EEG Analysis Using Neural Networks for Seizure Detection

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Abstract: - This study introduces an integrated algorithm for the purpose of discriminating between EEG channels (electrodes) leading or not to an ictal state, using interictal subdural EEG data. The importance of this study is in determining among all of these channels, all containing interictal spikes, why some electrodes eventually lead to seizure while others do not. A first finding in the development process of the algorithm is that these interictal spikes had to be asynchronous and should be located in different regions of the brain, before any consequential interpretations of EEG behavioral patterns are possible. A singular merit of the proposed approach is that even when the EEG data is randomly selected (independent of the onset of seizure), we are able to classify those channels that lead to seizure from those that do not. It is also revealed that the region of ictal activity does not necessarily evolve from the tissue located at the channels that present interictal activity, as commonly believed. The contributions of this study emanates from (a) the choice made on the discriminating parameters used in the implementation, (b) the unique feature space that was used to optimize the delineation process of these two type of electrodes, (c) the development of back-propagation neural network that automated the decision making process, and (d) the establishment of mathematical functions that elicited the reasons for this delineation process.

Key Words: - Seizure, interictal spikes, ictal, interictal activity

1 Introduction

The EEG interictal data recorded inside the brain can be processed to define similar patterns evident in those electrodes that lead to a given seizure to further facilitate surgical planning [1-3].

This study provides a mathematical framework for the study of interictal EEG leading or not to an epileptic seizure. The EEG of epileptic subjects can be divided into two main categories, interictal and ictal. The interictal EEG is the EEG taken when the patient is not having seizures or in between seizures [2]. Interictal activity is considered to be abnormal if it can occur in a patient with epilepsy in the absence of an actual seizure. The ictal EEG activity on the other hand is when the actual seizure occurs.

The study of this new application elicits how different patients react prior to a seizure in view of the collected EEG data such as to better detect such neurological disorders. The main objectives of this study are as follows: (1) to extract features that best characterize those EEG electrodes that lead to an ictal activity; (2) to establish mathematical derivations that provide not only quantitative measures, but also describes and locates the focus of an ictal activity;(3) to identify and formulate those patterns in EEG recordings that are inherent to those electrodes that lead to a seizure; (4) to correlate the clinical features with the EEG findings in order to determine whether the patient has a consistent source of ictal activity, which is coming from the location concerning the group of channels that present interictal activity; (5) to classify and to group those EEG channels that are known in advance to lead to seizures in order to extract similarities in their behavior, so a common behavioral pattern could be found; (6) to find a suitable classifier that discriminates in the feature space the two regions of electrodes leading and not leading to an ictal state.

2 Method

Eight children with medical refractory partial seizures that underwent pre-surgical evaluation have been analyzed in this study. The subdural EEG data was recorded using XLTEK Neuroworks Ver.3.0.5 (equipment manufactured by Excel Tech Ltd. Ontario, Canada). Sampling frequency of 500Hz with 0.1-70 Hz bandpass filter settings and 12 bits A/D conversion were used to obtain the digital EEG recordings.

To classify those electrodes that lead to an epileptic seizure, a program was developed in order to quantify the patterns that are inherent to those electrodes. Input data in this study was subdural EEG segments from 20 to 3600 seconds of duration of epileptic patients. The first step in the procedure involved identifying the pertinent electrodes in the overall interictal EEG recordings in which the seizures occurred. The physicians performed this task initially through visual inspection of the recorded data. A computer program was earlier [4],[6] developed in order to detect automatically interictal spikes so as to provide more accurate and consistent input data to the proposed classification algorithm.

The classification algorithm consists of the following steps. Results obtained are revealed in the next section in order to assess both the validity of such steps and the merit of each step for identifying a suitable linear classifier.

Step 1- Filtering the input EEG data

In this preprocessing step, filtering was performed applying the Singular Value Decomposition (SVD), which is based on the eigenvalues decomposition [7,8]. The larger singular values were retained (in this case the first five were deemed sufficient for the analysis), so a better approximation is obtained, or equivalently, more information is contained in that approximation and the other values are set to zero, thus a new matrix was created. The approximated matrix, containing less noise was used in the subsequent steps. This implementation concluded the filtering preprocessing step.

