Application of the Walsh Transform Towards Seizure Detection

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Abstract: - Epilepsy is a neurological disorder, a physical condition, which causes sudden bursts of electrical energy in the brain. Electrical activity in the brain has been studied for years in an attempt to detect seizures. This paper processes raw intracranial electroencephalographic recordings in the time prior and during a seizure.This study focuses on the design of orthogonal operators based on the Walsh transform in order to detect the onset of epileptic seizures in EEG data. The merits of the algorithm are: (a) in elaborating a unique analysis scheme that scrutinizes EEG data through orthogonal operators designed to extract patterns that best characterize seizures in epileptogenic EEG data; and (b) in establishing mathematical derivations that provide not only quantitative measures through the designed operators, but also characterize and locate the event of a seizure. In this study, EEG recordings from different patients are processed. A set of parameters is extracted from non-overlapping scrolling windows of 1 sec duration. The objective was to detect the seizure applying the operators of the Walsh transform using these parameters.

Key-Words: - EEG, Epilepsy, Seizure detection, Walsh Transform

1 Introduction

The National Institute of Neurological Disorders and Stroke estimates that more than 2 million people in the United States have experienced an unprovoked seizure or been diagnosed with epilepsy. For about 80 percent of those diagnosed with epilepsy, seizures can be controlled with some medicines.

EEG has been studied for years in an attempt to detect seizures. Anything that disturbs the normal pattern of neuron activity can lead to seizures.

In the area of epilepsy, where one of the most important goals is to detect seizures, the use of many measures has been practiced by various research groups for many years. This outcome is quite understandable given the challenge imposed by such a critical research endeavor. In the context of this study, many of the methods currently available in the specialized literature have been tested yielding different results. In an effort to conduct a detailed investigation on EEG data towards seizure detection, this study extracts a set of parameters from EEG data and analyzes its behavior in time, looking for patterns that would reveal that a seizure is developing in order to detect it. All observations will be discussed and assessments will be made for future studies on seizure detection. These observations could also help in the endeavor of seizure prediction.

The detection process is designed such as to allow physicians to make evaluative assessments of epileptic seizures, which in turn will enable targeted treatment. The use of the Walsh transform in analyzing epileptogenic data, and the application of its associated mathematical derivations proposed show promise not only for detecting seizures, but also in characterizing them with quantitative measures. Processes and methods for the automated detection of seizures can be very useful, especially during long-term EEG monitoring sessions, and may serve as a support mechanism to the decisions made by EEG experts.

In recent decades, a definite consensus was reached about the chaotic nature of the EEG signals and as a result, non-linear dynamics are extensively applied to these signals [1, 2]. Correlation integral is currently the most common basis on which the claim of chaotic dynamics has been made in biological systems [3, 4]. Correlation dimension oriented analysis applied to raw EEG and some variations including autocorrelation and entropy [5] are being directed with encouraging results, especially in the elusive problem of seizure detection, where promising results are claimed to be obtained [6].

One goal is to enable people with epilepsy to take less medicine than they currently do, and to be able to use it only when it is necessary. There are some cases in which medicine do not offer complete prevention of seizures; therefore. The quality of life of many epilepsy patients may be improved significantly if epileptic seizures can be successfully forecasted and clinical intervention, such as electrical stimulation or drug delivery, can then be used to suppress their emergence, or warn the patient of the forthcoming events. It is therefore extremely important to detect a seizure. Having a method for this end, it would be very helpful for the precise location of an epileptic focus and in this way a more targeted treatment could be addressed.

2 Methods

2.1 Data Collection

Subdural EEG recordings of 3 epileptic children were analyzed. A total of 12 different seizures were studied. Recording were performed during pre-surgical monitoring at the Miami's Children Hospital (MCH) using XLTEK Neuroworks Ver.3.0.5, equipment manufactured by Excel Tech Ltd. Ontario, Canada. This data was collected at 500 Hz sampling frequency and filtered to remove DC and high frequency components using a 0.1-70 Hz band-pass filter. EEG recordings were processed in the time prior to seizure.

The number of electrodes implanted differed from subject to subject. Intracranial recordings of three subjects were performed by using subdural strip or grid electrodes. In some cases, 4 contact depth electrodes were implanted.

