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WAVELET TRANSFORM ANALYSIS OF EEG SCANS FOR THE DETECTION OF EPILEPSY

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ABSTRACT

Epilepsy is a neurological disorder, in other words a central nervous system disorder, which results from various factors. It causes disruption in neural cell activity, which causes seizures, or unusual behavior, sensation and occasionally loss of consciousness. Although epileptic seizures does not negatively impact the patient but the occurrences during these seizures as well as the events following them is results in life-threatening issues. The irregularity of the brain activity during these seizures can possibly result in injuries and can even cause death in certain circumstances. The purpose of this paper is to develop a new processing method to analyze EEG wave sequences and to determine if the waves display characteristics of epilepsy. The method would greatly reduce the discrepancies in wave analysis that result from a neurological inspection by eliminating the effects of human bias. It would have the capacity to differentiate normal brain waves that is alpha, beta, gamma, theta, or delta waves, from that of a patient suffering from epilepsy. Through our method, different parameters would be measured to gain quantitative data determining and demonstrating the mental situation of the brain's neural activity. The EEG is process to remove the noise and unwanted signals. Then, time and frequency features are extracted from the EEG signals. Finally, using wavelet transformation, the extracted feature are processed to obtain epileptic characteristic. An open source database is used to evaluate our method.

Keywords: Computer Aided Diagnosis; Wavelet Transform; Electroencephalogram; Epilepsy; Digital Signal Processing.

INTRODUCTION

An electroencephalogram, also known as an EEG, is used to detect any abnormalities in the electrical brain activities and records them into wave patterns [1]. It is an instrument that is connected to a computerized machine which produces the waves. Electrodes, small metal discs, are placed inside the scalp and these electrodes collect the data of the neural activity of the brain. This data is recorded into the computer and later analysed by a neurologist. Neurologists and neurosurgeons most commonly use the EEG to evaluate several types of brain disorders including but not limited to Alzheimer's, certain psychoses, narcolepsy, and epilepsy [2].

Epilepsy is a neurological disorder, one on results from an inhibition of firing in excitatory neurons. It causes disruption in neural cell activity in both the central and peripheral nervous systems, resulting in seizures, unusual behaviour, sensation and occasionally loss of consciousness. The disruptions caused due to epilepsy can be recorded using EEG. When a patient is having an epileptic seizure, the electrodes situated in various parts of the scalp, detect the disrupted neural activity, and transform them into waves. These waves though similar to the normal brain waves, have much more noise that is observed in the wave patterns. Along with noise, there is also a lot more irregularity in the various parameters that stay within a certain limit under normal conditions.

In a normal functioning brain, the waves are divided into five different wave types each defining different levels of brain activity. The brain waves drastically different for a person sitting and studying versus someone lying in bed, about fall asleep. Delta waves are the lowest frequency waves, ranging between 0 to 3 Hz. These involve the rejuvenation of the body, restorative/deep sleep, and enhancing the immune system. Theta waves range from frequency of 4 to 7 Hz. Alpha waves are waves that are between 8 to 13 Hz in frequency. During alpha waves, the optimal functioning of the brain is associated with relaxation. Beta waves, on the contrary, are waves between 14 to 30 Hz. And these are associated with conscious focus, problem solving and memory. Lastly, Gamma waves include a frequency range of 31 to 100 Hz. During these waves, the optimal functioning includes binding senses, cognition, information processing, learning, perception, and REM sleep. For a normal person, these waves seem to range from the frequencies provided above. For a person currently suffering from epilepsy these waves are have a different frequency window; there is even a discrepancy in the waves of those predisposed to developing the condition. In addition, when a person suffering from epilepsy is having an epileptic seizure these waves are either too high or too low in amplitude depending on the stage of the seizure.

Brain waves of a patient suffering from a seizure consists various different features. A sharp spike is a pointed peak with duration of 70 to 200 milliseconds, while a normal spike is also a spark wave lasting between 20 to 70 milliseconds. It is a repeated process of a spike, which then leads to a slow wave. A spike-slow-wave complex is the slow wave that has amplitude that is higher than that of a spike with a lower frequency. At the same time, a frequency lower than 0.5 Hz signifies the onset of a seizure, and then the spike suddenly skyrockets to a higher frequency.

The recent years have witnessed the greatest advancement in biosignal processing technology which depends on the computer-aided diagnostic systems. Computer-aided diagnostic (CAD) systems can help improve the accuracy and precision of the biosignals recorded [3- 5]. Due to this, neurologists can have a better look at the localized intervals of frequency over the varying time intervals. By using these localized graphs provided by the CAD systems, repeating patterns and trends can be identified and utilized for better diagnosis and accurate treatments options [6- 9].