Step 2- Assessment of the EEG Nonlinear Dynamics

Since brain dynamics are nonlinear, this study investigated methods such as the calculation of correlation dimension integral, mobility and complexity.

The correlation dimension integral $R(r)$ given in equation (1) is a measure of spatial organization, where the space is occupied by a set of random points. It determines the degree of complexity in the EEG signal.

$$R(r) = \frac{1}{N^2} \sum_{j=1}^{N-1} \sum_{i=j+1}^{N-1} \theta\left(r - \left|X_i - X_j\right|\right) \qquad (1)$$

Where, r is the threshold value used to evaluate the similarity between two reconstructed vectors X_i and X_j. N is the total number of points in the time series. The vector X_i is a point in the embedded phase constructed from the input EEG signal as a single time series according to the following formula: $X_i = \left(X_i, X_i + \tau, X_i + 2\tau, \ldots X_i + (m-1)\tau\right)$, where m is the so called embedding dimension and τ is a time delay.

Additionally, the Hjorth's parameters, mobility and complexity were calculated using equations 2 and 3. Mobility (equation 2) gives a measure of deviation of the voltage changes with respect to deviation of the EEG voltage amplitude, while complexity (equation 3) provides a measure of excessive details with regard to the slightest possible signal's shape [9, 10]. The mobility is computed using the following formula.

$$M(y(t)) = (\sigma(y') / \sigma(y))^{\frac{1}{2}} \qquad (2)$$

where σ is the variance and y' is the first derivative of the primary signal y. The complexity, $C(y(t))$ involves the first derivative of the mobility $M(y')$ and the mobility of the signal itself $M(y)$ and it is expressed as:

$$C(y(t)) = (M(y')/M(y))^{\frac{1}{2}} \qquad (3)$$

Step 3- Extraction of features from the EEG data

The next step dealt with extracting features from the filtered EEG matrix using the aforementioned parameters of step 2 in order to discriminate between the two groups of electrodes. All these three parameters were computed for each electrode separately using successive epochs or non-overlapping windows of 1 second for all the recorded subdural EEG data. By computing these parameters, a behavior for each feature over time was established for each electrode.

Step 4- Implementation of regression lines for each electrode and parameter

As all the different parameters were represented in time, regression lines for all of these parameters were calculated in order to keep a suitable track of the behavior of each electrode with respect to the computed parameter. This also helps in determining a linear classifier that separates in the parameter vs. time space the two different classes of electrodes. One condition to make this study more relevant from a clinical point of view was to require from these two classes of electrodes to be totally independent in terms of source location, and synchronicity of the spike firing. After obtaining regression lines for all electrodes, two groups of regression lines per parameter were created. These computed linear approximations were used for each electrode to facilitate visualization of the overall trend of each electrode.

Step 5- Neural network structure for linear classification

At this stage, a plot of the three selected features revealed well defined electrodes clusters. No other features produced class clusters so compact and separated from each other. But extrapolation of this mechanism of classification in time did not work as anticipated since the time dynamics of the parameters strongly changed from one recording to the other, despite visible class clustering. In a parameter vs. time plot, the separating points between the two electrode groups changed from one recording to another.

This is best illustrated in Figure 1. Note that each plot is represented only for 20 seconds in two different segments of the EEG data. The real time, where the data was taken, is displayed at the bottom of the two plots.

In order to consider this relative change and yet make real-time classification possible, time independent analysis was performed by computing for each feature three statistical parameters, namely the mean of the regression line that represents the feature behavior, the standard deviation of the parameter over time and the power of the frequency spectrum of the feature over time.

The average and the standard deviation for each regression line were computed for each group of electrodes. Also, the Fourier Transform was applied to the behavior of each parameter over time and its power frequency was calculated for each electrode. These statistical parameters were then inputted to an artificial neural network (ANN) in order to obtain a linear classifier for each feature [6]. Linear decision functions could then be established for classifying the electrodes based on these statistical parameters. One decision function was created exclusively for each of the three parameters (correlation, mobility, and complexity). These specific decision functions would find the optimum separating plane between the two classes of electrodes in a 3D space where the axis are represented by the statistical parameters used (mean, standard deviation, and frequency power).

