Diagnostic Test for the Discrimination between Interictal Epileptic and Non-Epileptic Pathological EEG Events using Auto-Cross-Correlation Methods

M .POULOS
Department of Informatics
University of Piraeus, Greece,
P.O. Box 96, Corfu 49100, Greece,
Tel: +036932089117
+032661036581
emails: marios.p@usa.net
mpoulos@mland.gr

F. GEORGIACODIS
Department of Informatics
University of Piraeus, Greece,
80 Caraoli & Dimitriou str., Piraeus 185 34, Greece,
Tel: +036932089117
+032661036581
e-mail: fotis@unipi.gr

V. CHRISSIKOPOULOS
Dept. of Archives & Library Sciences, Ionion University, Greece
Kapodistriou, 49100 Corfu, Greece,
Tel + 30266148181
e-mail vchris@ionio.gr

A. EVANGELOU
Department of Exp. Physiology, School of Medicine, University of Ioannina, Greece,
University Campus of. Ioannina, 45110 Greece,
Tel +30651 97577
e-mail : evagel@uoi.gr

Abstract: In the present study the problem of discriminating between interictal epileptic and non- epileptic pathological EEG stages, which present episodic loss of consciousness, is investigated. The proposed method is based on a novel algorithm, which produces auto-correlated coefficients from an appropriate, selected EEG segment. The characteristic features of these coefficients are based on a prototype spectral variation of an extended spectrum in which alpha, beta and gamma activities are included. The statistical processing of the results of this method shows that it may be characterized as accurate for recognition purposes.

Keywords: Auto-Cross-Correlation Methods, Diagnostic Test, Epileptic, Interictal,.

1. Introduction

It is known that determining whether a person with "seizures", "spells" or other episodic, unusual behavior actually has epilepsy presents difficulties. For example episodic loss of consciousness need not signal epilepsy but could result from loss of blood supply to the brain from diseases of the blood vessels or the heart itself. Periodic low blood sugar and certain types of migraine headache may also lead to loss of consciousness (Brown et al., 1991). Therefore, Non-Epileptic Events (NEEs) may be due to different organic or non-organic disorders. The diagnosis of Non-Epileptic Attack Disorder (NEAD) involves both exclusion of organic causes of NEEs and elucidation of positive phenomena of this entity (Meierkord et al., 1991). The distinct entity of NEAD does not allude to any specific psychologic mechanism and this term includes a variety of synonyms like Pseudo Epileptic Seizure (PES), psychogenic seizure, pseudoseizure, hysterical seizure, hystero-epilepsy and functional seizure. The subject has recently attained renewed interest as intensive monitoring has diagnosed many cases of refractory seizures (20% or more) as non-epileptic seizures (Ramani, 1986).

In the case of Epileptic events, the condition where the brain itself is the cause of periodic spells, the classic diagnostic approach has always been to perform an EEG and search for epileptiform "spikes" or "spike and waves" which may signify epilepsy (Gibbs et al., 1943, Ramani et al., 1985). Electroencephalography remains a major complex technique in differentiating epilepsy and non-epileptic attacks like NEAD, syncope, narcolepsy, cataplexy, sleep disorders, etc. Proper clinical history and observation of an attack may not be sufficient for diagnosis and, therefore, ictal and postictal EEG, 24 hours ambulatory EEG and video EEG can be of immense help for the purpose. Long term monitoring (LTM) for epilepsy is the technological advancement to improve the yield of EEG data in differentiating Epileptic Seizure (ES) from Non- Epileptic Seizure (NES). LTM includes radio telemetry, cable telemetry and cassette recorders (Binnie, 1991). Suggestion and induction techniques along with simultaneous continuous video-EEG monitoring have been used to differentiate between EE and NEE. These include iv saline infusion, alcohol patch technique and hypnosis and NEEs could be induced in 77-82% cases (Barry et al., 2000, Walczak et al., 1994).

