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COMPARATIVE STUDY: EPILIPTIC SEIZURE PREDICTION SYSTEMS
(Unification of multiple systems to improve the accuracy)

Master's thesis for the degree of Master of Science in Technology submitted for assessment, Vaasa, 10 November 2018.

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ABSTRACT:

With the advent of technology, from the modes of communication to disease diagnosis, all the fields went through a drastic change. Epileptic seizure is also one of those neurological conditions whose predictability methods are being researched by e-health researchers in order to reach an accurate prediction method. An epileptic seizure is not fatal but can prove fatal if it occurs under certain circumstances that can put patient's life at risk. Therefore, prediction methods can help the caretaker or the emergency services early and allow precautions to be taken accordingly. This thesis is a comparative study of different epileptic prediction methods which have been provided by various researchers and have available literature. The features are being extracted from body vitals EEG, ECG, and an accelerometer. The purpose of implementing the feature extraction from different research papers was to achieve higher accuracy utilizing available methods in the literature. In case of a seizure, an alarm will be triggered to alert the patient along with alerting the caregiver(s). Moreover, the patient's data will be stored in a cloud to help the doctor with a better diagnosis. The unification of these methods envisions a system that can provide higher accuracy and lead to a better life quality for epileptic patients.

KEYWORDS: body vital, Epilepsy, features extraction, logic gates, prediction, truth table, unification.

ABBREVIATIONS

WHO	World Health Organization
EEG	Electroencephalography
ECG	Electrocardiography
iEEG	intracranial Electroencephalography
HRV	Heart Rate Variability
ANN	Artificial Neural Network
DWT	Discontinuous Wavelet Transform
CWT	Continuous Wavelet Transform
SVM	Support Vector Machine
PSD	Power Spectral Density
LF	Low Frequency
HF	High Frequency
FFT	Fast Fourier Transform
FT	Fourier Transform

1. INTRODUCTION

1.1 Thesis Statement

In the current era of rapidly emerging technologies, it's implementation in the sector of e-health is widely being appreciated. From diabetes to heart rate, all the measurements can be obtained in few seconds. Work is rapidly in progress for some conditions that are difficult to predict accurately. A similar neurological condition with an unpredictable nature is epilepsy. According to World Health Organization (WHO), about 50 million worldwide are suffering from epilepsy [36]. Such a spontaneous neurological condition can expose both the patient and the caregiver in grave danger. Moreover, this condition can occur to any individual regardless of age, gender or time.

Many neurologists and technologist have penned down their researches to find methods to accurately predict the onset of epileptic seizure. However, these prediction methods are not entirely accurate as vital signs differ from patient to patient, moreover, there are various types of epilepsies as well, which can alter the results. Therefore, in this thesis, various methods for the prediction of epilepsy are compared for their highlights and challenges. This comparative study will utilize the finest features from various researches to devise a predictability method based on Boolean function. With the advent of technology, many devices are already in market that can measure the body vitals, therefore, this thesis also aims to find the existing wearable devices to measure the body vitals and to use them for the prediction of seizure.

1.2 Motivation

My knowledge of this neurological disease was minimal until my father had an epileptic seizure. The exact cause of the seizure was unknown. Our world came crumbling down that day. He was prescribed with the high doses of medicines, and the side effect was excessive loss of weight. He was refrained from driving and doing any such task that required extra focus due to the unpredictable nature of a seizure. The unpredictable nature of this syndrome made me wonder about finding indications on the onset of a seizure and to look for the possible prediction methods.

1.3 Methodology

This thesis is based on comparative study of various seizure prediction methods. These methods are compared from all the possible present aspects, ranging from the ease of wear-ability of devices to the accurateness of results. The purpose is to achieve accurateness in the prediction of a seizure by keeping the false positive results to minimum, therefore, in order to achieve high levels of precision, finest features from different approaches have been amalgamated together. Apart from high accurateness and minimum false alerts, this thesis will also focus on the devices and gadgets that are already available in market to measure the body vitals. This approach uses the body vitals for seizure prediction, therefore, the time saving approach was to look for already existing gadgets that can be used for this thesis. This is the era of technology, so a lot of products were already available in market that could be used for EEG, ECG signal extraction, thus this approach was helpful and less time consuming. In this way, the main focus was given to the various feature extraction techniques and unification of these techniques.

1.4 Thesis Structure

The thesis begins with an introductory chapter that guides about the aims and motivations for choosing this thesis. Followed by Introduction is the background information that will shed some light on the epileptic neurological condition in terms on symptoms and how this condition affects the day to day life of patient. This will also clarify the need of a system to predict this disorder. Chapter 3 is covering the literature review that is mostly covering the work done in this field from the year 2000 and onwards. With the passage of years, the technology advances were evident therefore, the work done in the field of prediction kept on improving. This chapter includes summarizations of some of the literatures studied for the better insight of this topic. The summaries will highlight the goals, methodologies and the end results for the presented literatures.

Chapter 4 covers the analysis and augmentation part. This chapter will feature the study goals, and the key points for feature extractions. Chapter 5 combines the techniques and features mentioned in the chapter 4. This chapter will also highlight the already available devices and the gadgets in market that can be used for this approach. Chapter 6 defines the usage of the devices mentioned in chapter 5 along with the features extracted from the chapter 4 in order to achieve better results. This chapter also includes the Boolean functions and Boolean table to predict the seizure. Decision making process will utilize the techniques and features extracted from the previous chapters. Towards the end, future work and conclusion will high light the future aspects of this research along with present gains.

2. BACKGROUND INFORMATION

2.1 Epilepsy

Epilepsy is a neurological disorder which leads to unprovoked and chronic seizures, whereas a seizure is a sudden rush of electrical impulses in brain. Seizures are recognized on the basis of intensity and duration. A stronger seizure is easier to recognize in comparison to a mild one. Stronger one can last up to minutes and it can cause strong jolting and spasms throughout the body. A person experiencing the seizure can lose awareness of surroundings and might feel sick afterwards. Along with the type of seizure, the symptoms also vary from person to person. Some of them include:

- Déjà vu (The feeling of encountering a similar situation before even experiencing it, although the patient has never experienced it before, but he/she feels like they have experienced the similar event before)
- Loss of consciousness
- Haphazard movements
- dizziness or vertigos
- unresponsiveness
- loss of muscle control and bowel movement
- biting of tongue and grinding of teeth

2.2 Known causes of a seizure

Seizures result from the abnormal activity in brain. During a seizure, there is a sudden rush of electrical impulses in brain. There is no discernable cause of epilepsy in about half of the people with this neurological condition. However, epileptic condition can be traced to multiple factors which include:

- Traumatic injury to head as result of accident

- Brain tumor or strokes
- Meningitis, AIDS can also cause epilepsy
- Prenatal injuries and maternal drug usage Autism
- Dementia and Alzheimer’s disease
- Alcohol withdrawal
- low blood sugar level
- High Fever

2.3 Types of seizures

Symptoms of a seizure could be sometimes confusing with other neurological symptoms or mental illness. A Neurologist needs to be cautious while treating the patient with seizures and should perform thorough examination to characterize the symptoms of epilepsy. Based on the intensity, and the part of brain a seizure affects, they are classified into following categories:

- Partial Seizure

If a seizure occurs due to atypical activity in just one part of brain, they are referred as partial seizures. During a simple focal or partial seizure, the seizure might not render the person unconscious. This may also result in vertigos, alterations in sense of smell, feel or hearing. Whereas, in complex partial seizure, the seizure might result in loss of consciousness of the person along with unresponsiveness and disoriented movements.

- Generalized Seizures

If a seizure occurs due to the abnormal activity in all parts of the brain, it is then referred as generalized seizure.

2.4 Age affected by the seizure

Anyone can develop epilepsy regardless of age or sex, but it is more common in children and old people. The seizures are most common in children and older people, but it can occur at any age. There are certain conditions that can be associated with development of a seizure, for example, high fevers in childhood can be correlated with the occurrence of seizure in children. Autistic children are more susceptible to seizures. Moreover, in older adults the diseases like dementia and Alzheimer's can increase the risk of epileptic seizure.

2.5 Challenges associated with seizures

Occurrence of seizure at certain times can lead to hazardous circumstances, that can not only compromise the safety of person undergoing seizure but of others too. Some of the complications include:

- Falling during a seizure can result in injuries
- Having a seizure while swimming can increase the possibilities of drowning
- Seizures during pregnancy can lead to birth defects and other abnormalities in the unborn baby
- Epilepsy can affect emotional health of the people, it can sometimes lead to suicidal tendencies, depression and anxiety.

People with epileptic conditions should avoid the tasks that require focus and that can compromise their safety or of others.

2.6 Treatment of seizures

Epileptic seizures if diagnosed early can be treated and controlled via drug therapy. However, if the patient's response towards the medication is feeble then surgery may be used. The treatment of epilepsy depends on the frequency of seizures, age, health conditions and previous medical conditions. Therefore, it is necessary to diagnose the type of epilepsy accurately in order to provide the best treatment for it.

A person's learning, societal and mental abilities are liable to be affected with this condition. This can be a part of a treatment plan in which a team of doctors can provide all the necessary assistance. Therefore, it is necessary to take an early action as it will enable the person to deal with the effects of seizures and it will also help doctors to treat it more effectively.

Some of the treatments are:

- Anti-epileptic drugs: They can reduce or eradicate the seizures. However, the effectiveness depends on the usage and prescription.

- Nerve Stimulator: This device called Vagus Nerve Stimulator can prevent the occurrence of seizures by electrically stimulating the nerve that runs through the neck. It is placed under the skin of chest with the help of surgery

- Surgery: The brain surgery option can be used if a patient is unresponsive towards medication. The area of the brain causing the seizures is removed or operated for alterations.

- Diet: Ketogenic diet has been recommended for the epileptic patients. This diet consists of low carbohydrates and high fat contents.

More work is in progress to help minimize or eliminate the seizures with the help of electrodes implantation in brain. The generator of electrodes will be in chest that will send impulses to electrodes to minimize the seizure. In the similar fashion, a pace maker type of device is being designed to sense the seizures and then help reduce it by sending drugs or impulses.

3. LITERATURE REVIEW

3.1 Fast and Effective Real Time Seizure Prediction on Streaming EEG Signals

Preview

Epilepsy is a neurological disorder that affects the activity of brain and disrupts the routine tasks of the person with this condition. The quality of life of the person with this disorder gets obstructed because of the unpredictable nature of seizures. Therefore, the routine tasks like driving are guided to be prohibited. it is controllable with the help of drugs that tend to reduce or eliminate the seizures, but some patients might develop resistance to drug requiring the need for surgery.

(Ramina, Vanitha, 2017) has provided with fast real time epileptic seizure prediction using EEG signals in the publication. EEG signals measure the brain activity and they can differentiate between preictal signals from the normal ones. Few hours before a seizure, there is a subtle change in brain signals and this variation can be used to predict the occurrence of a seizure. Advanced facilities to measure brain activity using EEG can prove as a breakthrough in the field of seizure prediction. These facilities will in turn help the system to alert the patient of the upcoming seizure. This paper presents Neural Network Techniques that distinguishes a preictal signal from a normal one. The neural network architecture is trained using the signal preprocessing and signal-based integration techniques. Using this technique, the time complexity has been observed to be low, therefore, making the system easy to integrate in real time for direct streaming of EEG signals.