2.2 Data Analysis

2.2.1 Data Preprocessing

The primary objective was to analyze all electrodes; the last sixty minutes preceding a seizure and two minutes after seizure onset were analyzed. The size of the files of raw data was higher than one gigabyte because the files contained 1,800,000 samples; to that end, the software TextFileSplitter [7] was developed to split the files into readable pieces easier to handle. Most of the EEG recording text files cannot even be read by a personal computer by any visualization program (such as MS Excel or MS Notepad) because the amount of memory required to read the file significantly exceeds the available computer memory. TextFileSplitter was therefore developed to split such huge EEG recording text files into two separate files of less size such that they can be later read by a visualization editor.

Table 1 Subjects' information

Subject	Age (years)	Sex	Number of files
1	9	Male	3
2	11	Female	3
3	14	Male	6

Data sets used are from 3 subjects (two males, one female; age range, 9–14 years) with epilepsy in whom subdural strips and/or grid electrodes were implanted. Each subject has a different number of EEG files; the relevant information for all patients is given in Table I. For all subjects all files extend from 60 minutes prior to seizure onset.

2.2.2 Electrode Categorization

Previous studies on related matters [8] reveal that there is a tendency on the behavior of the electrodes that lead to seizure which is not given in those not leading to seizure. A portion of this research was devoted to confirm these previous findings. For this purpose, each set of electrodes was divided into three categories; those that led to seizure, those that contained interictal spikes and did not lead to seizure and those that did not contain interictal spikes and did not lead to seizure. To identify the different categories of electrodes; neurologists performed a visual inspection of the recorded data.

The analysis of data depending on these categories has been performed in this study with the only purpose of confirming observations, but not with the intention of searching for patterns that could be used for seizure prediction.

It was intended at the beginning to only use a certain group of electrodes so a better detection could be performed more accurately, however, results as illustrated in Figures 1 and 2, confirm that applying the Walsh operators to all electrodes, the detection could be performed more accurately. A better visualization could be observed based in the immediate change that occurs at the time of the seizure onset, which is represented by a vertical red line in the plots.

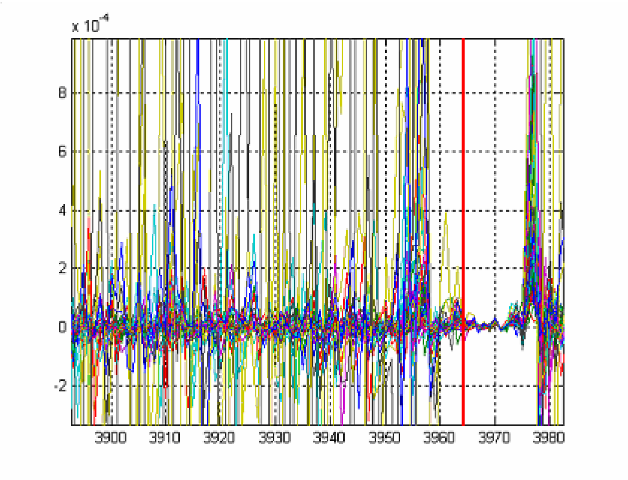


Fig. 1 Walsh first operator for all electrodes.

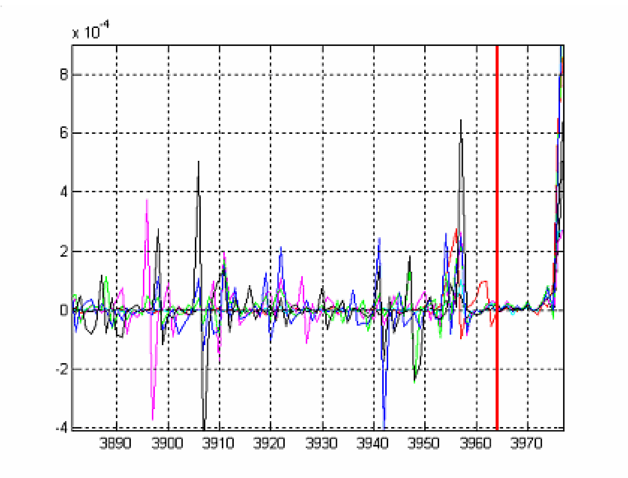


Fig. 2 Walsh first operator for electrodes that lead to seizure.