The concept of wavelet transform and its application has developed into the recent years as a very beneficial and successful method to develop a time-frequency analysis of any type of signal. Wavelet transform analysis uses the incoming fluctuating signals from any electronic device and interprets them as small wavelike functions. These wavelike functions are often called wavelets. Wavelet transform helps detect the sudden spikes or drops in a signal at a particular interval in time. Then, the minute change patterns which could not have been detected in the collected data could be identified and diagnosed further to improve the biosignal evaluation. Using this type of mathematical approach, the repeating patterns, disturbances, and the direction of the change of the particular signal being analysed can be determined. These types of details can help capture the discrepancies in the signal and obtain a clear view of the problem. Despite the discontinuities, methods to discard them have also been created to obtain a generalized pattern of the waves.

In this paper with the goal of developing a CAD system, we evaluate the application of wavelet transom to separate between EEG states and to find the seizure activity in epileptic patients. So we focus on using the patient data and analysing them using the wavelet transform and obtaining a general pattern of the normal EEG waves and that of an epileptic patient's EEG waves.

Litreature Survey

A design strategy is developed in [10] for an energy-efficient architecture to detect the onset of epileptic seizures using discrete wavelet transform-quasi-averaging. The performance of neural network-based classifiers are evaluated for detection of Spikes in the EEG [11]. A Support Vector Machine (SVM) method is developed for epilepsy detection in [12] to classify MRI extracted features. To detect seizures, the waveform morphology is characterized by a measure of sharpness and a train of abnormally sharp waves resulting from subsequent filtering are used to identify seizures [13]. Using acceleration signals, multiple temporal, frequency, and wavelet-based features are extracted in [14]. A system contains a series of algorithms to eliminate False Positives and a template method to confirm spikes are presented [15]. Association rule mining and transient events classification into four categories of epileptic spikes, muscle activity, eye blinking activity, and sharp alpha activity are presented in [16]. Epileptic MRI are segmented for pre-surgery evaluation in [17- 19]. After determining the features with the highest discriminative power, a nonparametric estimate of the probability density function is used to classify seizures. The most representative seizure type of 37 patients with drug-resistant focal epilepsy are evaluated in [20]. A seizure model for a priori known seizure and statistically optimal null filters as a building block for the detection of similar seizures is developed [21]. To lateralize the epileptogenicity in epilepsy patients, the response-driven multinomial models are developed based on multivariate imaging features [22, 23]. EEG features are extracted by multi-fractal detrended fluctuation analysis and classified by using SVM [24]. Recently, deep learning structures such as CNN (convolutional neural network [25-27] and Deep belief nets [28] are used for biomedical signal processing. A deep learning network under cloud computing framework is developed for analyzing epileptic seizures in [29, 30]. Partial directed coherence (PDC) analysis is used to detect the seizure intervals of epilepsy patients [31].

Methods

All For the purpose of this paper, a public dataset of patients with and without epilepsy was utilized. The dataset that was provided consisted of five sets, each consisting of 100 patients with different conditions. The patient data was combined to make the running of the data easier. It is possible to run each patient data individually, but compiling the data, reduced the burden on the user because it allows everything to be input at once. As a first step along with fixing a frequency range, it is very important to de-noise the waves. In order to obtain graphs, which can be analysed for their various parameters, an automatic 1-D de-noising is used. Basically, it filters the noise of a one-dimensional signal using waves. This makes it easier to compare the impacting parts of the wave instead of having the unnecessary external effects on the graphs. Figure 1 shows the result of background noise filtration.

The brain wave pattern obtained through an EEG follow the pattern of Fourier series. A Fourier series is an expansion of a periodic function, f(x), in terms of an infinite sum of sines and cosines. This summation utilizes the perpendicular relationships between the sine and cosine function for the calculation. The generalized Fourier series equation of the EEG waves is given by:

$$(x,y,t) = \sum_{n} (x,) \sin(w_n t+\theta n)$$

This equation takes the sum from 0 to infinity of the constant function of An, which is in terms of x and y and is given by the formula that is also organized into a Fourier series. The equation can also be represented as

$$A_n (x, y) = \sum_{l} \sum_{m} B_{lmn} \sin(k_{xl} + \theta_{xl}) \sin(k_{ym} + \theta_{ym})$$

Both the equation utilizes the frequency and the theta between the two functions to calculate the summations. So the equation for the EEG brain waves is modeled in the form of a Fourier series.