The training and testing process was carried out using a cross validation training technique. The network was trained with a 25 percentage of the EEG data and tested in the remaining.

Establishing an artificial neural network (ANN) that is trained to extract seizure-leading features of interictal EEG is a significance outcome, since this ANN: (1) can help to overcome the subjective factor associated with human classification; (2) can serve as a second expert for decision process validation; and (3) can be used for fast automated seizure leading channels detection, even for on-line recordings, sparing EEG technicians the tedious task of long-term monitoring.

The network configuration used in this research consist of 3 input neurons that correspond to the mean, standard deviation, and frequency power (μ,σ,Φ) of the parameter analyzed. The output would be 1 or -1, which indicates if a given channel leads to seizure or not, respectively.

The classifiers are three decision functions of the form:

$$f_\xi(\underline{X}) = w_1 \cdot \mu_\xi(\underline{X}) + w_2 \cdot \sigma_\xi(\underline{X}) + w_3 \cdot \Phi_\xi(\underline{X}) + w_4 \quad (4)$$

The subscript ξ is defined as follows:

$$\xi = \begin{cases} R & \text{for Correlation} \\ M & \text{for Mobility} \\ C & \text{for Complexity} \end{cases}$$

Where $\underline{X}$ is a vector containing the values of the specific parameter (correlation integral, complexity, or mobility) for all time windows; w_1, w_2, w_3, and w_4 are coefficients and $\mu_\xi(\underline{X})$, $\sigma_\xi(\underline{X})$ and $\Phi_\xi(\underline{X})$ are the mean, the standard deviation, and the frequency power of vector $\underline{X}$, respectively. Electrodes are classified as leading to seizure only if $f_\xi(\underline{X}) > 0$ for a specific feature.

The decision functions consisted of feed-forward ANNs trained via back-propagation. These ANNs are structured with 3 input neurons and 1 output neuron, with linear activation functions. This type of structure produces a linear classifier.

3 Results

Results of this study indicate that this EEG analysis technique allows defining two regions of electrodes, one for electrodes leading to an ictal state and another for the remaining electrodes that do not lead to such state. Also, using different parameters, characterization of the behavior of the interictal EEG over time is possible. The rate of missed detections as well as the rate of incorrect positive detections were extracted and are given in percentages in Table 1. As it can be observed, the complexity results are the best compared to the other two parameters. Two misclassification percentage rates are calculated: one for the group of electrodes leading to seizure (False Negative Rate) and the other for to the group of electrodes that do not lead to seizure (False Positive Rate).

Making the ANN converges and yielding accurate classification results should be emphasized as well as that the separability is achieved because of the choices of the 3 discriminant features of mean, standard deviation, and frequency power. This in itself constitutes a mayor contribution of this dissertation.

In assessing the examples treated before, the complexity parameter produces the most consistent and reliable results across all 8 patients included in the study.

The total number of electrodes that presented interictal activity was 75, out of which 30 lead to seizure onset and 45 did lead to an ictal state. The following evaluation results were obtained.

$$\text{Precision} = \frac{TP}{TP+FP} = 94\% \tag{5}$$

$$Sensitivity = \frac{TP}{TP+FN} = 97\% \tag{6}$$

$$Specificity = \frac{TN}{FP+TN} = 96\% \tag{7}$$

The terminology used is explained as follows: FP (Not leading to seizure), FN (Leading to seizure), FN (Leading to seizure), and TN (Not leading to seizure).

The complexity outcomes are given in Figures 2 and 3. The red (-) and blue (+.) channels are the ones leading and not leading to seizure. Note that the three features (μ,σ,Φ) have great potential for classifying electrodes leading to seizure, regardless on what type of classifier used with respect to the 3 parameters.

Key findings can be affirmed as follows: (1) it was found that at any window of time along the EEG signal (independent of time), acceptable classifiers could be obtained using just the complexity values; (2) A search for such decision functions across patients is ineffectual, because experiments reveal that such decision functions are patient dependent; (3) It is extremely important that when one is to search for such decision functions, electrodes should be analyzed only if they are localized in different locations and with recorded interictal spikes not happening simultaneously.