2.2.3 Parameter Extraction

Due to the high volume of information contained in the EEG raw data files, size reduction was necessary. Data files were segmented in one second time windows and parameters were extracted for all windows. The size of the set was thus reduced to a small number of parameters that are representative of the EEG. This set of parameters was then used for the study.

The following three parameters were considered:

- F_1: correlation integral.
- F_2: mobility
- F_3: complexity

There are other interesting features used in EEG processing, such as the Lyapunov exponent which is a complex mathematical quantity in which the amount of chaos in the brain is measured [9]. But they were not included in the analysis because they are computationally intensive. For compensation, the correlation integral was included in the list, which is a non linear feature related to the Lyapunov exponent.

Mobility and complexity are known as Hjorth parameters [10].

Mobility Mx, is computed as the square root of the ratio of the activity of the first derivative of the signal $A_{x'}$ to the activity of the original signal A_x :

$$M_x = \sqrt{\frac{A_{x'}}{A_x}} = \frac{\sigma_{x'}}{\sigma_x} \tag{1}$$

where x' represents the first derivative of the input EEG signal x.

Mobility gives a measure of deviation of the voltage changes with respect to deviation of the EEG voltage amplitude *Complexity* is defined as the ratio of the mobility of the first derivative of the signal to the mobility of the signal itself:

$$C = \frac{M_{x'}}{M_x} = \frac{\sigma_{x''}/\sigma_{x'}}{\sigma_{x'}/\sigma_x} \tag{2}$$

where x'' stands for the second derivative of the input EEG signal.

The complexity of a sinusoidal wave is unity; other waveforms have complexity values increasing with the extent of variations present in them. Complexity represents the deviation from the sine shape of the EEG signal.

Correlation integral is mostly used to detect randomness in data. It is given by:

$$C_{m,r} = C_r = \frac{1}{N}\sum_{k=1}^{N}\left[\frac{1}{N}\sum_{i=1}^{N}\theta(r - |x_i - x_k|)\right] \tag{3}$$

where N is the total number of samples in the EEG data segment inside the sliding window, $\theta(u)$ is the step function, and $|x_i - x_k|$ is the distance between x_i and x_k. The vector x_i used in the correlation integral is a point in the embedded phase constructed from the input EEG signal as a single time series according to the following:

$$X_i = \left(x_i, x_i + \tau, x_i + 2\tau, ...x_i + (m-1)\tau\right) \quad (4)$$

where m is the so called embedding dimension and τ is a delay. The correlation integral can be interpreted as the number of point pairs inside a hyper-ball of radius *r*.

2.2.4 Detection using Walsh Transform

The interesting aspect in this study is that Walsh operators satisfy the important concept of orthogonality and yet an analogy to discrete mathematical derivatives can be generalized in terms of their functional behavior [11, 12, 13].

For the ordered Walsh kernel matrix, the Walsh operator ω_N^r of r^{th} order and length N is defined based on the sequency value (number of sign changes in its ± 1 elements) and the dimension N considered. The order r is given by the sequency of the operator, and refers to the type of differences (derivatives) used between sample points [12]. The dimension N (N=2n) refers to the width of the operator, function of the number of points considered. Considering the digitized input signal, $f(t)$, the Walsh transform defined by W_N^r is given by the convolution ($*$) of ω_N^r with $f(t)$ as:

$$W_N^r = \omega_N^r * f(t) \quad (5)$$

The Walsh operator of 1st order and length 2, ω_2^1, is functionally equal to the 1st derivative, d^1:

$$\omega_2^1 = [1 \ -1] = d^1 = \frac{\partial}{\partial x} \quad (6)$$

The Walsh operator of 2nd order and length 4, ω_4^2, is functionally equivalent to the 2nd derivative, d^2:

$$\omega_4^2 = [1 \ -1 \ -1 \ 1] \cong d^2 = \frac{\partial^2}{\partial x^2} = [1 \ -2 \ \ 1] \quad (7)$$

For wider intervals of observation, the algorithm developed takes the results at different scales (resolutions) and adds them together to detect all potential transitions under different scaling. This is expressed mathematically as:

$$W^r = W_4^r + W_8^r + W_{16}^r \ \text{ for r} = 1{,}2 \quad (8)$$

In other words, sharpness/steepness of the signal identified in any of W_4^r, W_8^r, or W_{16}^r, (r =1,2), resulting in high-amplitude peaks, should yield a steep and sharp signal in W^r.