For the purpose of our method, the Fourier used requires to change the dataset given from time intervals into frequencies. Hence in order to establish this transformation of the datasets being used, the function Fast Fourier Transform (FFT) is used. The main function is to transform the data set being used into the length of the given value. The idea behind this transformation is to either pad or chop the inputted signal to achieve an optimal transform length. The transformation code reads:

$$f = f(s, 1024)$$

After using the Fast Fourier Transform, the dataset is then going to be analyzed. And the intensity of the waves collected is measured using the power spectrum. It measures the signal's power intensity in the frequency domain calculated using the Fourier series. The power spectrum is expressed by:

$$pp = f.* co(f)/1024$$

Maximum wavelet decomposition level is a function that helps to decompose any dataset in order to avoid the unreasonable maximum level values. It gives the maximum decomposition scale but the actual value taken is smaller. In other words, the function helps achieve a fixed frequency or time window, that way each dataset is measured and compared in that particular window. The frequency window for an epileptic seizure is between 0.5 to 29 Hz [32]. This coincides with alpha, beta, theta, and delta waves. Any frequency values above or below this decomposition level are voided from the graphs and the dataset collected. For the purpose of finding epileptic pattern, the db4 is used.

$$h_0 = \frac{1+\sqrt{3}}{4\sqrt{2}} \quad h_1 = \frac{3+\sqrt{3}}{4\sqrt{2}} \quad h_2 = \frac{3-\sqrt{3}}{4\sqrt{2}} \quad h_3 = \frac{1-\sqrt{3}}{4\sqrt{2}}$$

$$g_0 = h_3 \quad g_1 = -h_2 \quad g_2 = h_1 \quad g_3 = -h_0$$

$$a_i = h_0 s_{2i} + h_1 s_{2i+1} + h_2 s_{2i+2} + h_3 s_{2i+3}$$

$$c_i = g_0 s_{2i} + g_1 s_{2i+1} + g_2 s_{2i+2} + g_3 s_{2i+3}$$

Lastly, wrcoef is the function that is used to construct approximations based on the approximation and wavelet filters on the scale of the original signal. In other words, this function finds the coefficient of the decomposition level of each individual waves. And this coefficient is used to determine the correct equation for the Fourier series equation mentioned earlier [33]. The coefficients that were computed were then used to calculate each Fast Fourier Transformation individually for the alpha, beta, gamma, delta and theta wave.

$$theta = wrcoef('d', C, L,' db4', 5);$$

$$alpha = wrcoef('d', C, L,' db4', 4);$$

$$beta = wrcoef('d', C, L,' db4', 3);$$

$$gamma = wrcoef('d', C, L,' db4', 2);$$

These transformations were graphed in figures 2 and 3, one that overlaid them and another than split them apart to allow for a multi-faceted comparison of the waves. Outside of the wavelet functions track of the number of epileptic spikes as well as record the recording as abnormal are kept if a patient present with twenty-five or more spikes. All patient data is accounted for and the switch cases function to differentiate between the datasets for determining the y-axis scales of the graphs and for the determining the variations between the alpha, beta, gamma, delta, and theta waves. T-test [34-36] was used to evaluate whether the means of the extracted seizures and the normal groups are statistically different.

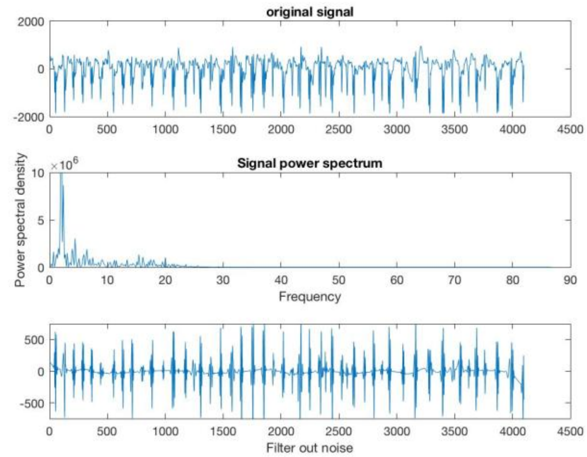

Fig. 1 The graph corresponds the initial plots of the EEG as well as the standardization using the Signal Power Spectrum and the plot of the background noise filtration.

Results and Analysis

Five sets which are denoted by (A-E) were used for this study. Each set has 100 single channel EEG segments of 23.6 sec duration with sampling rate 173.61 Hz. In sets A and B the EEG was recorded on five healthy subjects by standardized electrode placement scheme. In contrast, in sets C, D, and E the EEG was recorded from epileptic patients with presurgical diagnosis [37-38]. The data inputted into the code is displayed in the form a graph that can be easily read and used to explain to patients the breakdown of their brain wave function. Furthermore, the de-noising of background waves allows for differentiation by the method, so background signals are picked up as high amplitude waves that are miss classified as possible epileptic spikes.

