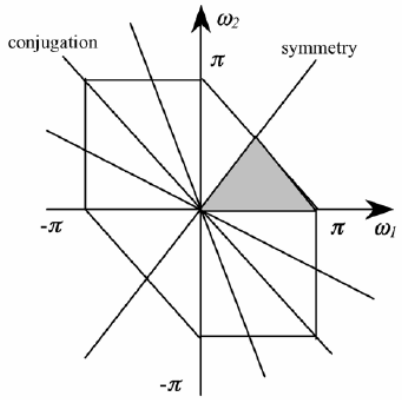

Fig 1. Symmetry regions of bispectrum.

The bispectrum is capable of detecting and quantifying phase coupling [14]. Consequently, the bispectrum

evaluated in the triangle region (Fig. 1) shows an impulse only at the point (ω_1, ω_2) indicating that only this pair is phase coupled. If the phase coupling is totally absent, then both third-cumulant sequence and bispectrum are zero. Thus, only the phase coupled components contribute to the third-cumulant sequence of a process. This will make the bispectrum a useful tool for detecting whether and where the quadratic phase coupling exists and how to discriminate phase-coupling components [14].

Fourier analysis decomposes signal into its frequency components and determines their relative strengths. the Fourier transform is defined as:

$$F(\omega) = \int_{-\infty}^{+\infty} f(t) e^{-j\omega t} dt \leftrightarrow f(t)$$

$$= \frac{1}{2\pi} \int_{-\infty}^{+\infty} F(\omega) e^{j\omega t} d\omega \qquad (3)$$

This transform is applied to stationary signals, that is, signals whose properties do not evolve in time. When the signal is non-stationary we can introduce a local frequency parameter so that local Fourier transform looks at the signal through a window over which the signal is approximately stationary. Therefore, we applied the STFT to the EEG signals under study. The STFT positions a window function $\psi(t)$ at τ on the time axis, and calculates the Fourier transform of the windowed signal as

$$F(\omega, \tau) = \int_{-\infty}^{+\infty} f(t) \psi^*(t-\tau) e^{-j\omega t} dt \qquad (4)$$

when the window $\psi(t)$ is a Gaussian function, the STFT is called a Gabor transform. It is generated by modulation transformation of the window function $\psi(t)$, where w and τ are modulation and translation parameters, respectively. The fixed time window $\psi(t)$ is the limitation of STFT as it causes a fixed time-frequency resolution. This is explained by the uncertainty principle (Heisenberg inequality-meaning one can only trade time resolution for frequency resolution, or vice versa) for the transform pair

$$\psi(t) \leftrightarrow \Psi(\omega)$$

$$\Delta t \Delta \omega \geq \frac{1}{2} \qquad (5)$$

where $\Delta\omega$ and Δt are the bandwidth and time spread (i.e. two pulses in time can be discriminated only if they are more than Δt apart) of $\psi(t)$, respectively, and

$$\Delta t^2 = \frac{\int t^2 |\psi(t)^2| dt}{\int |\psi(t)|^2 dt} \qquad (6)$$

$$\Delta \omega^2 = \frac{\int w^2 |\psi(\omega)|^2 d\omega}{\int |\psi(\omega)|^2 d\omega} \qquad (7)$$

When t increases, the window function translates in time. On the other hand, the increase in w causes a translation in frequency with a constant bandwidth [15, 16].

In the STFT-BW we calculated mean of components STFT at bandwidth of total power spectrum. This is sign of contributed peak of STFT in duration of time. This trend is designed with Matlab.

STFT_BW has quality information of signal that we used at this study and Comparison with usual STFT at discriminations of autism and control subjects.

D. Statistical analysis

One-way ANOVA tests were used to evaluate the statistical differences between the estimated FFT, STFT and STFT-BW values for ASD patients and control subjects. If significant differences between groups were found, the ability of these analysis method to discriminate ASD patients from control subjects was evaluated using receiver operating characteristic (ROC) plots [17,18].

For classification between autism and control subject's we used nearest neighbor classifiers. It consists of assigning a feature vector to a class according to its nearest neighbor(s). This neighbor can be a feature vector form the training set as in the case of k nearest neighbors (KNN), or a class prototype as in Mahalanobis distance. They are discriminative nonlinear classifiers. According to the so-called Mahalanobis distance $d_c(x)$ [19]:

$$d_c(x) = \sqrt{(x-\mu_c) M_c^{-1} (x-\mu_c)^T} \qquad (8)$$

This lead to a simple yet robust classifier, which even provide to be suitable for multicasts [20].

III. RESULTS AND DISCUSSION

FFT, STFT and STFT-BW were estimated for channels FP1, FP2, F7, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, PZ, P4, T6, O1, O2, A2, A1. The results have been averaged based on all the artifact-free 10s epochs (N = 2560 points) within the 10-min period of EEG recordings.

The Bispectrum values (mean $\pm$ S.D.) for ASD patients and control subjects and the corresponding p values are summarized in Table I. The ASD patients have'nt significantly differences for all 21 electrodes.

The average STFT values and standard deviations for the ASD patients and normal control subjects for the 21 electrodes don't have significant differences between both groups. and so the STFT-BW values (mean $\pm$ S.D.) are summarized in Table II. The ASD patients have significantly values ($p < 0.01$) at electrodes FP1, F3 and T5 and with ($p < 0.05$) at electrodes F7, T3 and O1 in Table II .

We evaluated the ability of the STFT-BW to discriminate ASD patients from control subjects at the electrodes in which significant differences were found using ROC plots. Table III summarizes the results.