Ideally, an EEG is performed during an actual clinical or "ictal" event during which time runs of epileptiform discharges would be expected. However, ictal events may be few and far between.

In practice most epileptics demonstrate epileptiform activity even in-between seizures (interictally). The human eye is the "gold standard" for recognizing epileptiform activity and to distinguish it from artifactual signals and from EEG activity that may mimic epileptiform activity but is benign ("normal variants"). However the unaided human eye cannot efficiently distinguish the specific details of interictal epileptic activity that are valuable regarding a final epileptic diagnosis (Gibbs et al., 1943, Ramani et al., 1985).

In the present study, in contrast with the aforementioned methods, we developed a diagnostic testing method to discriminate between interictal epileptic EEG and non- epileptic pathological EEG events, a method based purely on signal processing. This method is based on an algorithm presented in our recent study (Poulos et al., 2001). Specifically, this algorithm is based on the estimation of a number of auto-correlated coefficients extracted from an interictal epileptic EEG segment. Thereinafter these coefficients are correlated with the coefficients of EEG segments of epileptic and non-epileptic cases.

The novelty of this study lies in the fact that the auto-correlation coefficients are extracted in a particular spectrum in contrast to the traditional methods where the final diagnosis of epilepsy depends on searching for epileptiform "spikes" or "spike and waves" (Gibbs et al., 1943, Ramani et al., 1985).. In this way the autocorellation coefficients of a specific interictal epileptic EEG segment may be used as a pattern recognition tool for epileptic diagnosis.

Furthermore, taking into account latest research (Medvedev et al., 1999) we studied an extended EEG spectrum in which alpha, beta and gamma activities are included. Much of the analysis done previously on event-related activity has focused on the lower frequency ranges, specifically the alpha (8-13 Hz) and beta (15-25 Hz) bands (Crone et al., 1998). Spectral changes observed during event-related desynchronization (ERD) were denoted by a drop in energy coincident with a motor action (Pfurtscheller, 1979). Recently, further analysis has shown that the neuronal activity in the gamma band (>30 Hz) is also closely associated with cortical activation (Pfurtscheller et al., 1993).

The present study is developed in the following sections:

1. *Method*: The algorithms used are described.

2. *Experimental Part*: The technical features and the details of the EEG recordings are outlined.
3. *Results*: The results of the experimental part are described.
4. *Statistical Process*: The statistical process, which is based on the experimental results, are described in order to yield a statistical conclusion regarding the reliability of the proposed method
5. *Conclusion*: Finally, the general conclusion of the proposed method is outlined as well as its possible contribution to medical science.

2. Methods

2.1 The Basis of the Algorithm

This study is based on the *hypothesis that the shape of a segment of an EEG signal may be described by the degree of asymmetry around a characteristic point [9]*. The degree of asymmetry of a segment is obtained via the Pearson criterion (Zar, 1999) and is described by the following equation:

$$S = \frac{\bar{\boldsymbol{X}} - M_O}{s}, \tag{1}$$

where:

- S is the degree of asymmetry,
- $\bar{\boldsymbol{X}}$ is the mean value of the signal segment,
- M_O is the value of the characteristic signal (data) point,
- s is the standard deviation of a signal segment.

The degree of asymmetry may be characterized as an appropriately fit index because it includes all the necessary characteristics of the EEG for our purpose. In other words, using the highest peak of the spectral density of an EEG as a symmetric axis, the extracted index in the interictal epileptic case features the positions of the waves and spikes. Moreover, it also carries the general feature of the distribution across the spectrum. This consideration may be characterized as innovative because it is possible to detect characteristic differences between pathological cases that yield similar EEG recordings such as those referred to in the introduction. Furthermore, in the present study we chose to extend our research to include gamma activity, 5-70 Hz (fig. 1).