The graphs after running our code on the dataset that was used the determine the functionality show that patients from dataset E show the most sporadic brain wave functions, indicative of epileptic patients. This is consistent with the actually data collection which states that patients of dataset E were the patients who suffered from epilepsy and were the most symptomatic. On the contrary, dataset A and B were patients who were normal functioning adults. The program is consistent in its findings, showing long amplitude waves that are most similar to that of non-epileptic patients.

Datasets C and D were scans done on patients during seizure free intervals. The graphs of these patients are in the gray area when it comes to diagnosis based on wave activity. These are usually the cases with are left to the most bias from a physician's standpoint. Some may deem the waves sporadic enough to make the diagnosis, while others may be more conservative before starting treatment for epilepsy. The program creates a standardization in this aspect and clearly shows that patients from dataset D are more expressive of the symptoms. The initial plots of the EEG as well as the standardization using the Signal Power Spectrum and the plot of the background noise filtration is shown in Fig. 1. This figure shows the steps of our noise reduction technique. The five states of EEG and the overlay plot of extracted waves are shown in Fig 2 and 3, respectively.

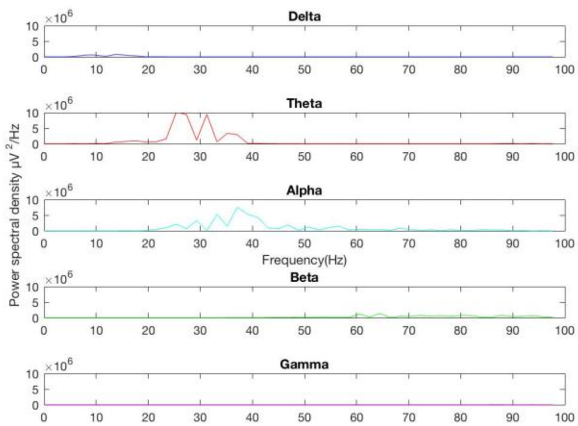

Fig. 2 The overlay plot of the extracted five waves.

Based on our evaluation of common wavelets, we have used Daubechies 4 (db4) to analyze epileptic EEG data. Since seizure activities at EEGs commonly occur in 0.5-29 Hz, the detailed coefficients of wavelet output have been investigated to find this frequency range. First by considering sampling frequency of the data which is 173 Hz, the maximum frequency of data is obtained at 86 Hz using Nyquist criteria. Therefore, the frequency range of 0.5-29 Hz is covered in scales of 2, 3, 4, and 5 and the seizure is covered in d2-d5 scales.

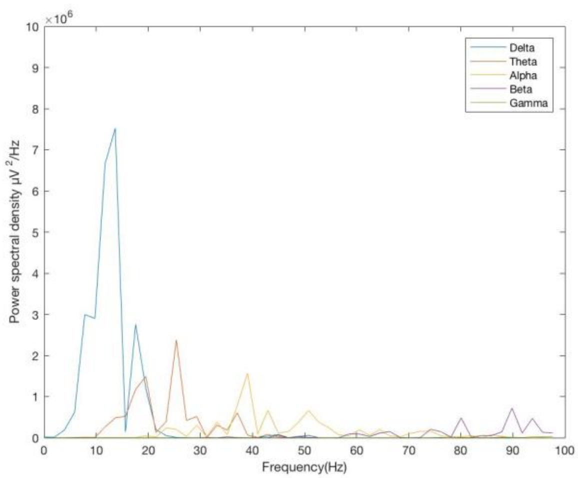

Fig. 3 The graph corresponds the initial plots of the EEG as well as the standardization using the Signal Power Spectrum and the plot of the background noise filtration.

Conclusion

The purpose of this paper was to develop a hard coded analysis of EEG wave functions, with are depicted in the graphs. Moreover, the breakdown the waves in the alpha, beta, gamma, delta, and theta categories allow for a deeper understanding of how the seizure activity compares to that of normal brain function in various scenarios. Moving forwarding, our method should be further developed to a greater degree of accuracy to analyse the spikes. Furthermore, the scientific community working on the disease at a clinic level should be surveyed for the neurologist and neurosurgeon's interpretation of the graphs. Reaching a consensus on the parameter for identification of the disease is crucial if there is hope to standardize the diagnosis. Our, program would still be able to differentiate between mild and severe cases of the condition, but it is important to have a clinical standard. The end goal is to develop a fully functionally program that would itself distinguish between period of high brain activity and actual seizure onset resulting from having epilepsy.

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