Signal Patterns are analyzed using EEG signal streaming, once these signal patterns are recognized it can lead to accurate seizure prediction. However, the challenging part lies in the analysis of the signals, which is nonetheless a complex process because signal pattern varies from person to person. Therefore, there is need of precise study of signal patterns that distinguishes the brain signals of an epileptic patient from a healthy one.

System Architecture

The system Architecture proposed by (Ramina, Vanitha, 2017) includes two phases. The first one being the signal identification in which differentiates between preictal signal from the normal one. The input EEG signals are used to develop the predictive model for seizure detection. In the second phase, the artificial neural network model is used to predict the occurrence of the seizure.

1. *Pre-processing of the signals:* The signals from EEG, apart from required data also contain some unnecessary data i.e. noise. This noise can affect the accuracy of the results. Therefore, pre-processing techniques are required to minimize the redundant signals and to only extract the useful ones.

2. *Dataset:* Signal from a single person (be it preictal or normal one) consists of sixty (60) minutes. If it is a preictal signal, then the signal prior to 1 hour and 5 minutes of the seizure is recorded. The seizure occurs 5 minutes after the recording. Each file is divided in files of 10 minutes each. Each file has its own sampling frequency, sequence number, time slot and data length.

3. *Pre-processing of the data:* Signals have to be arranged on the basis of their sequence numbers. Sequence numbers are arranged according to the channels. This paper uses 16 channels; therefore, data has to be converted to a single dimensional data using slicing techniques. To convert the data in single dimension, apply transpose function and add a sequence number to the end. Sequence numbers with a positive magnitude represent the normal signals and the negative magnitude represents the preictal ones.

4. *Signal Identification phase:* Preictal signals obtained from single user might be different from the preictal signals of another user. Therefore, keeping in view this variation of signals, data training needs to be done using Artificial Neural Networks (ANN). Secondly, the data needs to be shuffled prior training to avoid

biased training. 75% of the data has to be used for training whereas the rest of the 25% for testing.

ANN is sensitive to data therefore; data normalization has to be performed. This approach uses 17 attributes in total, 16 data attributes and 1 class attribute. Data Attributes can be normalized using min-max techniques. Class attributes contain normal and preictal signals therefore, they are normalized using equilateral techniques.

- Min-max Normalization: Only continuous data can be normalized using min-max normalization. Since EEG readings are continuous so they can be normalized. Min-max normalization finds a value that lies within the range [c, d].

$$B = ((A - minimum\ Value\ of\ A)/(maximum\ value\ of\ A - minimum\ value\ of\ A)) \times (D - C) + C$$

Formula for min-max normalization [1]

- Equilateral Normalization: Unlike min-max normalization, equilateral normalization only normalizes the discrete data. It increases the number of columns in correspondence with the value stored in the attribute that is being normalized. The prediction of a signal being a normal or preictal one and the corresponding stages are discrete values. Therefore, they are normalized using this technique.

- Network Creation and training of the data: Artificial Neural Network (ANN) is similar to our nervous system. A basic ANN network contains three layers; input layer, processing layer also known as hidden layer and output layer. Each layer has its own set of neurons depending on the processing. Each neuron is assigned a default weight by its own processing layer. ANN is first trained using the training data so that it reaches a certain threshold level for error. This approach uses three layered model. The input layer uses ActivationLinear function comprising 16 neurons. These neurons correspond to 16 input EEG signals. The processing layer uses ActivationTANH function and it consists of 17 neurons. First 16 neurons from the input layer corresponds to 16 neurons in the processing layer. The final neuron is a biased neuron. This neuron helps in shifting the activation function that makes the prediction efficient. The output layer also consists of ActivationTANH function and it contains only 11 neurons. Supervised learning is used in this approach. Therefore, Resilient Propagation is used for feedforward ANN (Ramina, Vanitha, 2017).

Seizure Identification

The prediction model proposed by (Ramina, Vanitha, 2017) consists of continuous monitoring of the EEG signals so that alarm can be triggered if a certain threshold is reached. In order to monitor patient's brain activity in real time, streaming EEG signals are fed as input to the signal identification architecture. The sampling frequency for this approach is set to 33.6 Hz so every second generates 400 signals. There are 16 channels for signal generation, therefore, every second, 400 records with a total of 60 attributes each need to be processed by neural network architecture. The signals are being processed individually therefore, predictions are provided individually for each signal. for each signal, the maximum predicted value is considered as the final prediction. The model is trained using the preictal signals 6o minutes before the occurrence of seizure. Therefore, this model can predict the seizure 60 minutes before its occurrence. There are 6 levels of seizure classification. Level 1 is the initial low intensity danger stage while level 6 is the critical stage. In continuous EEG streaming, both normal and preictal signals are fed to input. In case of preictal signal on low intensity, patient is considered to be lowest dangerous level because sometimes normal signals also show some variations which can be classified as preictal ones. Therefore, signals need to be continuously monitored, if they maintain their preictal state for the next 10 minutes then the patient is classified to be in danger level 2. At this stage, a notification is sent to the patient about the stage and time left in the actual seizure. If the condition still prevails, then the patient is classified to be in danger level 3. Now the patient is considered to be in mid-level danger zone. Once this stage is reached, the patient is continuously warned of the danger level and is notified to move to a safer zone or a medical center.

Until level 4 is reached, patient can relapse to normal level by the use of medication or the alarm could have been falsely triggered due to other similar impulses from brain similar to seizure ones.

This proposed architecture also requires the support of a hardware system because the alerts being proposed here are only triggered as software updates. This architecture is proposed based on the assumption that EEG signals are being obtained from the patient fed to the system in real-time.

Results

This approach uses Matlab for the processing of data. The format of the dataset for EEG is the form of .mat file, where data contained in the file is separated and a class attribute is added to the data, this class attribute contains the information about the signal being a normal one or preictal one. For preictal signals, the class labels are the levels i.e. the first sequence is level 1, the second sequence is level 2 etc. Positive class values represent normal signals and negative values represent preictal signals i.e. level -1 is preictal level 1. (Ramina, Vanitha, 2017)

3.2 Frequency Analysis of Healthy and Epileptic seizure in EEG using Fast Fourier Transform

Introduction

Frequency analysis can be made from EEG signals which can be in turn used for seizure detection. In this approach, EEG frequency range is measured from EEG signals, then this frequency range which is being obtained from EEG signals is divided into 5 sub domains; alpha (α), beta (β), gamma (γ), delta (δ), and theta (θ). After classification of frequency range, fast Fourier transform is used to compare the EEG signals of epileptic patient with the healthy subject.

Nowadays, EEG signals are widely used to indicate which state a person is in, e.g. state of sleep, awake and stress is demonstrable via EEG signals. Moreover, EEG is also being used for early detection of brain tumors, diagnosing seizures and for sleep analysis. In clinical diagnosis, doctors usually analyze the EEG signals in time domain using simple signal analysis, which increases the room for uncertainties. Since, EEG signals are non-stationary, and they vary continuously in time and frequency domain, therefore, it is difficult to extract all the feature information by a certain signal analysis method. The function for extracting the feature information of rhythms in EEG signals is automatically integrated into virtual EEG device, which is given by Gabor's transform.

$$g_D(f,t) = \int_{-\infty}^{+\infty} x(t)_{gD} \,.\, (t' - t) e^{-j2\pi f t} dt'$$

Fig 2. Function for Gabor Transform [2]

The function for classifying the frequency bands in sub categories of alpha (α), beta (β), gamma (γ), delta (δ), and theta (θ)is given by the following equation:

$$I^{(i)}(t) = \int_{f(i)min}^{f(i)max} I(f,t) df$$

Where $i = \alpha, \theta, \delta, \beta$

Function for the classification of frequency bands [2]

Following table represents the frequency range according to the nature of rhythms of EEG signals [2]

Table 1. Frequency range and their respective nature of EEG rhythms [2]

Delta	0.5 to 4 Hz	In Deep sleep, coma or serious brain disorder
Theta	4 to 8 Hz	In Stress and deep meditation
Alpha	8 to 13 Hz	In Relaxation state
Beta	13 to 30 Hz	In attentive state
Gamma	>30 Hz	Associated with motor neuron function

Fast Fourier Transform is applied on the basis of the frequency range i.e. frequency range of the 5 sub categories.

"EEG signals were recorded from 4 different channels C3, C4, P3, and P4. The frequency range was adjusted to 8 Hz-30Hz using band pass filter. This approach used 20 subjects in the age group of 22-40 years with 64 channels and sampling frequency was 256Hz." (Meenakshi, Singh, 2014) [2]

Proposed Method

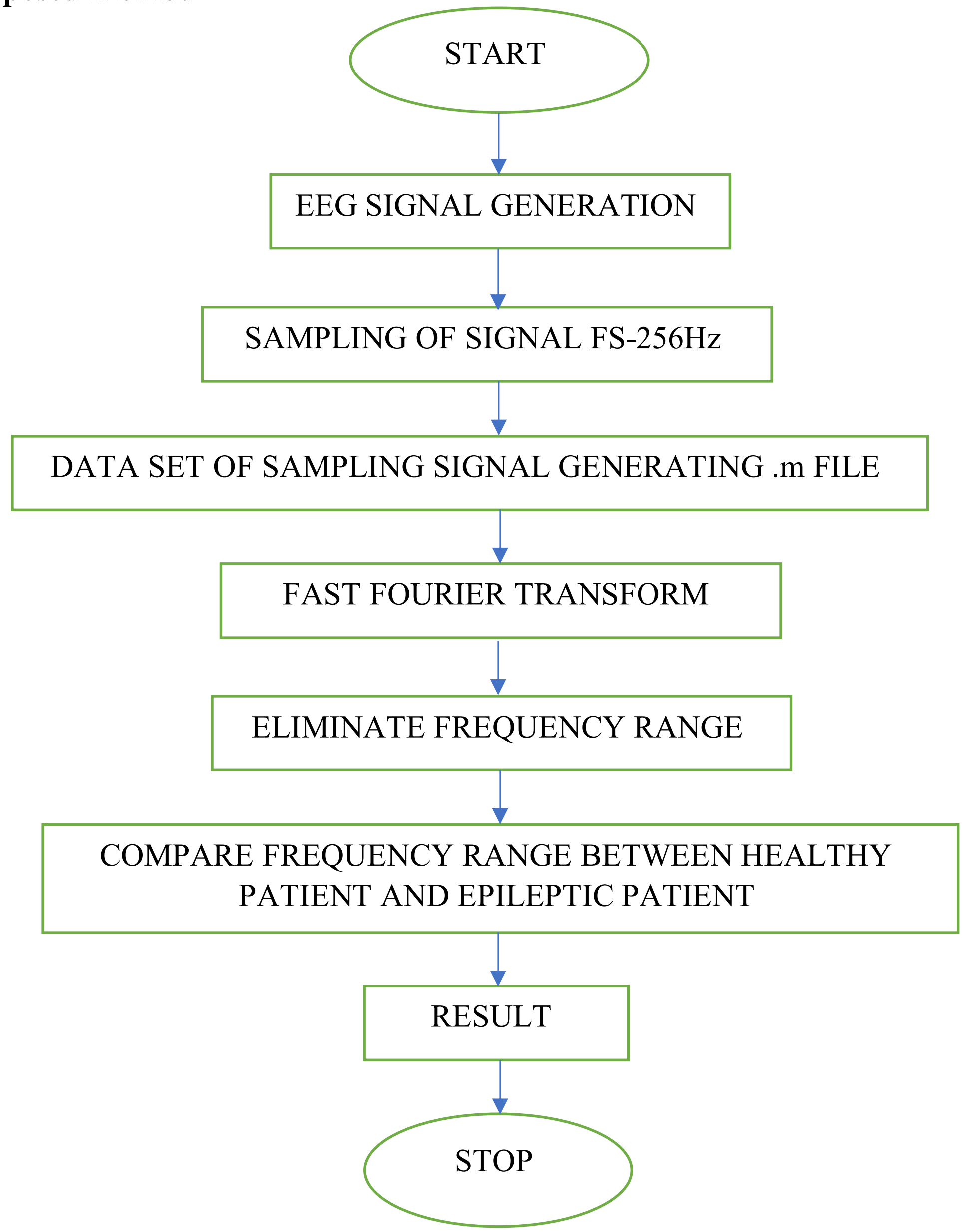

Figure 1. Flow chart representation for the comparison of healthy patient's frequency with epileptic one

The objective is to compare the EEG signals of an epileptic patient with a healthy subject using two Fast Fourier Transforms. This approach used 5 different frequency ranges for classification of frequency bands obtained from EEG signal. The EEG signals of an epileptic patient consists of spike waves, slow waves, sharp waves and their combination.