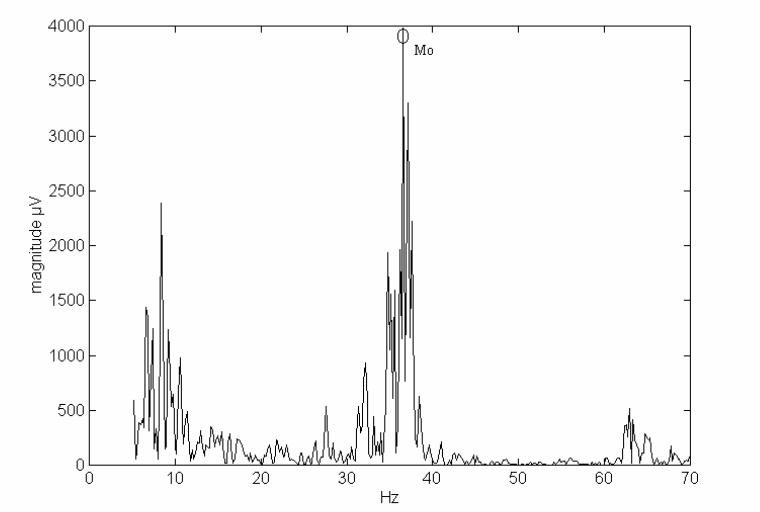

Figure 1. *Spectral analysis of an EEG signal. Only the sub-band (5 -70 Hz) is shown.*

2.2 The Autocorrelation Coefficients

In this study we considered that the original EEG signal *x(n)* was segmented into k sequential overlap segments. Thus, we created sequence (w_k),

$$\text{where: } \{w_k\} = \{x_{1+hk}, x_{1+hk+1,...,} x_{1+2hk+f}\} \tag{2}$$

and $k = 0,1,2,...,\dfrac{n}{2h}$ *with* f and h the constants described in the experimental part.

In our case we considered that each EEG segment $x(w_k)$ with a length of *N* was partitioned into k non-overlapping sequences with a length of L so that *kL=N.* The *k* non-overlapping sequences can be expressed as:

$$x_m(w_k) = x(w_k + mL), w_k = 0,1,...,L-1 \text{ and } m = 0,1,...,k-1.$$

Thereinafter the Power Spectral Density $\hat{P}_B$ of each EEG overlap segment $x_m(w_k)$ was computed using Bartlett's periodogram method (Haukin, 1996) as follows:

$$\hat{P}_B(e^{j\omega}) = \frac{1}{N}\sum_{m=0}^{k-1}\left|\sum_{w=0}^{L-1} x(w_k + mL)e^{j\omega}\right|^2 \tag{3}$$

It is considered that the Bartlett estimate $\hat{P}_B(e^{j\omega})$ is an asymptotically unbiased and consistent estimate of the power spectrum $\hat{P}_x(e^{j\omega})$.

Furthermore, we considered that a sequence of frequencies {f} = {f_1,f_2,f_3,…,f_n} is the same length as set $\hat{P}_B$, the values of f_1 and f_n being determined in the experimental part. Then, if f_g is the element of {f} sequence which corresponds to the P_g element of the {P} sequence,

where: $$P_g = \max(\hat{P}_B(e^{i\omega})) \quad \text{and} \quad 1 \le g \le n \tag{4}$$

then equation (1) ,taking into account equations (3,4), is modified as follows:

$$S_k = \frac{\bar{\hat{f}} - f_g}{\sqrt{\dfrac{\sum\left|\hat{P}_B(e^{i\omega})\right|^2 - \dfrac{\left|\sum \hat{P}_B(e^{i\omega})\right|^2}{N}}{N-1}}}, \text{ where } \hat{P}_B \text{ is given by equation 3} \tag{5}$$

Thereinafter, we considered set {D} of sequences which consist of the following:

$$\{D\}=\{\hat{D}_1,\hat{D}_2,\ldots,\hat{D}_{k-1}\},$$

where: $\hat{D}_1=\{S_1,S_2\}$, $\hat{D}_2=\{S_1,S_2,S_3\}$, $\hat{D}_3=\{S_1,S_2,S_3,S_4\}$,…, $\hat{D}_{k-1}=\{S_1,S_2,S_3,\ldots,S_k\}$.