Table 2, provides a summary of the results for of all the patients. The arrows indicate if for a given parameter, the values of the red group of electrodes are higher or lower with respect to the blue group of electrodes. As can be observed, for 5 patients out of 8, the complexity values for those electrodes that lead to an ictal state are higher than the values of those electrodes that do not lead to seizure. Also, the mobility values for these five patients behave in the same manner. Two patients behave in a similar fashion, and their complexity and mobility values are reversed if we compare them with the other five patients.

Table 2 Lower ⇓ or higher ⇑ values of the leading to seizure with respect to the not leading to seizure channels.

Patient	*Mobility (M)*	*Complexity (C)*	*Correlation (R)*
1	⇑	⇑	⇓
2	⇑	⇑	⇓
3	⇓	⇓	⇑
4	⇑	⇑	⇓
5	⇑	⇑	⇓
6	⇑	⇑	⇓
7	⇓	⇓	⇑
8	⇓	⇑	⇑

A closer look at this table reveals the following conditions: If we assign a negative (-) to ⇓ and a (+) to ⇑, then, the following relations hold:

$$\begin{aligned} &C * R < 0 \\ &M * R < 0 \\ &M * C > 0 \\ &M * C * R < 0 \end{aligned} \tag{8}$$

These relations as established in equation 8 constitute another mayor observation in this study. It could be concluded that the integration of these 3 parameters could augment our results.

4 Conclusion

The likelihood of the success of surgery is increased when all test results point to a single epileptogenic focus [11-14]. The unique contribution of our study is to understand better the characteristics of the different interictal epileptiform activities. In all of these performance values of the 3 parameters implemented, it can be said that the results obtained show great promise in delineating electrodes that lead to seizure from those that do not. It is fitting to note that when our results failed to discriminate between these two sets of electrodes, a clinical analysis revealed that those electrodes were indeed situated in the same region and their interictal spikes were happening simultaneously. As this study will involve a higher number of patients as they become available, additional results will provide more credence to our findings.

The uniqueness of this algorithm is in the establishment of a mathematical foundation capable of extracting features from interictal EEG signals using the above mentioned parameters, which served as change indicators for our analysis. The integration of several parameters (correlation integral, mobility, and complexity) constitutes a unified method for assessing differences in the EEG channels.

Acknowledgments

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References:

[1] B. Greenstein & A. Greenstein, *Color atlas of neuroscience,Neuroanatomy and Neurophy.*, Thieme Stuttgart New York, 2000.

[2] F. H. Martini, *Fundamentals of anatomy & physiology* (Fifth edition, New Jersey 07458, Prentice Hall, 2001).

[3] A.S. Gevins & A. Remond, *Methods of analysis of brain electrical and magnetic signals. Handbook of EEG and CclinicalNneurophysiology,* Elsevier: Amsterdam, 1987.

[4] M. Adjouadi, M. Cabrerizo, M. Ayala, D. Sanchez, P. Jayakar, I. Yaylali, & A. Barreto, A new approach to the analysis of epileptogenic data using statistically independent operators, *Journal of Clinical Neurophysiology*, *Vol. 22(1),* January/February 2005, 53-64.

[5] M. Adjouadi, M. Cabrerizo, M. Ayala, P. Jayakar, I. Yaylali, & A. Barreto, Interictal spike detection using the walsh transform, *IEEE Transactions on Biomedical Engineering, Vol. 51*, *No. 5*, May 2004, 868-873.

[6] M. Ayala, M. Adjouadi, I. Yaylali, & P. Jayakar, An optimization approach to recognition of epileptogenic data using neural networks with simplified input layers, *Biomed. Sciences Instrumentation*, *Vol. 40*, 2004, 181-186.

[7] A.C.K Soong & Z.J. Koles, Principal-Component localization of the sources of the background EEG, *Biomedical Engineering, IEEE Transactions*, *42*(1), 1995, 59-67.

[8] L. Zhukov, D. Weinstein, & C. Johnson, Independent component analysis for EEG source localization, *IEEE Engineering in Medicine and Biology Magazine*, *19*(3), 2000, 87-96.