“Sometimes, when the patient is irresponsive a seizure, the spike wave and sharp wave might not even emerge, instead there might be slow waves and some complex waves. The flow chart of the proposed method is represented above” (Meenakshi, Singh, 2017)

Comparison of Plots taken from epileptic patient and healthy subjects

Source: (Meenakshi, Singh, 2017)

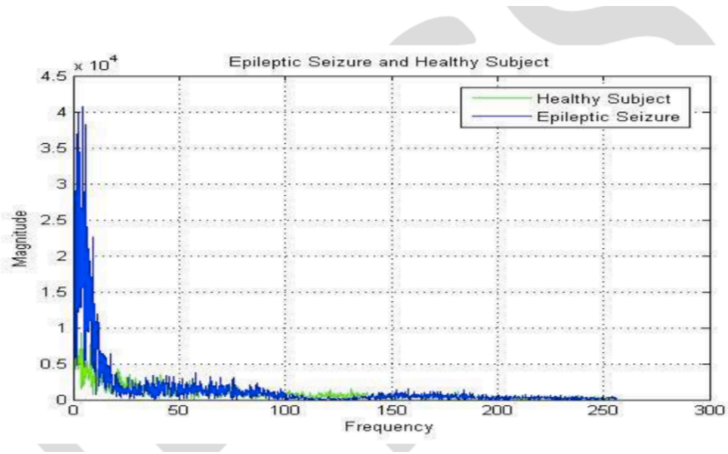

Figure 2. Fourier transform of epileptic patient vs. a healthy [2]

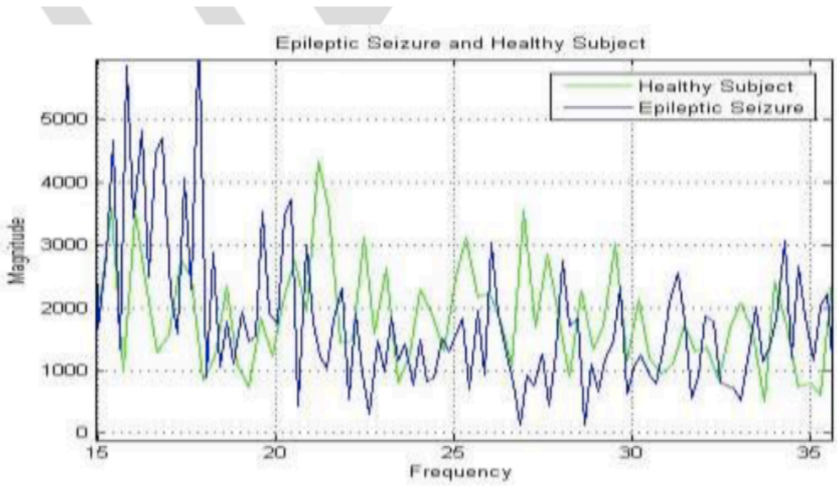

Figure 3. Frequency Elimination by using bandpass filter [2]

Results

In the method proposed by (Meenakshi, Singh, 2014) feature extraction for the purpose of analysis and comparing EEG signals of an epileptic patient with that of a healthy person is no doubt, a complex process. By following, this approach of comparing the frequency plots of an epileptic patient with the healthy person, it was found that the frequency of spikes in epileptic seizure is less in comparison to the spikes of the healthy subject. Moreover, the results also show that it is possible to predict an epileptic seizure by using multichannel frequency analysis. On the similar manner, frequency analysis of EEG signals can also provide significant information about other disorders such as coma, brain developmental disorders, brain injuries, traumas, sleep disorders and mental disorders.

3.3 Analysis of EEG records in an epileptic patient using wavelet transform

Preview

Analysis of EEG signals can provide a significant insight and better understanding of underlying causes of an epileptic seizure.

“Wavelet transforms have been used efficiently to represent various aspects of non-stationary signals such as discontinuities, repetitions, and other patterns. In this approach, discrete Daubechies and harmonic wavelets are used for the analysis of EEG signals”. (Adeli, Zhou, Dadmehr, 2002)

In the method proposed by Adeli, Zhou and Dadmehr, Wavelet decomposition helps in extracting momentary features accurately and also helps in analyzing various neural rhythms effective for studying small scale oscillations emitted from brain. Moreover, careful analysis of wavelets can also help to analyze the changes occurring in brain during epilepsy onset.

Introduction

"Wavelet decomposition can be used for extracting features that can in turn provide significant information on mechanisms causing various brain disorders. In this approach, wavelets transforms are used to analyze epileptiform discharges in EEG with absence seizure". (Adeli, Zhou, Dadmehr, 2002)

"Epileptiform discharge is an uncommon EEG pattern characterized by spike wave, sharp wave complex presentation throughout most of the all the recordings" (Orta, Chiappa, Quiroz, 2009).

Whereas in absence seizure, a person may blank out for few seconds, with absence seizure the person does not necessarily lose conscious or falls down. Therefore, most of the times, they go unnoticed. Neurologists diagnose absence seizure by monitoring the 3Hz spike and complex wave.

"The visual analysis of EEG recordings includes the following features; frequency, wavelength, voltage, amplitude, reactivity to eye opening etc." (Adeli, Zhou, Dadmehr, 2002)

The frequency range of EEG is wide but only 0.3-30 Hz counts of significance importance. The frequency bands for EEG can be classified into 5 categories:

- *Delta (<4Hz):* Corresponds to slow brain waves, exists in deep sleep in normal adults.
- *Theta (4-8Hz):* Corresponds to sleep in children as well as adults.
- *Alpha (8-14Hz):* Corresponds to relaxation and inactiveness. Alpha waves get disrupted by eye openings and by thinking processes.

- *Beta (14-30Hz):* They have less amplitude than alpha waves and corresponds to stress and tension.

- *Gamma (>30Hz):* Gamma waves are usually filtered out because their less clinical significance.

Methodology

Epileptic seizure on EEG recording is usually characterized by synchronous discharges from brain with considerably intensified amplitude. This abnormality can occur in whole brain, like in generalized seizure which is detectable by all the channel across the brain or this anomaly could only occur in certain regions of brain which is usually observed in partial seizures. Currently, EEG data is usually visually analyzed by neurologist. Fourier Transforms have also been used for analyzing EEG signals. The wavelets transform for EEG signals are not explored yet, therefore this paper will used wavelet transforms and their localization properties to analyze the EEG records of epileptic patients.

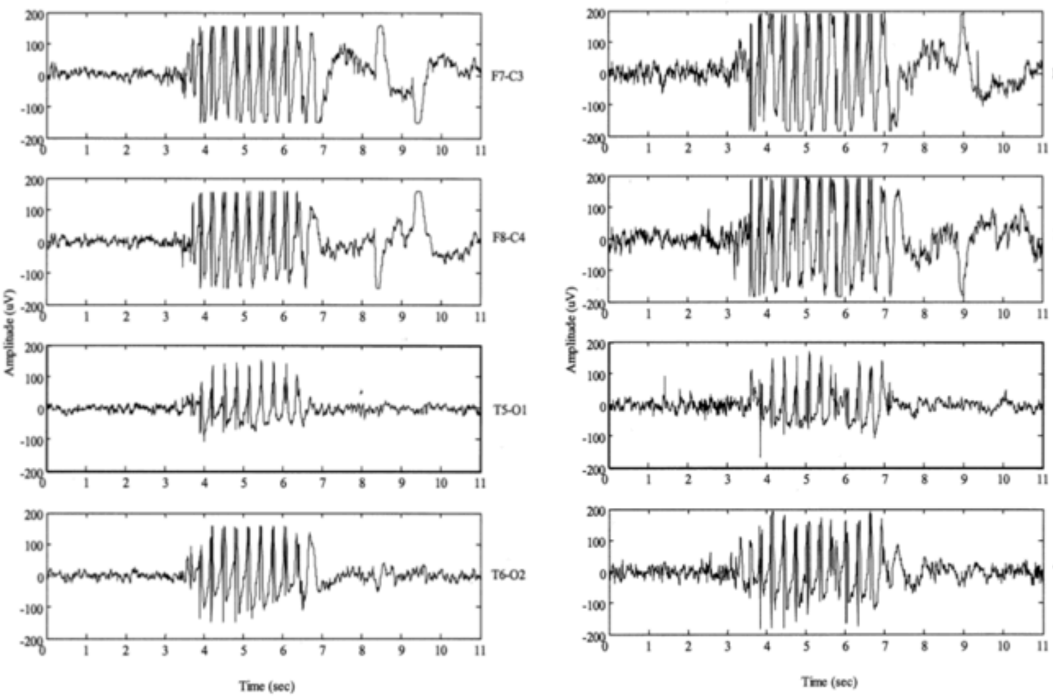

Figure 4. EEG segment with two absence seizures epileptic discharges from the same patient

Source: (Adeli, Zhou, Dadmehr, 2002)

“Four channels of EEG (F7-C3, F8-C4, T5-O1 and T6-O2) recorded from a patient with two absence seizures, epileptic discharges are shown the Fig 4.” (Adeli, Zhou, Dadmehr, 2002)

Wavelet Transforms

“Wavelet transforms are a mathematical mean for performing signal analysis when the signal frequency varies over time. For certain classes of signals and images, wavelet analysis provides more precise information about the signal data than the other signal analysis techniques.” [6]

Using wavelet transforms, one can extract certain required features from signals in both time and frequency domain. There are two types of wavelet analysis:

- “Continuous Wavelet Transform: The signal is divided into wavelets over time and frequency domain.In CWT, the signal is coordinated and convolved with basic functions for wavelets”. [3] Even it is continuous waveform, still the data needs to be digitized in CWT.

- Discrete Wavelet Transform: In DWT, the product of signal with the basic wavelet function is performed at discrete points.

If f(t) is a square Integral function of time t, then CWT of f(t) is defined as following equation [3]:

$$W_{a,b} = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{|a|}} \Psi * (\frac{t-b}{a}) dt$$

And the wavelet function is defined as:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi(\frac{t-b}{a})$$

Then the equation for CWT can be expressed as:

$$W_{a,b}\int_{-\infty}^{+\infty} f(t)\psi^*(t)dt$$

In the above-mentioned equation if the points a, b are measured at discrete values then, DWT is obtained. The parent signal can be reconstructed accurately from wavelet co-efficient if the basis function is orthogonal. In this way, by employing DWT, all the redundant information of CWT can be eliminated by the implementation of orthogonal basis function.