Then the autocorrelation coefficients of the proposed method were computed as follows:

$$\hat{C} = [C_1, C_2, C_3, \ldots C_{K-1}] \tag{6}$$

where:

$$C_1 = \sqrt{\frac{\sum\left|\hat{D}_1\right|^2 - \dfrac{\left|\sum \hat{D}_1\right|^2}{N}}{N-1}}$$

In conclusion, these extracted autocorrelation coefficients may be characterized as a mapping of the variation of spectral density of an EEG as can be seen in figure 2.

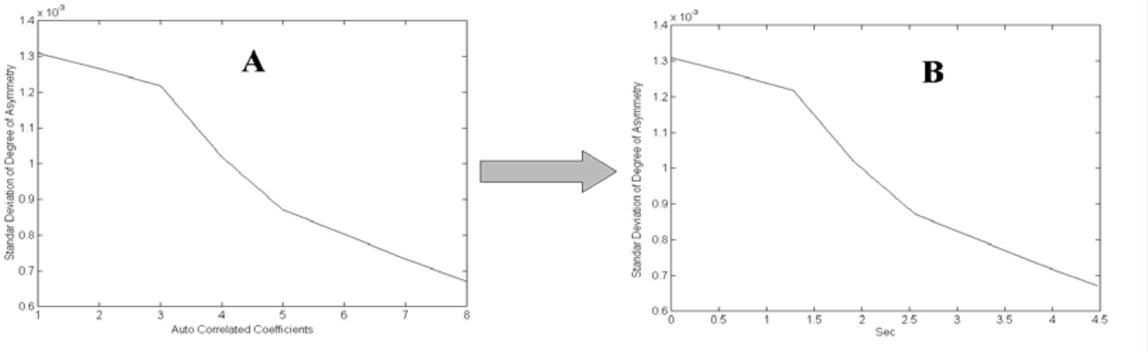

Figure 2. *In figure* ***A*** *an example of the variation of the autocorrelation coefficients is presented. In figure* ***B,*** *figure* ***A*** *is transformed in order to present the variation of the standard deviation in relation to time.*

2.3 The Cross-Correlation Procedure

In this stage the extracted set of auto-correlation coefficients $\hat{C}_x$ of an interictal epileptic EEG case were submitted to the cross-correlation procedure (Morrison et al., 1976) along with another set $\hat{C}_y$ (interictal epileptic or non-epileptic case) as described below:

$$r = \frac{\sum_{i=1}^{k-1} (\hat{C}x_i - \bar{\hat{C}}x_i)(\hat{C}y_i - \bar{\hat{C}}y_i)}{\sqrt{\sum_{i=1}^{k-1} (\hat{C}x_i - \bar{\hat{C}}x_i)^2 \sum_{i=1}^{k-1} (\hat{C}y_i - \bar{\hat{C}}y_i)^2}} \quad (7)$$

The extracted cross-correlation coefficient is a number between -1 and 1, which measures the degree to which two variable sets are linearly related. In our study we considered that the auto-correlated unknown EEG set has a perfect positive linear relationship with the auto-correlated interictal epileptic set $\hat{C}_x$ when the cross-correlation coefficient is approximately 1.