[9] R. C. Gonzalez, & R. E. Woods, *Image transforms - digital image processing,* Addison-Wesley Publishing Company, 1993.

[10] Proakis, J. G. and Dimitris, G. M., *Digital signal processing - principles, algorithms and applications*, Prentice Hall, Third Edition, 1996.

[11] A. B. Barreto, J. C. Principe & S. A. Reid, STL: A spatio-temporal characterization of focal interictal events, *Brain Topo*, v*ol. 5, No. 3*, Human Sciences Press, NY, 1993, 215-228.

[12] L. D. Iasemidis, A. Barreto, R. L. Gilmore, B. M. Uthman, S. A. Roper, & J.C. Sackellares, Spatiotemporal evolution of dynamical measures precedes onset of mesial temporal lobe seizures, *Epilepsia*, *vol. 35*, 1994. 133-134.

[13] M. Adjouadi, M. Cabrerizo, M. Ayala, "Seizing lesions in 3-D", IEEE Potentials, Vol. 24, Issue 5, December/January, 2006, pp. 11-17.

[14] M. Cabrerizo, M. Adjouadi, M. Ayala, A. Sesin, "3D Epileptic Foci Detection Using an Integrated Neuro-Imaging Approach", WSEAS Transactions on Information Science and Applications, Vol. 2 (7), August 2005, pp. 987-995.

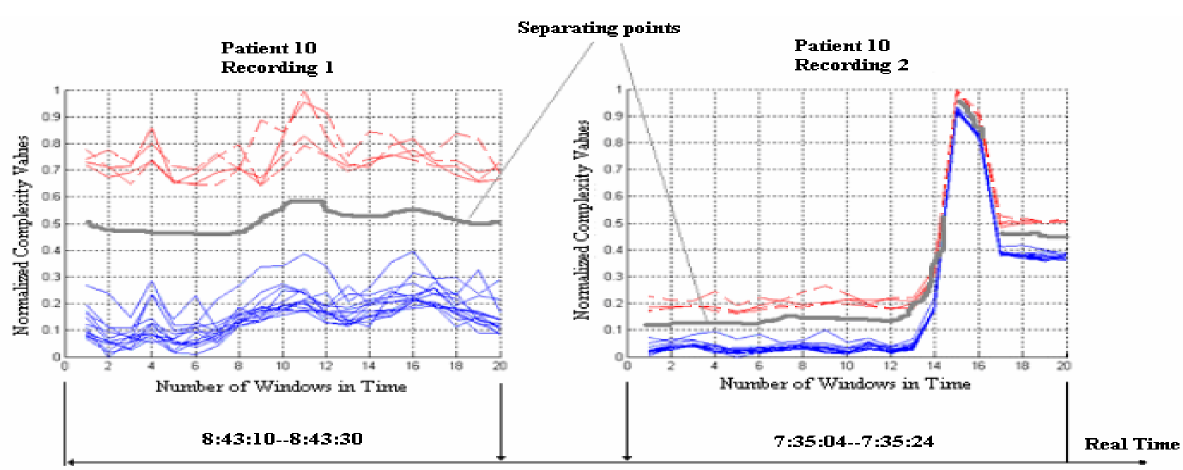

Fig. 1 Electrode clusters changing their relative location in the feature vs. time plot.