Advantages of Wavelet Transforms

Wavelet transform are implemented to extract certain features from signals which other signal processing techniques will fail to capture. Since EEG waves are non-stationary waves varying continuously in time and frequency domain, therefore wavelet transform is very effective for feature extraction in EEG signals. Usually EEG signals are visually analyzed in clinical diagnosis and another common method for the analysis of EEG signals being used is Fourier transform. In Fourier transform, the EEG signal is transformed to an exponential or sinusoidal function in frequency domain. Therefore, Fourier transform is useful for extracting feature from periodic and non-periodic signals in frequency domain. Hence, it is not suitable for feature extraction from transient signals, thus the frequency spectrum produced by Fourier Transform lacks localization in time domain. As a result of Fourier Transformation, the behavior of signal in non-traceable.

Moreover, the co-efficient of Fourier Transform will change by adding data over time. On contrary, wavelet transform can effectively extract features from transient signals on both time and frequency domains. In addition to this, wavelet transform can provide frequency information with time localization if the basis function is of finite duration.

Characterization of 3Hz spike and wave-complex absence seizure by wavelet transform

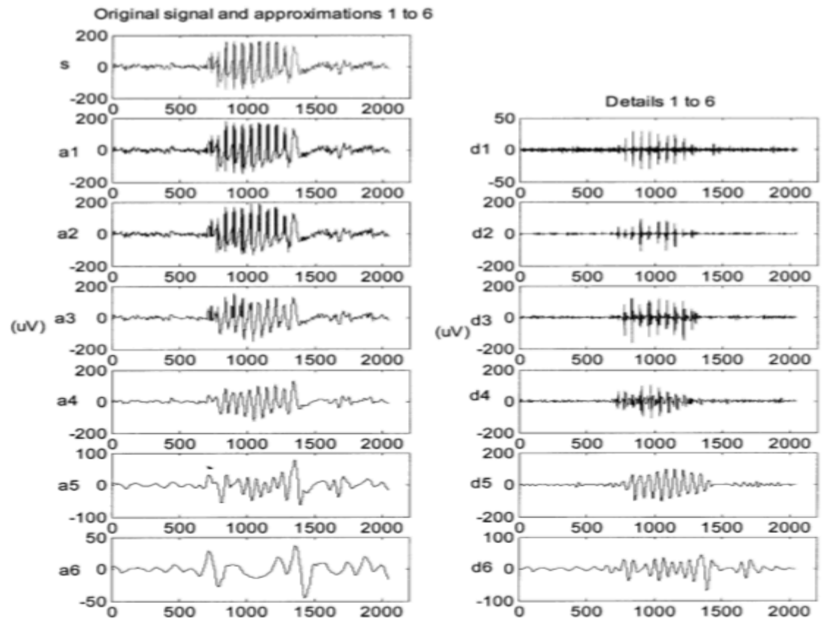

Figure 5. Absence seizure discharge of Figure 4. And their Daubechies order 4 wavelets of T6-O2

Source: (Adeli, Zhou, Dadmehr, 2002)

Fourier Transform uses sinusoidal functions for analyzing signals whereas, there are families of functions in wavelet transforms. Daubechies wavelets are known for their orthogonality property and efficient filter implementations. Daubechies wavelets of order 4 were found to be suitable for the analysis of EEG signals of epileptic patients. The other orders of wavelets did not represent spikes properly. (Adeli, Zhou, Dadmehr, 2002)

Fig. 5 shows the absence seizure epileptic discharge shown in Fig. 4 and their Daubechies order 4 wavelets of T6-O2 where the seizure starts at approximately 750th point and ends at about 1300th point. The inspection of these graphs that have used wavelet transforms shows that spike and wave trains are well captured in transformed signals.

Harmonic wavelets

Band separation in frequency domain can be attained effectively by using harmonic wavelet functions. Since, it can also help to locate the essential frequency bands accurately, therefore, it is an appropriate choice for analyzing EEG signals. The discrete harmonic wavelet function can be represented by the following equation: [3]

$$w(2^j x - k)\frac{(e^{i4\pi(2^j x-k)} - e^{i2\pi(2^j x-k)}}{i2\pi(2^j x - k)}$$

"The results of discrete harmonic wavelet transforms can be represented by a series of complex valued wavelet coefficients. The moduli of these complex valued wavelet coefficient represent the energy of the original signal at different frequency band. By investigating these complex wavelet coefficient moduli, the time-frequency characteristic of the original signal can be obtained" (Adeli, Zhou, Dadmehr, 2002). In absence seizure, the energy of spike wave is concentrated in level j=3, whereas in slow wave it is concentrated in level j=5. The frequency range for spike wave is 12.5-25 Hz whereas for slow wave the frequency range is 3.125-6.25 Hz.

Conclusions

By monitoring two analyzing methods used for this approach i.e. Daubechies order 4 and harmonic wavelet decomposition, following conclusions were made:

- In the frontal region, a greater amplitude for both high and low frequency component was observed as compared to the frequency components of occipital region.

- In the frontal region, the high frequency oscillation can be seen at a relatively earlier stage of epileptic discharge and the amplitude variation was of about 1/4th of 3 Hz spike and wave complex. Whereas, the occurrence of the low frequency wave was observed at the later stages of the same spike wave.

- In occipital region, low frequency waves with high amplitudes were observed at the beginning and end of the first seizure. Whereas, during the second epileptic seizure, low frequency waves with high amplitude were observed on three points of the seizure; in beginning, mid and end of the seizure. Therefore, it can be concluded that second seizure is the sum of two seizures with short duration.

- From Daubechies order 4 wavelet transform and harmonic wavelets, it can be concluded that right hemisphere of brain has more intense high frequency components than the left hemisphere of brain.

- The high frequency signals with a range of 50-100Hz have low amplitudes and can be ignored in clinical analysis because of their less significance in diagnosis.

"Daubechies order 4 wavelets and harmonic wavelets are an effective tool for wavelet analysis of spike and wave EEG signals" (Adeli, Zhou, Dadmehr, 2002). The future research work using the similar approach can be used to design a model automatic prediction of an epileptic seizure.

3.4 Automatic seizure detection using wavelet transform and SVM in long-term Intracranial EEG

Introduction

Epilepsy is a brain disorder characterized by sudden electrical discharges by the brain cells. It could be limited to certain parts of brain like in focal seizures or could be in all the parts of brain like in general seizure. Analyzing the signals using EEG for the diagnosis of epilepsy is an effective tool in clinical analysis. The neurologists usually monitor the signals EEG signals visually for the identification of the seizure. Continuous visual analysis of EEG signal is an extraneous task, moreover, the accuracy of analysis is also subjected to uncertainties. Therefore, visual analysis of EEG signals in clinical diagnosis is expensive and unreliable. An automatic seizure detecting system can not only aid neurologists to improve the current seizure diagnosis mechanisms, but it will also contribute towards the detection of other brain disorders. The research on developing automatic seizure detection methods was first initiated in 1970s. Most of the algorithms developed for the seizure detections used frequency domain analysis, wavelet transforms and artificial neural networking techniques.

Since EEG signals are non-stationary, therefore, discrete wavelet transform method can help in feature extraction from EEG signals. For, effectively predicting the onset of seizure, careful extraction of features such as energy, wavelet features and amplitude have to be made. After the extraction of effective features, an appropriate classifier is essentially required. Support Vector Machine (SVM) can be used a classifier for this approach because of its powerful pattern classification abilities. SVM is equipped with learning algorithms that helps in analyzing and classifying the data. SVM classifies the examples in either of the two categories separated by a clear gap.

This approach uses DWT based algorithm for the seizure detection from EEG signals. “The intracranial EEG (iEEG) epochs were decomposed into 5 frequency bands with 5 scales and 3 frequency bands at scales 3,4 and 5 were selected from the subsequent processing” (Liu, Zhou, Yuan, Chen, 2012)

EEG epochs are extracted in specific time frames in continuous EEG signals. These time frames are termed as epochs. EEG epochs are an effective tool for studying event related EEG dynamics.

Intracranial EEG Dataset

In this approach by Yinxia Liu, Weidong Zhou, Qi Yuan and Shuangshuang Chen,the iEEG data used for this research was obtained from University Hospital of Freiburg, Germany. The dataset consists of iEEG from 21 patients with 87 seizures. Each patient’s data consists of 24-26 hours of non-seizure data and 2-5 hours of seizure data. A total of 6 contact areas were selected, three of them were focusing on epileptic center and the rest three in other locations where seizure was spreading out. The time for seizure onset was estimated by a group of experts. In order to achieve high SNR ratio, iEEG data acquisition was performed with a Neurofile NT digital video EEG systems with a sampling rate of 256 Hz and 16 bit analogue to digital convertor. The iEEG datasets were preprocessed by a 50 Hz notch filter and a band pass filter between 0.5 Hz-120Hz. (Liu, Zhou, Yuan, Chen, 2012)

Training data: For training data, a total of 210 segments were used with 105 segments of seizure and 105 segments for non-seizure data. 256 points constitute 1 sec, each segment contains 1024 points. The total length of training segment was 840 seconds. Seizure/non-seizure parts were marked by the group of experts and they were randomly chosen for the training of seizure/non-seizure segments.

Testing data: "A total of 80.14 hours of iEEG data containing 82 seizures in 21 patients were selected as test data. There were 2359 seizure segments and 69753 non-seizure segments, and the length of each segment is 1024 points too" (Liu, Zhou, Yuan, Chen, 2012).

Feature Extraction

Fourier Transforms lack localization in time domain whereas with the help of wavelet transforms, it is possible to extract features both in time and frequency domain, therefore, for the purpose of extracting features from EEG signals to track epileptic activity, wavelet transforms are preferred over the Fourier transform. For this approach, Discrete Wavelet Transform (DWT) is used for the analysis of EEG signals. It is also essential to match the wavelet with the similar shape and frequency with that of the seizure's characteristics. This approach employs Daubechies 4 wavelets. Daubechies wavelets were introduced by Ingrid Daubechies. Daubechies wavelets are a family of orthogonal wavelets. There is a scaling function associated with each wavelet of this class.

“The smoothing feature of db-4 wavelets makes it more appropriate to detect changes of iEEG signals and that’s why db-4 wavelets were selected for the present study” (Liu, Zhou, Yuan, Chen, 2012)

The frequencies obtained from iEEG signals were categorized in 5 different frequency bands with detail co-efficient.