2.4 The Selection of the characteristic interictal epileptic set $\hat{C}_x$

The selection is based on the claim that a particular characteristic segment of an epileptic EEG may carry specific epileptiform features (Mormann et al. 2000). For the determination of this segment we used a method that is based on the overlapping segmentation of the original EEG. The algorithm of this method is described as follows:

1. An original EEG segment $x(n)$ of length l was segmented into g overlap segments of lengths l_1 with overlap window w. It must be noted that the determination of these lengths (l, l_1, w) was based on previous studies (Barlow, 1985) and this was corroborated in the experimental part of the present study. The correlation of these lengths is determined as follows (see figure 3):

$$gw + c = l, \quad \text{where: } 0 \le c \le l_1 \tag{8}$$

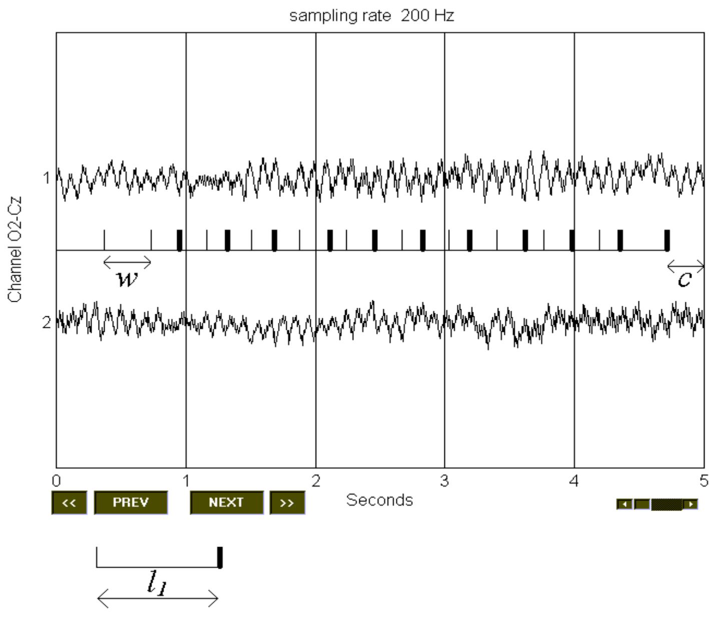

Figure 3. *An example of the overlapping segmentation of two EEGs of 5 sec duration each. In case 1 there is an interictal epileptiform EEG segment while in case 2 there is a non-epileptic EEG segment. In both cases the gamma activity is evident.*

It should be noted that the values of parameters g, w and l_1 are determined in the experimental part and depend on EEG recording conditions such as the sampling rate, the duration of recording and the adapted filters. For better comprehension in our experiment we adopted as the most suitable values for the above parameters: *w=200, l=36000,* l_1*=4000, g=180, thus c=l-gw=36000-180*200=0 ,* these values are also mentioned in the experimental part.

2. Thereinafter the selected EEG segments were submitted to the autocorrelation procedure as described in section 2.2.

3. Then the extracted sets of auto-correlated coefficients $\{\hat{C}_1, \hat{C}_2, \hat{C}_3, ...\hat{C}_g\}$ were cross-correlated with the first set $\hat{C}_1$ according to section 2.3. Hence, a set of $\hat{r}_g$ cross-correlated coefficients was produced,

   where: $\hat{r}_{1g} = \left[r_{11}, r_{12}, ..., r_{1g} \right]$

4. The value $\bar{\hat{r}}_{1g}$ was calculated.

5. Finally, from the above set $\hat{r}_{1g}$, the coefficient that was nearest in value to $\bar{\hat{r}}_{1g}$ was selected as the ideal cross-correlated r_x coefficient. This meant that selected set $\hat{C}_x$, when cross-correlated with the other sets, yielded a new set $\hat{r}_{xg}$ of cross correlated coefficients with the best linear relationship,

   where: $\hat{r}_{xg} = \left[r_{x1}, r_{x2}, ..., r_{xg} \right]$

For this reason estimated set $\hat{C}_x$ may be characterized as ideal for our purpose.