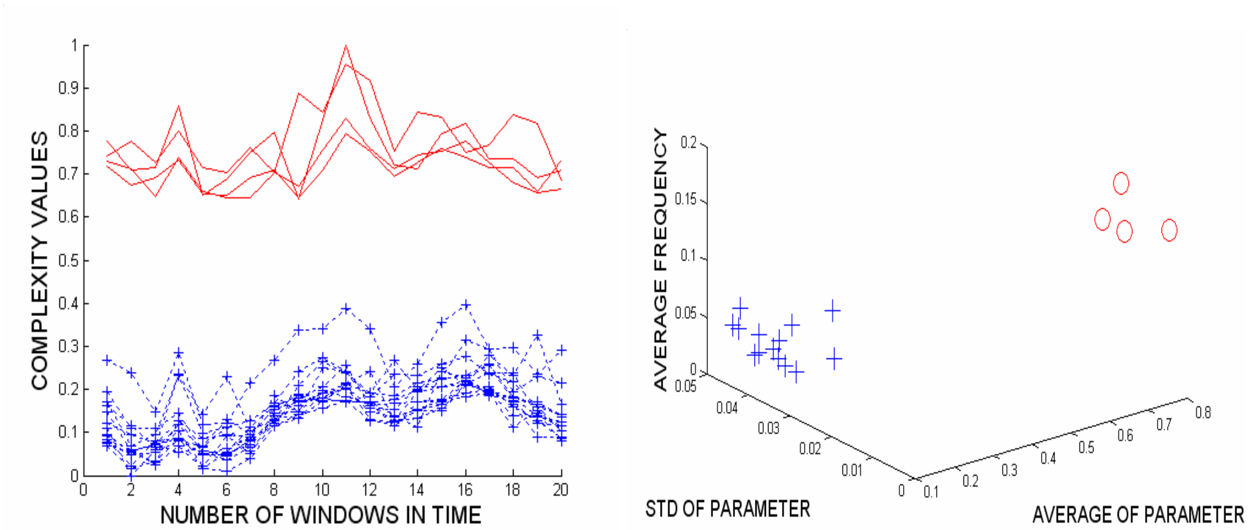

Fig. 2 Complexity results for patient 4.

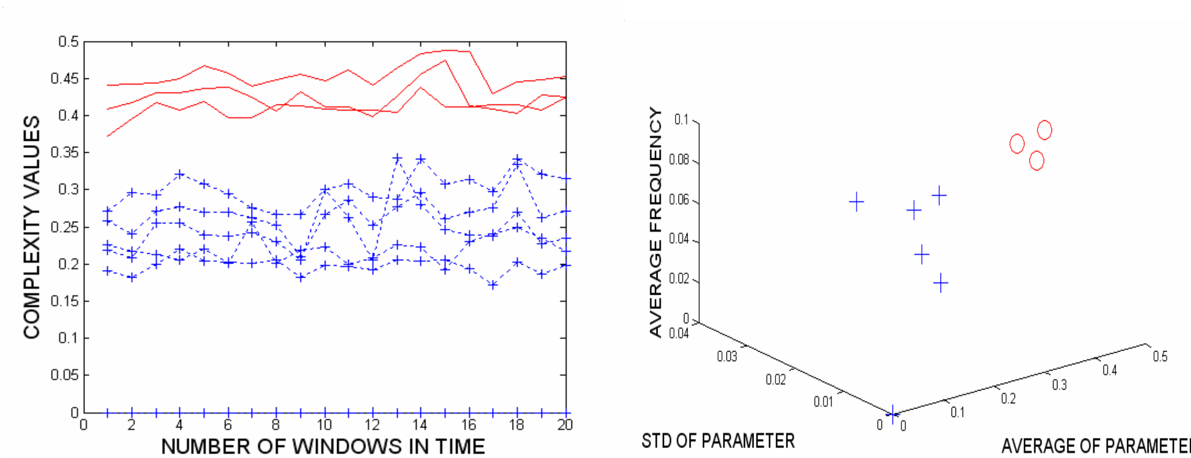

Fig. 3 Complexity results for patient 6.

Table 1 Percentage of misclassification (results have been averaged across all EEG segments).

Patient List	*Correlation FNr*	*Correlation FPr*	*Mobility FNr*	*Mobility FPr*	*Complexity FNr*	*Complexity FPr*
Patient 1	40.7 %	0.0 %	14.3 %	12.9 %	14.3 %	0.0 %
Patient 2	37.5 %	0.0 %	20.0 %	0.0 %	0.0 %	0.0 %
Patient 3	0.0 %	8.2 %	0.0 %	0.0 %	0.0 %	0.0 %
Patient 4	33.3 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
Patient 5	0.0 %	5.0 %	0.0 %	0.0 %	0.0 %	0.0 %
Patient 6	28.6 %	0.0 %	14.3 %	0.0 %	14.3 %	0.0 %
Patient 7	42.8 %	0.0 %	28.6 %	0.0 %	14.3 %	0.0 %
Patient 8	42.8 %	5.0 %	14.3 %	0.0 %	0.0 %	0.0 %