Table 2. Frequency distribution into bands [7]

Frequency bands	**Detail co-efficient**
64-128 Hz	d1
32-64 Hz	d2
16-32 Hz	d3
8-16 Hz	d4
4-8 Hz	d5

Although, there is no defined spectrum for the occurrence of seizure, but they mainly occur between 3-29 Hz. Hence, d3, d4 and d5 (Fig. 7) can be used to extract features such as relative energy, amplitude, index for fluctuation etc. Following important features were extracted using db-4 wavelets:

Relative Energy: "For the Daubechies wavelet, the sum of square of co-efficient of the wavelet series is the energy of EEG signals" (Liu, Zhou, Yuan, Chen, 2012).

$$E(l) = \sum_{i=1}^{N} D_i^{2*}\tau/N$$

Where τ is the sampling interval and N is the number of DWT co-efficient D_i presented at scale *l*. [7]

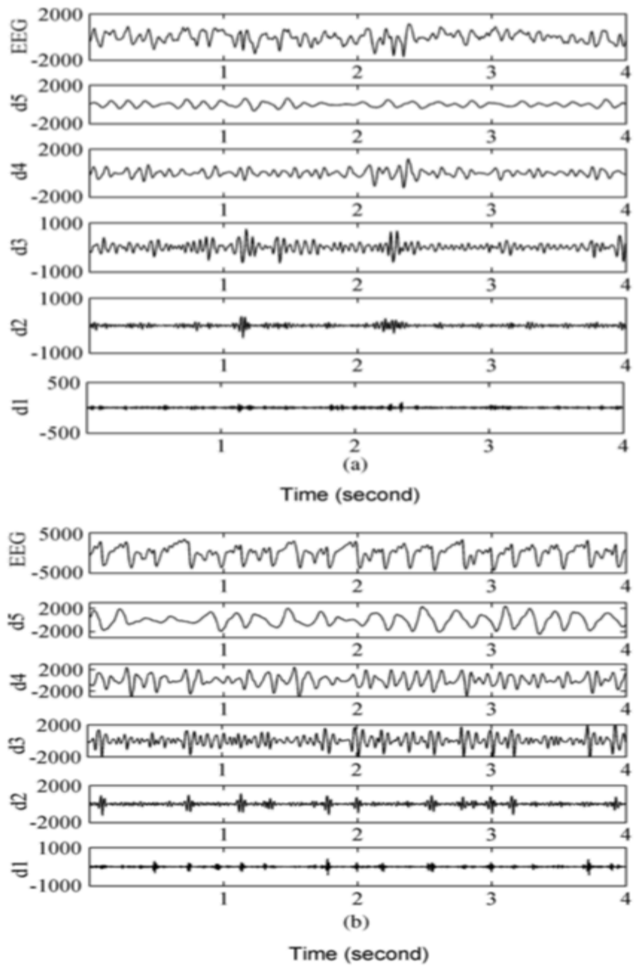

Figure 6. Decomposition of EEG by DB4 wavelet into details (d1-d5) signals. (a) Normal signal. (b) Seizure signal. [7]

Source: (Liu, Zhou, Yuan, Chen, 2012)

- **Relative amplitude**: When a seizure occurs, there is an increase in amplitude relative to the background. Amplitude is computed relative to the background and iEEG epochs are subjected to normalization. After analysis, there were relatively larger amplitude values associated with seizures. Moreover, co-efficients of variation and fluctuation index were also extracted.
- **Standard Deviation:** Standard deviation represents the proximity of the various features near the mean value (μ). Whereas the co-efficient of variation effectively measures the variations in the amplitude of signals. Fluctuation index was extracted because the iEEG signals for seizure exhibit greater Fluctuation index than non-seizure iEEG signals.

Support Vector Machine

SVM is now widely implemented in pattern classification, it was initially designed for binary classification. SVM is used for categorization of a given example on a hyper plane. This hyper plane is a line that separates the two categories and the given example will fall in either of these two sides of hyper plane.

Post Processing

In this approach, the output obtained by SVM was classified as 1 or -1, with 1 representing non-seizure iEEG and -1 representing seizure iEEG. The value of SVM is not always exactly 1 or -1 instead it varies between 1 and -1, therefore, post-processing of output obtained via SVM is always essential. Post-processing scheme consists of smoothing, multi-channel decision fusion and collar techniques (Liu, Zhou, Yuan, Chen, 2012).

Multi-channel decisions are made, to increase the accuracy and to reduce the false positive detections. Seizures are detected on the following basis:

- The epochs will only be labelled a seizure if there are atleast two seizure detections from two channels instantaneously.

- If only one channel detects a seizure, then the preceding and proceeding epochs in the same channel will be used to govern if the current epoch is a seizure or non-seizure epoch.

- An epoch that is adjacent to a seizure epoch will also be marked as a seizure.

To avoid being mistaken by the beginning and ending of the seizure as interictal, collar technique is applied to prevent eliminating the signal segment at the beginning and the ending of the seizure.

Conclusions

"The sensitivity of this approach varied from 50-100% with 18 patients having sensitivities above 90%. In this study 82 seizures were used to test algorithm and 79 were detected correctly" (Liu, Zhou, Yuan, Chen, 2012).

Correct and extraction of features can influence the detection and prediction of seizure greatly. Therefore, high performance can only be achieved in seizure predicting algorithms if right choice is made for extracting the feature. Moreover, a combination of various features provides accuracy and reliability in seizure studies.

3.5 Heart Rate Variability Features for epilepsy seizure prediction

Introduction

An epileptic attack results in chronic seizures and anti-epileptic drugs, surgeries or nerve stimulators are used for treating this disorder. However, the effect of medication is sometimes rendered useless on some patients because of its ineffectiveness. Due to unpredictable nature of this disorder, serious injuries can occur to the patient as a result of it and to the people surrounding them as well. Therefore, the quality of life is greatly affected due to the unforeseen nature of the seizures. For the detection and prediction of seizures, neurologists usually rely on the results extracted from EEG but for continuous monitoring of the patients' vital signs in daily life, EEG is not a feasible option. It requires the wearing of scalp electrodes continuously which could be quite uncomfortable. Hence, ECG can be used to monitor the heart rate of the patient because heart rate changes significantly before the onset of a seizure.

ECG signals consists of peaks varying in amplitude, and the highest peak is termed as R wave. The interval between two consecutive R waves is R-R interval (RRI). In recent seizure predicting algorithms, HRV (Heart Rate Variability) analysis has been implemented using Holter monitor. The fluctuations of R-R interval in ECG are termed as HRV (Heart Rate Variability). HRV analysis using Holter monitor is difficult to implement because operating Holter monitor requires skills. Moreover, it was expensive. In order to overcome these limitations, the wearable HRV sensors can be manufactured and used for seizure prediction.

Heart Rate Variability Analysis

HRV analysis has been used for monitoring and detecting various cardio-vascular diseases. There are many features that can be extracted from ECG waves. However, there is a need to determine the appropriate features required for the accurate prediction of epileptic seizure. Following are some HRV features extracted from ECG signals.

1. *RR Interval:* Raw RRI data gathered from a healthy person is represented in the *Fig.7 (a).* Raw data is difficult to be analyzed without prior sampling at equal intervals of time. *Fig.7 (b)* shows the resampled RRI data after interpolation.

2. *Time-Domain indexes: "*Using the resampled RRI data, various time domain features can be directly calculated such as mean of RRI (**meanNN**), standard deviation of RRI (**SDNN**), the total mean square of difference of adjacent RRI (**RMSSD**), variance of all RRI (**Total power),** the number of pairs of adjacent RRI, whose difference is more than 50 ms, divided by total number of RRI represented as **PNN50**, and the number of RRI divided by the height of the histogram of all RRI measured on a discrete scale with bins of 1/128 second known as **HRV triangular index"**. (Hashimoto, Fujiwara, Suzuki, Miyajima, Yamakawa, Kano, Maehara, Ohta, Sasano, Matsuura, Matsushima, 2013)

3. *Frequency Domain Indexes:* With the help of resampled RRI data, Power Spectral density (PSD) can be constituted to obtain frequency domain features as shown in *Fig. 7(c).*

LF: "The power of the low frequency band (0.04-0.15 Hz) in PSD. LF represents the modulations of sympathetic and parasympathetic nervous systems" (Hashimoto, Fujiwara, Suzuki, Miyajima, Yamakawa, Kano, Maehara, Ohta, Sasano, Matsuura, Matsushima, 2013).

HF: "The power of the High Frequency band (0.15-0.4 Hz) in PSD. HF reflects parasympathetic nervous system activity" (Hashimoto, Fujiwara, Suzuki, Miyajima, Yamakawa, Kano, Maehara, Ohta, Sasano, Matsuura, Matsushima, 2013).

LF/HF: This ratio represents the balance between the activities of sympathetic nervous system and parasympathetic nervous system.

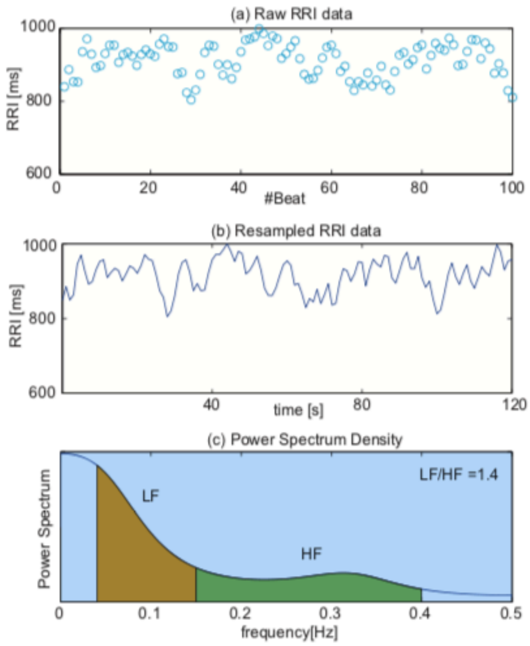

Figure 7. An example of RRI data analysis: (a) raw RRI data. (b) Resampled RRI data and (c) PSD and its LF/HF

Source: (Hashimoto, Fujiwara, Suzuki, Miyajima, Yamakawa, Kano, Maehara, Ohta, Sasano, Matsuura, Matsushima, 2013)

Application to the Clinical Data

The interictal and preictal RRI data was recorded by capturing seizure video, ECG and EEG signals simultaneously for 24 hours continuously using the long-term video EEG monitoring system (Neuro Fax EEG-1200, NIHON KOHDEN). [16] The onset of the seizure was marked by two epilepsy experts. The EEG data was stored as preictal data for 15 minutes before and 5 minutes after the occurrence of seizure. Whereas ECG data was recorded for about 20 minutes during interictal period to help with seizure prediction model. The ECG signals were recorded from 5 patients. The table below represents their attributed including types of seizures and ages.

Patient	Sex	Age	Type	Anamnesis	Prescription* [mg/day]
A	male	27	generalized	drug-resistant epilepsy	VPA 1200, LEV 2000, CZP 2
B	male	46	partial	right frontal lobe lesionectomy	VPA 1600, CZP 800, ZNS 400, TPM300
C	male	25	partial	gyrus and mesial frontal lobe lesionectomy	CBZ 800
D	male	30	partial	drug-resistant epilepsy	CBZ 400, CLB 10
E	male	14	partial	focus could not be identified	TPM 550, PHT 250, CLB 20, LTG 400

Figure 8. Table representing patient attributions

Source: (Hashimoto, Fujiwara, Suzuki, Miyajima, Yamakawa, Kano, Maehara, Ohta, Sasano, Matsuura, Matsushima, 2013)

From the ECG data, RRI (R-R) interval were calculated. The raw data was resampled so that it was easier to analyze. "This approach used the sampling interval of 1 second and in order to interpolate RRI, 3rd order spline was used. A rectangular sliding window was used for the resampled RRI data and a HRV features were extracted. The size of the window was 3 minutes and it was estimated by trial". (Hashimoto, Fujiwara, Suzuki, Miyajima, Yamakawa, Kano, Maehara, Ohta, Sasano, Matsuura, Matsushima, 2013)

TABLE II
COLLECTED DATASET

Patient	Preictal	Interictal
A	A1 - A3	-
B	B1	B'1 - B'4
C	C1, C2	-
D	-	D'1 - D'4
E	-	E'1 - E"4