The value for the area under the ROC curve can be interpreted as follows: an area of 0.90(electrode FP1 for example) means that a randomly selected individual from the control subject's group has a STFT-BW value larger

than of a randomly chosen individual from the ASD patient's group in 90% of the time. A rough guide to classify the precision of a diagnostic test is related to the area under the ROC curve. With values between 0.90 and 1 the precision of the diagnostic test is considered to be excellent, good for values between 0.80 and 0.90. Far fair if the results are in the range 0.70-0.79, poor when the value of the area under the ROC curve is between 0.60 and 0.69, and bad for values between 0.50 and 0.59.

TABLE I: THE AVERAGE BISPECTRUM VALUES OF THE EEGS FOR THE ASD PATIENTS AND CONTROL SUBJECTS FOR ALL CHANNELS

Electrode	ASD patients (mean±S.D)	CONTROL SUBJECTS (mean±S.D.)	STATISTICAL ANALYSIS (ρ value)
FP1	0.250±0.318	0.051±0.017	0.123
FP2	0.159±0.168	0.067±0.050	0.187
F7	0.138±0.144	0.078±0.035	0.301
F3	0.128±0.101	0.054±0.027	0.082
Fz	0.127±0.099	0.077±0.020	0.216
F4	0.111±0.073	0.067±0.038	0.164
F8	0.097±0.108	0.066±0.027	0.474
T3	0.109±0.154	0.063±0.036	0.448
C3	0.107±0.102	0.093±0.059	0.744
Cz	0.123±0.110	0.110±0.054	0.824
C4	0.120±0.087	0.083±0.032	0.308
T4	0.125±0.148	0.075±0.021	0.388
T5	0.139±0.151	0.076±0.014	0.294
P3	0.144±0.128	0.112±0.076	0.568
Pz	0.140±0.135	0.111±0.037	0.590
P4	0.139±0.113	0.073±0.022	0.154
T6	0.147±0.156	0.210±0.275	0.555
O1	0.132±0.129	0.089±0.025	0.405
O2	0.133±0.134	0.081±0.016	0.333
A2	0.102±0.150	0.040±0.014	0.304
A1	0.139±0.177	0.080±0.25	0.026

It can be seen from Table III value of ROC for FP1, F7, F3, T3, T5 and O1 have significant with STFT-BW for classification.

Finally, we used nearest neighbor classifiers for classification between autism and control subject's for STFT-BW at the 21 electrode. Using STFT-BW we obtained the highest classification (82.4%). Results are summarized in Table IV.

It should be noted that the used sample group is small, as a result, our findings are preliminary and require replication in a larger patient population before any conclusion can be made of its clinical diagnostic value. Moreover, the significant different of EEG seen in autism disorders with STFT-BW.

V. CONCLUSIONS

We evaluated the ability of Bispectrum and STFT to discriminate ASD patients from control subjects. No significant discriminate were found between both groups.

Using STFT-BW we obtained the highest classification (82.4%) between both groups. With STFT-BW we found significant at FP1, F3 and T5 with ($p<0.01$) and F7,T3 and O1 with ($p<0.05$). The results also demonstrate that there are pathophysiology differences between children with autism. However suggest disorganization of cortical networks at autism patients.

Diagnosis autism with quantitative EEG (qEEG) is the best of our knowledge, because it is available and non-expensive procedures and also it's non-invasive method for children.

TABLE I I: THE AVERAGE STFT-BW BISPECTRUM VALUES OF THE EEGS FOR THA ASD PATIENTS AND CONTROL SUBJECTS FOR ALL CHANNELS

Electrode	ASD patients (mean±S.D)	CONTROL SUBJECTS (mean±S.D.)	STATISTICAL ANALYSIS (ρ value)
FP1*	0.184±0.114	0.384±0.121	0.003
FP2	0.260±0.161	0.355±0.175	0.266
F7*	0.170±0.113	0.371±0.172	0.011
F3*	0.185±0.115	0.342±0.072	0.006
Fz	0.203±0.109	0.294±0.127	0.134
F4	0.278±0.134	0.257±0.115	0.744
F8	0.280±0.161	0.216±0.097	0.367
T3*	0.178±0.143	0.311±0.086	0.046
C3	0.244±0.174	0.369±0.082	0.100
Cz	0.267±0.147	0.278±0.114	0.868
C4	0.331±0.158	0.201±0.119	0.088
T4	0.253±0.157	0.280±0.153	0.726
T5*	0.166±0.086	0.309±0.102	0.007
P3	0.188±0.097	0.282±0.151	0.139
Pz	0.231±0.194	0.294±0.147	0.482
P4	0.251±0.161	0.250±0.069	0.996
T6	0.244±0.099	0.354±0.120	0.278
O1*	0.189±0.111	0.327±0.132	0.034
O2	0.214±0.149	0.313±0.146	0.194
A2	0.225±0.156	0.201±0.061	0.709
A1	0.211±0.127	0.239±0.097	0.635

SIGNIFICANT GROUP DIFFERENCES ARE MARKED WITH AN ASTERISK

TABLE III:TEST RESULTS STFT-BW AND FFT METHODS ON CHANNELS IN WHICH THE DIFFERENCES BETWEEN BOTH GROUPS WERE SIGNIFICANT WITH ROC CURVE

COMPONENT	ELECTRODE	AREA UNDER THE ROC CURVE
STFT-BW	FP1	0.900
	F7	0.814
	F3	0.914
	T3	0.814
	T5	0.843
	O1	0.800

TABLE IV: CLASSIFICATION RESULTS WITH STFT-BW COMPONENT

Cases	Predicted group membership		total
	Autism	normal	
Autism	8	2	10
normal	1	6	7
Autism	80.0	20.0	100.0
normal	14.3	85.7	100.0

A 82.4% OF ORIGINAL GROUPED CASES CORRECTLY CLASSIFIED.

Further work are needed using other EEGs analyses for having better percentage of discrimination from both groups, normal and autism patients.

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