With the analogy drawn earlier from mathematical derivatives, can be redefined to use only Walsh operators in a similar functional outcome and yet in an integrated approach to preserve orthogonality as follows:

$$W_2^r . W^r = \mathrm{W}_2^{\mathrm{r}} \cdot [\mathrm{W}_4^{\mathrm{r}} + \mathrm{W}_8^{\mathrm{r}} + \mathrm{W}_{16}^{\mathrm{r}}]; \mathrm{r} = 1$$
$$W_{2+r}^r . W^r = \mathrm{W}_{2+\mathrm{r}}^{\mathrm{r}} \cdot [\mathrm{W}_4^{\mathrm{r}} + \mathrm{W}_8^{\mathrm{r}} + \mathrm{W}_{16}^{\mathrm{r}}]; \mathrm{r} = 2 \quad (9)$$

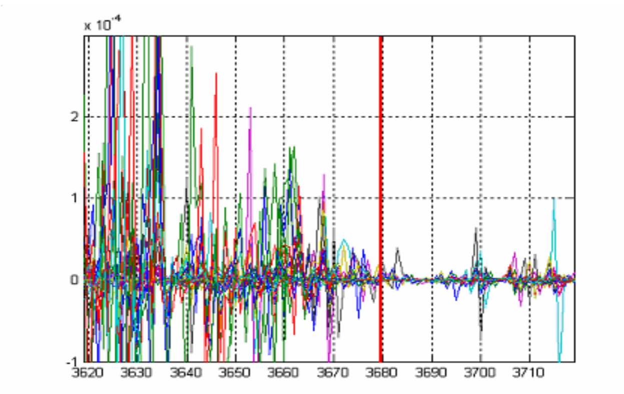
In this equation (9), recall that W_2^1 is functionally equivalent to the first derivative and that W_4^2 is functionally equivalent to the second derivative.

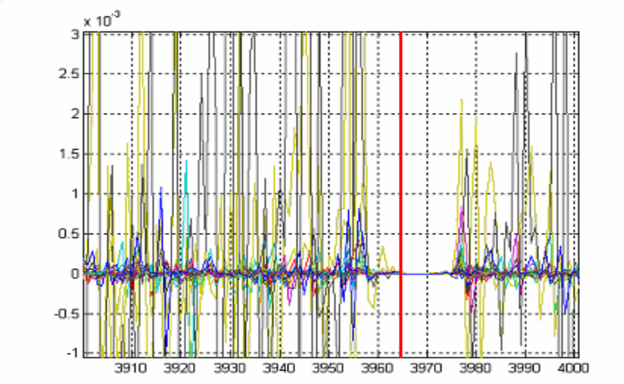
3 Clinical Results

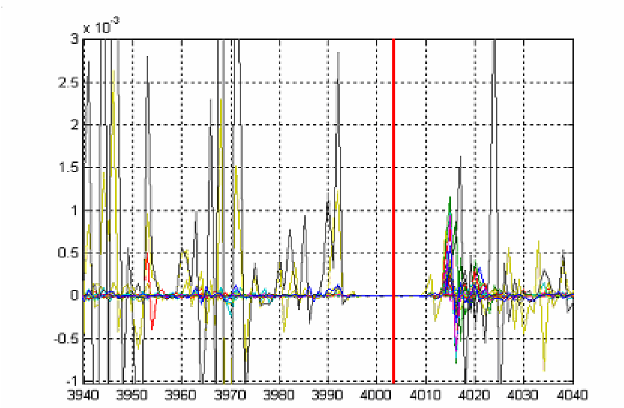
After computing each subject's EEG parameters, the first and second operators of the Walsh Transform using the different resolutions explained above were convolved with the three parameters extracted form the EEG. For both operator, the results using the correlation integral as the parameter were the best since the amplitude at the time of the onset was considerably reduced. An abrupt change is evidently observed in the signal at the advent of a seizure and during the seizure itself. These results were plotted for visual inspection in the process of detection. Our system successfully detected 10 seizures out of 12, yielding a sensitivity of 83%, which is acceptable taking into consideration the total number of seizures available.