Figure 9. The dataset from patients showing the episodes of seizures

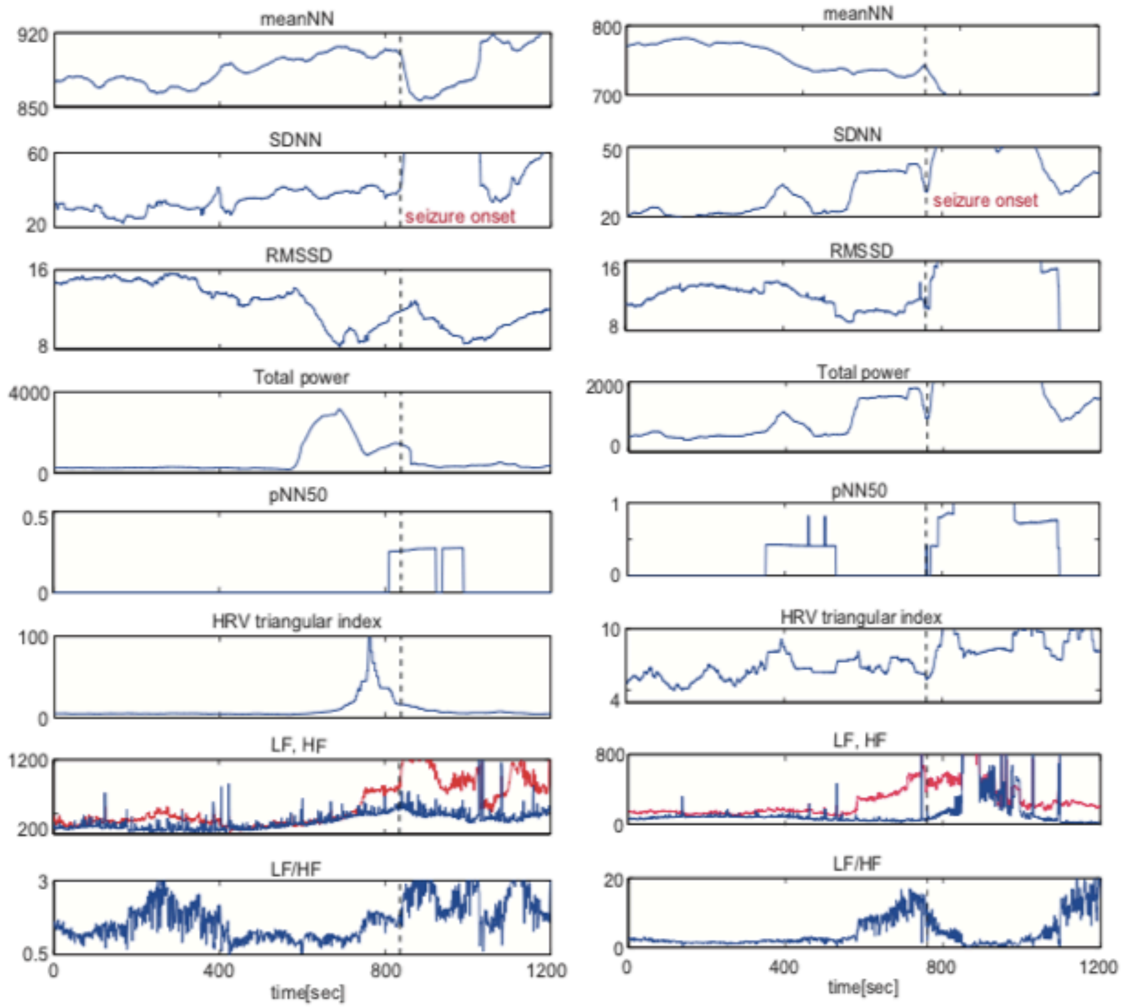

Figure 10. (a) Analysis results of episode A1 (b). Analysis results of episode B1

In the graphs in Fig.11, the blue and red line in second last graphs represent LF and HF. These graphs also depict that RRI changes significantly after the occurrence of seizure which also indicates that seizure also affects the autonomic nervous function of the body such as heart rate. Upon observing the seizure episode A1 and B1, about 3 minutes before the seizure onset in episode 1, RMSDD, pNN50 and HRV triangular index changed. Whereas in episode B1, these features did not change greatly. Patient A had generalized seizure and patient B had partial, but the trend of frequency domain did not differ in both types of the seizures. The other seizure episodes were almost same as that of A1 and B1, therefore they have not been shown here.In the Fig. 11, HRV features from interictal period B'1 are shown. "LH changes synchronously with HF in interictal period although only LH greatly changed before the seizure onset in the preictal period" (Hashimoto, Fujiwara, Suzuki, Miyajima, Yamakawa, Kano, Maehara, Ohta, Sasano, Matsuura, Matsushima, 2013)

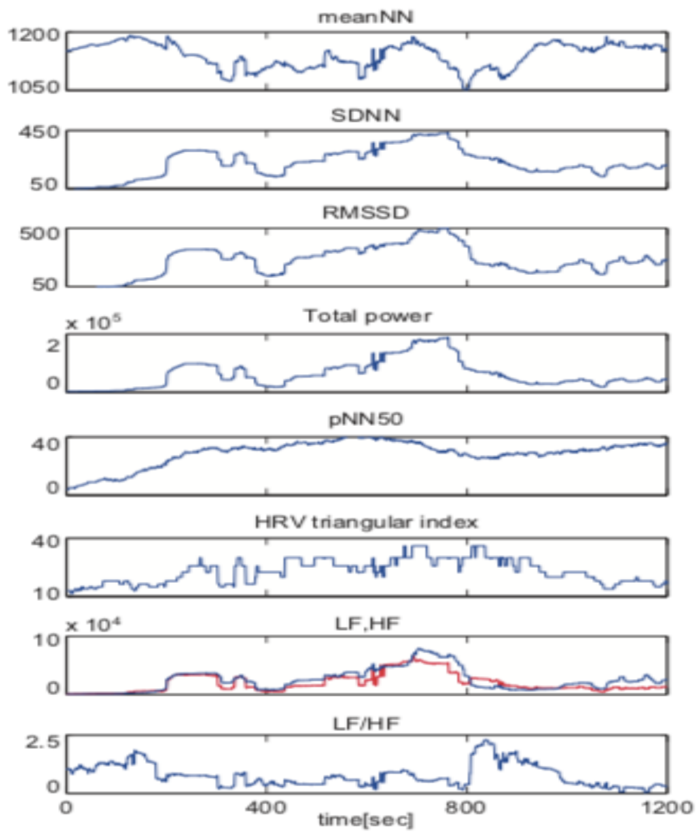

Figure 11. Analysis results of episode B'

Source: (Fig. 10 and Fig 11) Hashimoto, Fujiwara, Suzuki, Miyajima, Yamakawa, Kano, Maehara, Ohta, Sasano, Matsuura, Matsushima, 2013.

Conclusions

In this approach, HRV data was analyzed to design a prediction system. The frequency domain features such as LF and LF/HF, changed before the seizure onset varying from one to ten minutes in all episode, but the changes in these features differ from one seizure to another.

3.6 Detection of seizure like movements using a wrist accelerometer

Introduction

Seizure itself is not as harmful as the injuries as a result of seizure could be. Therefore, patient and the caregivers are always concerned about the injuries that can occur as result of falling or hap-hazardous movements. Hence, the timely prediction of the seizure can lead to a number of solutions that can benefit the patient and will also enable the caretaker to take first aid steps or to alert the emergency services. In this approach, a wearable wrist-worn accelerometer is used to detect the seizure like movements.

Methodology

In the method proposed by Lockman, S. Fisher, and M. Olson, the subjects were from the age group of 3-85 years old. The smart watch used the sensors to detect the movements of the subject, upon detection, the signals are then transmitted to another link such as a computer, or a smart phone via Bluetooth. The events are then logged in using date/time, duration of the movement and complete set of motion data which can be viewed in graphic plot.

When sensors on the watch detect seizure-like movements, the smart watch starts beeping rhythmically and in 5-10 seconds a broadcast of detection signal is made. When the device detects the similar to seizure movements, it starts sending out alerts that consists of beeps and the alarm indicator on the watch also glows up. The subject will be notified to cancel the alarm if it was triggered as a result of false alarm so that it further prevents the broadcast of alerts to the caregiver. For the detection of seizure like movements, the watch contains 3D accelerometer sensors to detect fine movements of ankle or wrist on which the device is worn. For detection alerts, the smart uses pattern recognition algorithms along with feature analysis to make a final call for the decision.

“A sensitivity setting of 1-100 allows user to adjust detection threshold in case of excess or insufficient detections”. (Lockman, S. Fisher, M. Olson, 2011)

The accelerometer obtains the x, y, z coordinate signals and these coordinates are termed as features. Analysis of the characteristics over a small interval of time such as few seconds is a local analysis, whereas analysis of characteristics over a larger interval, 10 seconds or longer is a global analysis. Epilepsy experts simulated the movements similar to tonic-clonic and tonic seizures while wearing the watch and recorded the data from accelerometer produced as a result of these movements. Afterwards, motion data was also recorded from the patients targeted for this study to give the final touch to the algorithm.

"The seizure detecting algorithm was installed on small embedded CPU processor. The printed circuit board was designed with accelerometer sensors, together with a small rechargeable lithium ion battery to power the board. The board was further miniatured to the size of LCD on traditional wrist watch. The application software was enhanced with the ability to record data and manage wireless/Bluetooth communication with mobile devices" (Lockman, S. Fisher, M. Olson, 2011) Hardware/software specifications are illustrated in the table below:

Device Specifications.

A. Hardware
1. Miniature board: 3D accelerometer sensor, small CPU processor, flash memory and battery
3. Compact: size of a traditional wristwatch, $40 \times 35 \times 12$ mm
4. Built-in rechargeable battery: lithium ion battery with a 24-hour life
5. Bluetooth wireless communication with mobile devices
6. Built-in "cancel" button that can be used by the patient to signal a false alarm
7. Built-in "help" button that can be used by patient to summon help at ANY time; most useful for patients experiencing auras prior to seizures/convulsions
7. Power in via USB port
8. Power/battery charge indicator (for recharging): LED
9. Red alarm LED to indicate alarm being transmitted
10. Buzzer or beep to issue an audio alarm
B. Software: Data and alert management, recording; mobile communication
1. Detection engine
2. Simple interface to adjust detection thresholds (from 1 to 100) and duration
3. Recording of seizure data
4. Alerts to mobile devices
5. Automatic synchronization with mobile devices???
6. Bluetooth and mobile communication management software
7. A PC-based application for medical professionals to review and analyze patient data and seizure patterns

Figure 12. Table representing hardware and software specifications

Source: Lockman, S. Fisher, M. Olson, 2011

"Video/EEG monitoring system by Nihon Kohden Corporation was used to video monitor the patients along with continuous EEG recording. In order to check for the seizures if they were detected by the device, previous 24 hours of the patient were reviewed for analysis. Moreover, the information from the caregiver was also collected to know if there had been any behavioral seizure. Afterwards, the data captured by the device is evaluated separately and then correlated with the routine EEG monitoring results to categorize the epileptic events, non-epileptic events and non-detections. (Lockman, S. Fisher, M. Olson, 2011)