3. Experimental Part

3. 1. Signal acquisition

In our study two (2) data types were recorded. On the one hand 42 interictal epileptic EEGs from diagnosed epileptic individuals were recorded and on the other hand 44 EEGs from diagnosed pathological cases, who had presented loss of consciousness, were also recorded. It must be noted that for all the EEGs of both data types it was impossible to diagnose with the eye or with known computer methods based on detection using "spikes" or "spike and waves". That is because in the interictal epileptic cases we selected original EEG segments which were devoid of characteristic epilepticform spikes, see figure 3. Furthermore, the epileptic and non-epileptic EEG segments belonged to different adult individuals.

All recordings were taken using a digital electroencephalograph with RHY-100 Stellate software. Subjects were at rest, with closed eyes. Voltage difference (in μVolts) was recorded between leads O2 and CZ. The selection of these leads is justified because it is known that from these regions of the scalp can be extracted those faster activities such as alpha, beta and gamma. All EEG recordings lasted for twenty (20) continuous seconds (the duration having been selected after experimentation), thus producing a 4000 samples long record each at a 200 Hz sampling rate. Further processing was carried out off-line, in Matlab 5.2, on a Pentium PC. Furthermore, for the extraction of characteristic interictal epileptic set $\hat{C}_x$, an interictal epileptiform EEG was recorded lasting three (3) continuous minutes, thus producing a 36000 samples long record.

3. 2. EEG signal processing

All (42+44=86) EEGs recorded were submitted to the auto-correlation procedure as described in section 2.2. We ascertained that the best results were extracted using n=2000, F=1000, h=128 and k=8 in equation 2. Furthermore, after experimentation we adopted those frequencies between 5 and 70 HZ as the most suitable spectrum for each EEG segment. In total 86 auto-correlation vectors were yielded, each of size (1x8). In table 1 an example of two characteristic vectors of the extracted auto-correlation coefficients can be seen. After that, the complete database of EEGs (epileptic and non epileptic) was submitted to the auto-correlation procedure and thereafter each of the extracted auto-correlated sets was cross-correlated with the interictal epileptic set $\hat{C}_x$ (section 2.4) in order to ascertain their degree of linear relationship. For the extraction of the interictal epileptic set the determination of the parameters of equation (7) took place as follows:

$w=200,\ l=36000,\ l_1=4000,\ g=180,\ thus\ c=l-gw=36000-(180*200)=0$

Table 1. *An example of two auto-correlation coefficient sets.*

Auto-Correlation Coefficients *(C)*	
Interictal Epileptic EEG	**Non- Epileptic EEG**
0.0280	0.0059
0.0238	0.0021
0.0192	0.0025
0.0169	0.0023
0.0146	0.0024
0.0117	0.0021
0.0105	0.0016
0.0091	0.0017

Hence, for this extraction 180 auto -correlated sets of coefficients were produced from the original epileptiform EEG and the appropriate set $\hat{C}_x$ was selected according to section 2.4.

4. Results

In table 2 the results of the cross-correlation coefficients, which were extracted according to the processing procedure described in sections 2 and 3, are presented.

In more details, this table shows that the cross-correlated coefficients in the interictal epileptic EEG case range between 0.80 and 1 while in the non-epileptic case they range between 0.05 and 0.90. The first general conclusion to be drawn is that the interictal epileptic sets present a better correlation with the interictal epileptic set $\hat{C}_1$ than the non epileptic sets because their values are nearer the unit.

Table 2. *The extracted cross correlation coefficients r.*

Cross-Correlation Coefficients (*r*)			
Interictal Epileptic EEG		**Non -Epileptic EEG**	
0.93	0.99	0.67	0.78
0.95	0.91	0.84	0.72
0.98	0.86	0.08	0.68
0.96	0.93	0.67	0.27
0.93	0.90	0.80	-0.14
0.89	0.93	0.34	0.68
0.90	0.94	0.87	-0.78
0.99	0.95	0.23	0.89
0.82	0.96	0.47	0.91
0.99	0.91	0.13	-0.09
0.96	0.85	0.71	0.85
0.98	0.94	0.13	0.15
0.89	0.95	0.71	0.37
0.86	0.93	-0.05	0.11
0.80	0.97	-0.33	0.72
0.83	0.92	0.24	0.78
0.98	0.81	0.08	-0.05
0.93	0.94	0.90	0.88
0.92	0.88	0.63	0.56
0.95		-0.56	0.87
0.94		0.59	0.24
0.91		0.67	
0.90		-0.21	