Several sample outputs of our seizure detection algorithm is displayed in Figure 3. The red vertical line represents the seizure onset.

As it can be observed from Fig 4 and 5 using Mobility and Complexity as our parameters, the change in magnitude at the time of the onset is not as high when compare to the change using the correlation integral.







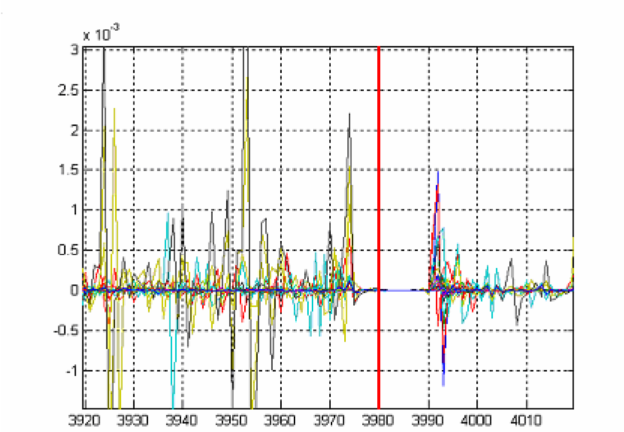


Fig. 3 Walsh first operator to correlation integral.

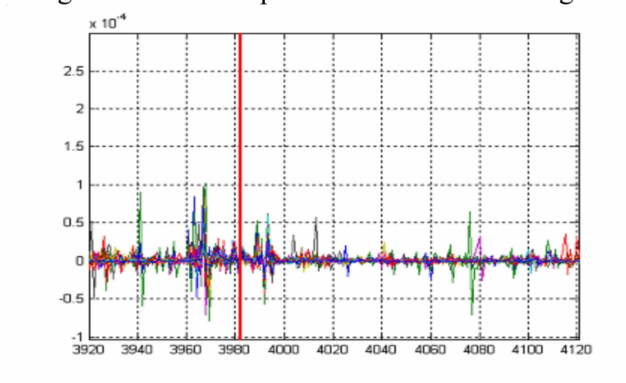


Fig. 4 Walsh first operator to mobility.

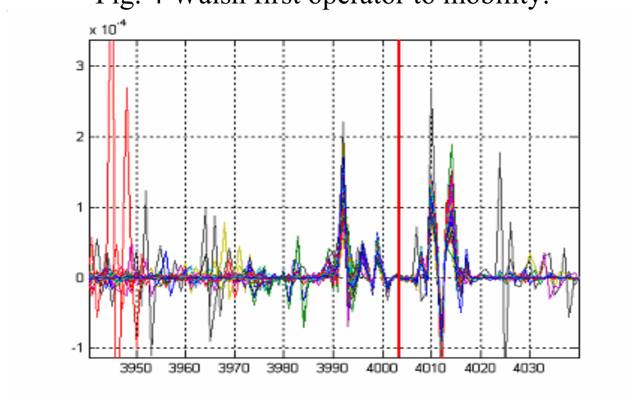


Fig. 5 Walsh first operator to complexity.

4 Conclusions

For this study we formulated and evaluated characterizing parameters of subdural EEG signals using orthogonal operators designed based on the Walsh transformation. We translated each of the observable characteristics into mathematical expressions such that each and every one of the characteristics is implemented in the development of our algorithm. The uniqueness of this algorithm is in the establishment of a mathematical foundation capable of detecting an epileptic seizure with nominal computational requirements.

A new technique was presented for seizure detection from different EEG data. In order to accentuate the fast oscillatory activity that is most of the time present during seizures, the first and second operators of an orthogonal transform was applied to the matrix that is composed of the parameters extracted from the EEG.

Its clinical success in detecting seizures from long duration EEG data makes the method suitable for real-time detection applications.

In this study, a total of 12 EEG files recorded at least 60 minutes before a seizure were scrutinized from 3 different points of view called parameters. As this research will involve a higher number of epileptic patients as they become available, additional results will provide more weight to our findings.

Acknowledgments

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