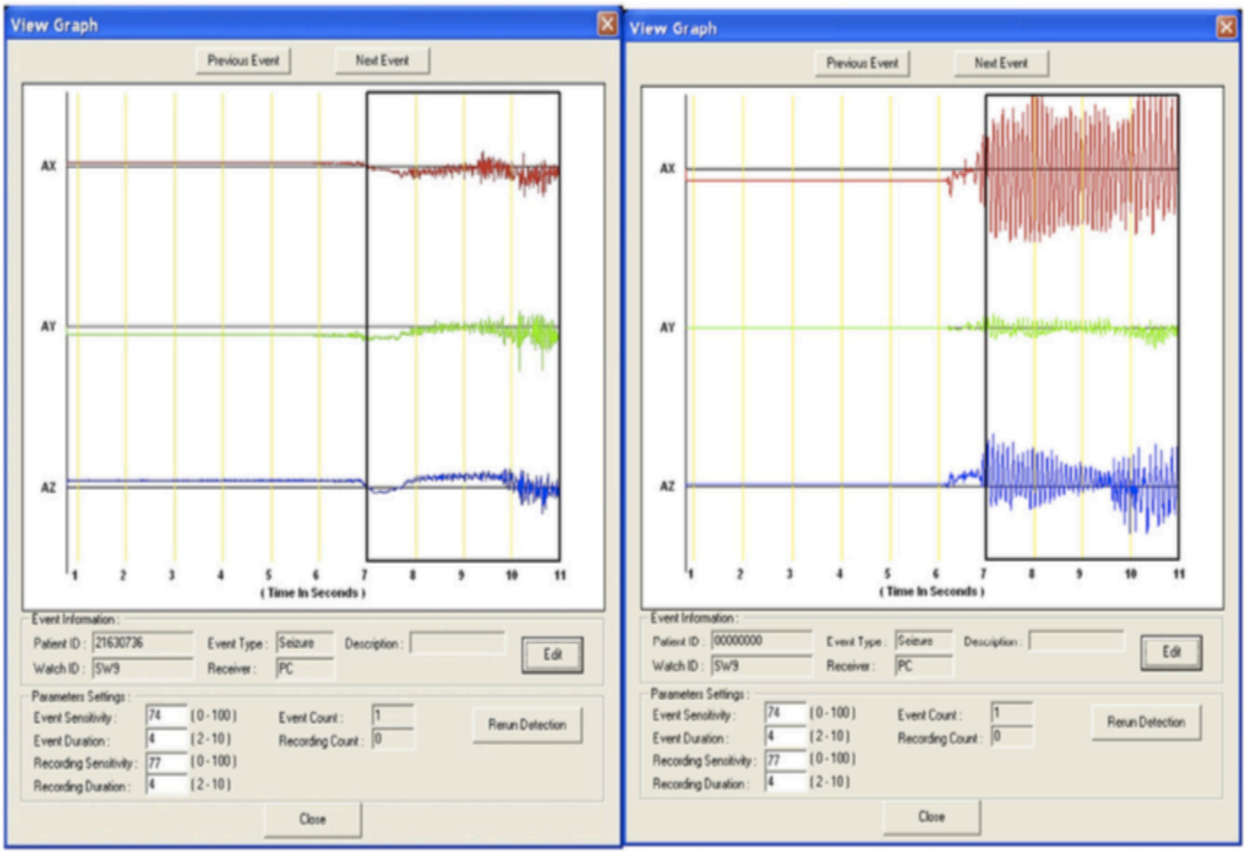

Figure 13. Computer display of motion detected during tonic-clonic seizure (left) and vigorous head scratching (right). AX, AY and AZ indicate accelerometer axes. The black boxes around the motion detections from 7 to 11 seconds indicate these movements were detected

Source: Lockman, S. Fisher, M. Olson, 2011

Results

A total of 40 subjects were monitored between March 2009 to June 2010. In a total of 8 seizures, 7 were detected by the device. One seizure that went undetected was due to uncharged battery. Rhythmic movements were also detected with 4-15 seconds of clonic movements. 5 seizures occurred when patients were asleep, 1 when patient was sitting and 1 when patient was on exercise bicycle. The time between initial tonic phase ranged from 5-43 seconds. (Lockman, S. Fisher, M. Olson, 2011)

The smart watch tracks the pattern of motion similar to that of General Tonic clonic seizure. There were 204 non-seizure movements in a total of 40 subjects. Only 1 detection was termed as false that occurred during the sleep. This study shows that with the help of this approach, detection of tonic-clonic seizure has been made possible by detecting the pattern of motion. Due to an error in device's battery, one false negative result was detected. To eliminate the possible chances of error, the battery life of the device was extended up to 30 hours. Since, this device tracks the motion patterns to detect the seizure the detection rate for non-seizure event is high. Therefore, if a detection is made, patient is provided with a cancellation option, to reduce the false positive detections. A patient can also have a risk of seizure while being asleep, therefore, the device can be worn at night while sleeping when the occurrence of false positive detections would be less. Partial seizures, unlike generalized tonic-clonic seizures, do not produce severe jumbled movements therefore, the smart watch did not detect the partial seizures.

4. ANALYSIS AND AUGMENTATIONS

4.1 Preliminary Study

The lifelong and everlasting effects of epilepsy on the quality of life are no less than the impacts caused by any other chronic disease. Moreover, the unpredictable nature of epilepsy not only traumatizes the patient but also keeps its family, and caregivers in a constant worry. The greater the intensity of the seizure, the worst the negative impacts on the quality of life. Moreover, the social stigma that can surround the patient could be by far a greatest challenge to overcome. According to International League Against Epilepsy, about three quarter of the people living with epilepsy can lead a normal life, free of seizure, if appropriate treatment is provided. [18]

Epilepsy affects the quality of life of the patient greatly. Let it be the patients or their families, the concern of next possible seizure is always there. Moreover, the uncertainty of this disorder, restricts the day to day life of the patient. The patient with epileptic disorder is recommended to avoid activities that require attention such as driving, therefore, if the nature of the job of the patient requires driving then he might not be able to keep that job. Moreover, with this medical condition, there are certain risks involved during pregnancy. Anti-epileptic drugs can cause birth defects in the developing baby including cleft lip, cardiac defects and urogenital defects.

Fear of the occurrence of seizure is always accompanied with the fear of helplessness. In case of the occurrence of seizure, a person may or may not lose conscious depending on the type of seizure. If a person undergoing seizure losses awareness, then seizure first aid should kick in time to prevent an emergency. It can include giving a rescue treatment or alerting the emergency services.

Keeping in view all risks posed by the occurrence of the seizure, it is desirable to have an effective way to predict the occurrence of seizure. Advance prediction will not only help the patient to take precautionary measures to minimize the risks involved with the occurrence of seizure, but it will also help the neurologists to better understand the changes involved during the stages involved in the onset of seizure.

There are various approaches being developed till date to predict an epileptic seizure. These approaches include:

- Analyzing the brain signals obtained via EEG, the analysis is performed by epileptic experts or neurologists to give an accurate prediction. Measuring EEG signals require wearing of an electrode cap, which detects the electrical changes in the brain signals.

- Analyzing electrical activity of heart, using electrodes placed on skin or limbs. Analyses is can be made on the basis of heart rate variations.

- Measuring the movements of the subject by wearing an accelerometer.

- Motion trajectory analysis using video detection systems.

- Mattress sensors to detect the seizure during sleep.

- Monitoring the respiratory abnormalities using Respiratory monitor.

- Analyzing skin temperature to predict any abnormality that can lead to a seizure.

4.2 Introduction

Central nervous system is controlled by brain which is made up of tiny brain cells called neurons. Electrical impulses are transmitted by neurons to control the bodily functions. During a seizure, there is a sudden rush of electrical impulses from brain, that disrupts the normal functioning of brain causing disorientation, loss of conscious, dizziness, changes in vision, sudden jerking or shaking of arms and legs, falling, etc. [19]

Epilepsy can affect the people of any age group, sex or ethnicity. The seizure can cause fatal injuries to the patient and can also compromise the safety of the surrounding people. The seizure itself is not fatal but the patient's disorientation and lose of awareness can result in serious injuries which can prove fatal. Doctors can have difficulty in diagnosing a seizure. The seizure needs to be monitored to have an insight about the frequency of the occurrence, the activity the patient was conducting when the seizure occurred. Therefore, Prediction of epileptic seizure is not only vital for the patient undergoing the seizure but also for the neurologist to help them better understand the processes occurring internally before the onset of seizure in order to ensure the best treatment.

The current techniques to predict seizure either lack efficient prediction i.e. quick response system in real-time, or they are less accurate and consequently can trigger false alarms. Hence, in the analysis and prediction of a seizure, there is a race between time and precision. Incorporating both in one technique is therefore, a hard nut to crack. Thus, the need lies in achieving the best of both i.e. efficiency and reliability. Keeping in view the wear-ability of the device(s) to predict the seizure, it should be designed by taking the comfortability in to the account, so that it does not hinders the day-to-day life of patient or makes him stand out from the rest of the group. Moreover, the device should be able to transmit the recorded data over a wireless network or Bluetooth link so that alerts can be responded immediately in case of a trigger.

In the light of the stated essentials, this thesis uses the amalgamation of the most approachable features extracted from different techniques in order to achieve accurateness and effectiveness. To achieve accuracy, the signals from EEG, ECG and motion pattern from accelerometer will be analyzed to extract the desirable features in order to determine the possibility of a seizure event. EEG will provide the signals representing the electrical activity of the brain, ECG will provide with Heart Rate Variability (HRV), and a 3D accelerometer will keep a track of movement patterns. The extracted features from the signals and body vitals will be fed in to an Artificial Neural Network to produce the most accurate results based on the weight of each technique.

4.3 Feature Extraction

The signals obtained from ECG or EEG need to be analyzed by the experts in order to diagnose the disease. However, the analysis carried out by neurologists, or epilepsy experts can always have a room for inaccuracies and errors. Moreover, the signals contain redundant information apart from useful one, which is undesirable for any diagnosis, e.g. EEG contains a wide range of frequency components however, the range for clinical interest lies between 0.3-30Hz (Adeli, Zhou, Dadmehr, 2002). It is therefore, essential to eliminate the surplus data and to only extract the required information that can help with the diagnosis. This can be achieved with the help of filters. The intended approach will use the appropriate features from the three parameters i.e. EEG, ECG and accelerometer to predict a seizure.

Extraction of features from EEG

Analyzing EEG signals

As we perform our various activities and as our senses work, the brain is constantly active in running the show. It highlights and filter the information most relevant to us. Brain constantly emits electrical impulses and EEG is the physiological method to record the electrical activity being produced by the brain. It also allows to analyze the activity of particular area of brain. Depending upon the state of brain, the frequency patterns vary, and this is the key point in analyzing EEG signals. Analyzing EEG signals and diagnosing the state of the brain can be bit tricky. It, no doubt, requires a certain level of expertise to analyze and to collect the relevant information from the signals. An EEG test usually takes 30 to 60 minutes. It involves attaching electrodes on the scalp to monitor the brain activity. In some cases, EEG recording can take place for 24 hours, these recordings usually use video monitoring also side of EEG recording to capture the seizure activity. EEG signal changes significantly before the onset of the seizure, therefore, seizure can be detected and predicted from few hours to few minutes prior to the onset. Signal symmetry varies from person to person.

Pre-processing of signal

EEG signals being recorded by the electrodes as the result of brain activity are raw signals. EEG experts and neurologists have to analyze and interpret signals before coming to a conclusion. Just like any other signal, EEG signals also contain noise, therefore it needs to be eliminated before processing the signal. Moreover, for the clinical purposes, the frequency range of EEG is between 0.3 to 30 Hz (Adeli, Zhou, Dadmehr, 2002). Hence, bandpass filters can be applied to eliminate the surplus frequency ranges. (Ramina, Vanitha, 2017) states that preprocessing is also required to increase the accuracy of the results and to minimize the errors due to redundancy.