5. Statistical Process

5.1 Tests of (least-squares) Correlation Coefficients

In our case, we needed to test if *r* was significant. In such tests, *r* is the sample-derived estimate of *ρ*. Then we considered that the null hypothesis is: $H_0 : \rho_0 = 0$. Therefore, the sampling distribution of *r* for a population that has zero correlation $(\rho = 0)$ has a mean value of $\mu = 0$ and. Hence, a t-statistic can be calculated as:

$$\sigma = \sqrt{\frac{(1-r^2)}{k-2}}$$

$$t = \frac{r-\mu}{\sigma} = \frac{r}{\sqrt{\frac{(1-r2)}{k-2}}} = \frac{r\sqrt{k-2}}{\sqrt{1-r^2}} . \tag{8}$$

The next step was to determine the appropriate value of the *r* coefficient in order to characterize it as a significant linear relationship between the correlated sets in our experiment. Thus, having $k = 8$, and the degree of freedom $v = k - 2 = 6$ we chose $a = 0.01$ and thus found critical $t_{\alpha/2} = 3.707$. Then the significant value of *r* was calculated as follows:

$$t_{\alpha/2} = \frac{r\sqrt{k-2}}{\sqrt{1-r^2}} \Rightarrow 3.707^2 = \frac{6r^2}{1-r^2} \Rightarrow r = \pm 0.83$$

In conclusion, in our case, coefficient *r* may be characterized as significant when the null hypothesis is rejected $(1 \leq |r| \leq 0.83)$. Taking this into account, table 2 is modified to table 3.

***Table 3**. The total score of statistical processing of the cross correlated coefficients.*

Cross-Correlation Coefficients (*r*)			
Interictal Epileptic EEG		**Non- Epileptic EEG**	
Significant Related	**Non-Significant Related**	**Significant Related**	**Non-Significant Related**
38	4	8	36

5. 2 Sensitivity and Specificity of the Statistical Results

In accordance with the above results, the significant related coefficients may be characterized as positive correct recognition (interictal epileptic sets) and the non-significant related coefficients (non-epileptic sets) negative correct recognition. Therefore, we can calculate the sensitivity and specificity indexes of the results in table 3. According to the above notation, sensitivity is the proportion of positive cases correctly recognized by the test while specificity is the proportion of negative cases correctly recognized by the test. For the results of table 1, these values were calculated as follows:

$$Sensitivity = \frac{a}{a+c} = \frac{38}{38+8} = 0.83$$

$$Specificity = \frac{d}{b+d} = \frac{36}{4+36} = 0.90,$$

where: a is the number of true recognition cases of tested interictal epileptic sets.

b is the number of false recognition cases of tested interictal epileptic sets.

c is the number of false recognition cases of tested non-epileptic sets.

d is the number of true recognition cases of tested non-epileptic sets.

5. Conclusion

A diagnostic test for the recognition of interictal epileptic and non- epileptic pathological EEG stages using auto-cross-correlation methods is addressed in this work-a problem that has not yet been seen in a signal processing framework, to the best of our knowledge. The statistical results of the proposed method corroborate the latest research (Medvedev et al., 1999) in that it is possible to correlate alpha, beta and gamma activities with epileptic activity. This conclusion is justified because in the experimental part the selected spectrum of each EEG segment that participated in the proposed method, contained dominant alpha activity and fewer beta and gamma activities, which, however, influenced significantly the results.

Furthermore, the experimental results of the spectral analysis show that the algorithm that is described in equation (5) corroborates the hypothesis that the shape of a segment of an EEG signal may be described by the degree of asymmetry around a characteristic point (Poulos, et al., 2001). Moreover, the satisfactory values of sensitivity and specificity increase the possibility of the use of this method in distinguishing between epileptiform and non-epileptic EEGs.

Finally, this study may be used in the future as a basis for similar diagnostic tests in the encephalographic area.

6. Acknowledgements

The Dept. of Informatics, University of Piraeus, Dept of Exp. Physiology, School of Medicine, University of Ioannina and Library Sciences, Ionion University, supported this research.

7. References

Barlow J. S. Methods of analysis of nonstationary EEGs with emphasis on segmentation techniques: a comparative review. Clin. Neurophysiology 1985; **2**(5): 267 - 304.

Barry JJ, Atzman O, Morrell MJ. Discriminating between epileptic and non-epileptic events: the utility of hypnotic seizure induction. Epilepsia 2000; 41(1): 81-84.

Binnie CD. Long-term monitoring, Comprehensive Epileptology. New York: Raven Press).1991. p.88-110.

Brown MC, Levin BE, Ramsay E, Katz DA, Duchowny MS. Characteristics of patients with non-epileptic seizures. J Epilepsy 1991; 4(5): 225-229.

Crone, NE, Miglioretti, DL, Gordon B, Lesser, R. Functional Mapping of Human Sensorimotor Cortex with Electrographic Spectral Analysis: II. Event-related Sychronization in the Gamma Band. Brain 1998; **121**(12): 2271-2299.

Gibbs FA, Gibbs EL, Lennox WG. Electroencephalographic classification of epileptic patient and control subjects. Arch Neural Psychiatric 1943; 50(2): 111-128.

Haukin S. 1996, *Adaptive Filter Theory*. New Jersey: Prentice Hall; 1996 p. 136-138.

Meierkord, H, Will R., Fish DR, Shorvon SD. The clinical features and prognosis of pseudoseizures diagnosed using video-EEG telemetry. Neurology; 1991; 41 (10):1643-1646.

Medvedev A, Willoughby JO. Can hypersychronisation of fast (gamma) activity lead to generalized epileptiform discharges? Proceedings, Epilepsy Society of Australia 1999; 41.

Mormann F, Lehnertz K, Andrzejak RG, Elger CE. Characterizing preictal states by changes in phase synchronization in intracranial EEG recordings from epilepsy patients Epilepsia 2000; 41(7): 167-172.

Morrison N, Donald F. Multivariate Statistical Methods. New York: McGraw-Hill Book Company; 1976. p.128-130

Pfurtscheller G. Evaluation of event-related Desynchronization (ERD) Preceding and Following Voluntary Self-paced Movement. Elecroencephalogr Clin NeuroPhysiol 1979; **46**(1): 138-146.

Pfurtscheller G, Neuper C, Kalcher J. 40-Hz Oscillations During Motor Behavior in Man. Neurosci. Lett. 1993; 162(2):179-182

Poulos, M. Rangousi M, Chrissicopoulos V, Evangelou A. EEG Spectrum analysis for the extraction of approximately stationary features, Proceedings of Fifth International Conference on Mathematics Methods in Scattering Theory and Biomedical Technology, BIOTECH'5, Corfu, Greece, October 2001, p. 382-394.

Ramani V. Intensive monitoring of psychogenic seizures, aggression and dyscontrol syndromes. Adv. Neurol, 1986; 46(2): 103-127.

Ramani V, Whalen S, Loewenson R. Ictal characteristics of pseudo-seizures. Arch. Neurol. 1985; 42(9): 1183-1187.

Walczak TS., Williams DT., Berten W., Utility and reliability of placebo infusion in the evaluation of patients with seizures. Neurology 1994; 44(3): 394-9.

Zar JH. *Biostatistical Analysis*. New Jersey: Prentice-Hall; 1999. p.72-73.