Feature Extraction

Many techniques have been implemented till date to extract the features from EEG. For the purpose of feature extraction, dataset obtained from the EEG signals can be divided into frames of 60 minutes, as proposed by (Ramina, Vanitha, 2017). As a further application, each frame will have its own sampling frequency, sequence number, time slot and data length. This will help the ordering of data sets with respect to their sequence numbers. This technique proprosed by Ramina and Vanitha for fast and effective real time seizure prediction on streaming EEG signals required a lot of preprocessing of data sets. In order to predict a seizure effectively on real time, this technique can pose some delays in decision making process.

Another way to extract the features from EEG signals in real time is by using Fourier transforms. Fast Fourier transform was applied on the basis of frequency range by Meenakshi and Singh in their writing on Frequency analysis of healthy and epileptic seizure in EEG using Fast Fourier Transform (Meenaskshi, Singh, 2014). The sampling frequency was set to 256 Hz. EEG signals are non-stationary signals i.e. they vary continuously in time and frequency domain, so the signals are transformed to an exponential or Sinusoidal function in frequency domain. Therefore, Fourier Transforms are only suitable for feature extraction from periodic/non-periodic signal in frequency domain. According to (Zhou, Dadmehr, 2002), It is hence not an appropriate choice to extract features from EEG signals since it lacks time domain localization. [3] Also, (Zhou, Dadmehr, 2002) suggested that the on a certain point where Fourier Transform and other techniques lack time domain localization, wavelet transform will come to the rescue. They used wavelet transform to analyze epilepiform discharge in EEG with absence seizure. Wavelet transform are equipped with the families of function unlike Fourier Transform. Amongst these, Daubechies wavelets of order 4 were suitable for EEG analysis of epileptic patient. Daubechies of order 4 were chosen because they well represented the spikes produced by absence seizure. However, this study by (Zhou, Dadmehr, 2002) was limited for the analysis of 3Hz spike wave observed in absence seizure. Whereas, another study by (Liu, Zhou, Yuan, Chen, 2012) uses the same approach of implementing discrete wavelet transforms for automatic seizure detection. [7] They proposed the automatic detection and prediction of the seizure by the extraction of features such as energy, fluctuation index, and amplitude.

For the analysis of EEG signals Discrete Wavelet Transform was used whereas to match the shape and frequency of seizure wave with that of the wavelet, Daubechies wavelet of the order 4 were used. The smoothing feature of db-4 wavelet rendered it suitable to detect the changes of iEEG signals therefore, it was selected for this study. Moreover, initially the frequency range was divided into 5 bands, however, the occurrence of the seizure lies between 3-29 Hz, therefore, only 3 out of 5 bands with this frequency range were used for feature extraction. The features extracted from 3 frequency bands using db-4 wavelets include: relative amplitude, relative energy, and fluctuation index. (Liu, Yuan and Chen, 2012)

Feature extraction from ECG

Heart-Rate of the patient changes significantly during the onset of a seizure along with other cardiac abnormalities (Zijlmans, Flanagan, Gotman, 2002). The fluctuations between the highest peak (R waves) in ECG signals is termed as Heart Rate Variability (HRV) and the analysis of HRV can be used to detect seizures (Hashimoto, Fujiwara, Suzuki, Miyajima, Yamakawa, Kano, Maehara, Ohta, Sasano, Matsuura, Matsushima, 2013).

The features extracted from ECG waves to be used for the following prediction method are RR interval (to resample the raw data), time domain indexes (such as mean of RRI, standard deviation, etc.) and frequency domain indexes (such as Power Spectral Density). The recording of data for preictal signals occur 15 minutes before the onset of seizure and 5 minutes after the onset of seizure, in this way, there is a room of 15 minutes for prediction. The frequency domain features such as Power of Low Frequency (LF) and Ratio of Power of LF to HF (LF/HF) changed before the seizure with 1 to 10 minutes in all the episodes of seizures, whereas the time domain features did not change in all the seizure episodes. Moreover, the trend of frequency domain did not differ in both types of seizures i.e. generalized and partial seizures (Hashimoto, Fujiwara, Suzuki, Miyajima, Yamakawa, Kano, Maehara, Ohta, Sasano, Matsuura, Matsushima, 2013. This shows, this approach can be used for the prediction of both type of seizures since the trends of frequency domain remained same for either types of the seizures.

Feature Extraction from Accelerometer

Accelerometer can be worn on wrist or ankle by the patient. The 3D sensor detects the seizure like random movements. Within a time-frame of 5-10 seconds a broadcast of detection signal is made in order to alert the user. This sensor is of more use for the detection of Tonic-Clonic seizures in which patient has greater chances of losing conscious and thereby producing hap-hazardous movements prior to the fall. The accelerometer extracts (x,y,z) coordinates and these are then used for seizure detection. (Lockman, S. Fisher, M. Olson, 2011)

In a study proposed by (Beniczky, Polster, Kjaer, Hjalgrim, 2013), Tonic Clonic seziures can be detected by a wireless wrist-worn device equipped with an accelerometer. The device for seizure detection had been developed by Danish care Technology ApS (Denmark). It contains 3D accelerometer, a micro-processor and a rechargeable battery. The sensor can measure the movements in the 3 axes. The life time of the battery is 24 hours. The device is fully automatic therefore no post-processing is required. The device has same accuracy for nocturnal seizures as well. It can be worn as a wrist watch and has a two-way wireless communication with a portable unit. Upon detection of a seizure, not only the alarm is triggered but the record for seizure detections is also recorded to keep the doctor aware of the seizure diary (Beniczky, Polster, W. Kjaer, Hjalgrim, 2013).

However, detection of a fall cannot be made very accurately with the help of an accelerometer because of lack of incorporation with body postures while falling. It might give too many false detections since body posture is changing rapidly during the fall. Therefore, infrared sensing can be implemented to detect a fall and to trigger an alarm. With this technique infrared sensors needs to be installed in where the subject is inhabiting (Miguel, Brunete, Hernando, Gambao, 2007). Using a normal video camera could have been an alternative but it might compromise the privacy of the subject. The patient might feel being watched all the time due to privacy concerns.

This method has been incorporated in the toilets of hospitals and elderly homes for fall alerts, the same technique can also be used for seizure fall alerts.

Post-Processing

Post-Processing of EEG signals

Based on the model proposed (Liu, Zhou, Yuan, Chen, 2012), relative amplitude, fluctuation index and relative energy were extracted from EEG signals. Support Vector Machine (SVM) was implemented using a hyper plane to categorize seizures and non-seizures EEG. inhabiting. The values from the output of SVM are not sharp 1 or -1, instead they vary between 1 and -1. Therefore, smoothing of the output obtained from SVM is necessary. For the sake of ease, the output after post-processing can be categorized as 0 and 1 for non-seizure and seizure EEG signals.

Post-processing of ECG signals

Just like EEG signals, ECG also require post processing after feature extraction. There were two types of the features being extracted from HRV signals, in time domain and in frequency domain (Hashimoto, Fujiwara, Suzuki, Miyajima, Yamakawa, Kano, Maehara, Ohta, Sasano, Matsuura, Matsushima, 2013). The features in time domain (mean RRI, standard deviation, etc.) did not change significantly in the episodes of seizures. Whereas, the features in frequency domain (Power of Low Frequency, Ratio of power LF/HF) changed significantly before the onset of the seizure. Moreover, the frequency domain features can also be used effectively to predict generalized seizure as well as partial one. The changes, however, in the features vary from seizure to seizure. Therefore, in order to accurately predict the onset of the seizure ANN can be implemented to train the data first to recognize all the possible variations of seizure plots and then testing will be done to predict the seizure. Hence, extraction of features from ECG is also essential from feasibility's point of view. There are wearable wrist watches and bands already available to measure ECG and heart rate in a continuous manner. One such watch is CRONOVO smart watch [24]. The ANN algorithm can be embedded in a wrist watch that is capable of measuring ECG, in that way the small wearable device will not hinder the day to day life of the user.

Post-processing of the data from Accelerometer

Since the device from Danish Technology ApS (Denmark) for the detection of seizure using accelerometer is fully automatic therefore there is no need of post-processing of the data.

5. UNIFICATION OF THE SEIZURE DETECTING TECHNIQUES FOR THE CURRENT APPROACH

The aim of using unification approach for this thesis is to achieve accuracy along with efficiency. Most of the systems designed till date focus on achieving either one of the approaches, i.e. fast real time processing or accuracy (minimum false alerts). In order to predict an epileptic seizure, the approach needs to take in account all the impediments for example, lacking coherence, slow real time processing and too many false positive alerts. To avoid these events, the best features from different techniques namely EEG, ECG and accelerometer were chosen. The purpose of using three different techniques is to cover up for the flaws encountered by an individual technique and to offer the back up using another technique. Secondly, epileptic conditions not only affect the brain, but they also affect other vitals of the body such as heart rate, temperature, motion patterns, etc. Thus, instead of using only ECG signals for prediction is not accurate enough to alert the automatic triggers without prior checking the other vitals too. In a nutshell, this approach will provide the vitals from brain using ECG signals, from heart using EEG signals and motion patterns using 3D accelerometer sensors.

Figure 14. Cronovo's wearable smart watch to measure ECG signals. Source: cronovo.com

Patient will be recommended to wear the smart watch monitoring the body vitals and motion patterns all the time. This will feed the signals from ECG monitoring and accelerometers to decision making systems in real time. Moreover, the electrode cap from EEG can be worn as long as the impedance doesn't get affected with the friction produced from the scalp. It will alter the results or might give false positive alerts. Using the electrode cap with gel will get sticky and uncomfortable therefore, dry electrodes will be used in this case. Moreover, since we aim to focus on the patients' comfortability so wireless cap will be preferably used to avoid any hindrance in day to day life. One such system is designed by imec, Holst center and Panasonic. The designed cap is more like a head set and is based on ultra-low power electronics. The data is transmitted in real time to a receiver located up to 10 m from the system. The system has operating time of 22 hours will 8 channels of EEG. [26]

Figure 15. imec\s EEG measuring wearable headset.

Source: phys.org

The onset of seizure will be decided by three techniques will individually, independent of the decisions from the rest of techniques. All the three individual decisions will be used in the decision-making process to make a final call on the prediction of the seizure. If decision shows true positive results for prediction, then alarm will be triggered on the smart watch of the patient. The patient will be given the option of cancelling the alert, in case of a false alert. The time for the cancellation can vary from 30-45 seconds. If alarm is not canceled, then emergency services or the care taker will be alerted (depending upon the emergency contact information embedded in the system).

Figure 16. Wearable device to track motion pattern for tonic clonic seizure designed by Danish care Technology

Source: danishcare.co.uk

6. ACQUIRING DATA AND BOOLEAN FUNCTION IMPLEMENTATION

6.1 Data Acquisition

The signals from EEG, ECG and the data from accelerometer will be wirelessly transmitted to a cloud server from the wearables devices. A working internet connection will be required to achieve efficient prediction on seizure's onset. Signals will be sent over to a cloud server that will process the signals individually, for example, the EEG signals will be processed individually and so will be the ECG signals. This will help the system to make decisions independently. Whereas, the collective and the final call will be made after taking all the exclusive decisions in to the account.

The cloud server will not aid in decision making process but will also keep a log of all the vitals being sent by the wearable gadgets. In doing so, this will help the neurologist to study the records of the seizures to provide better treatment. The algorithm for detection will be embedded in the system that will make the final call for the prediction and will trigger the alarm upon the onset.

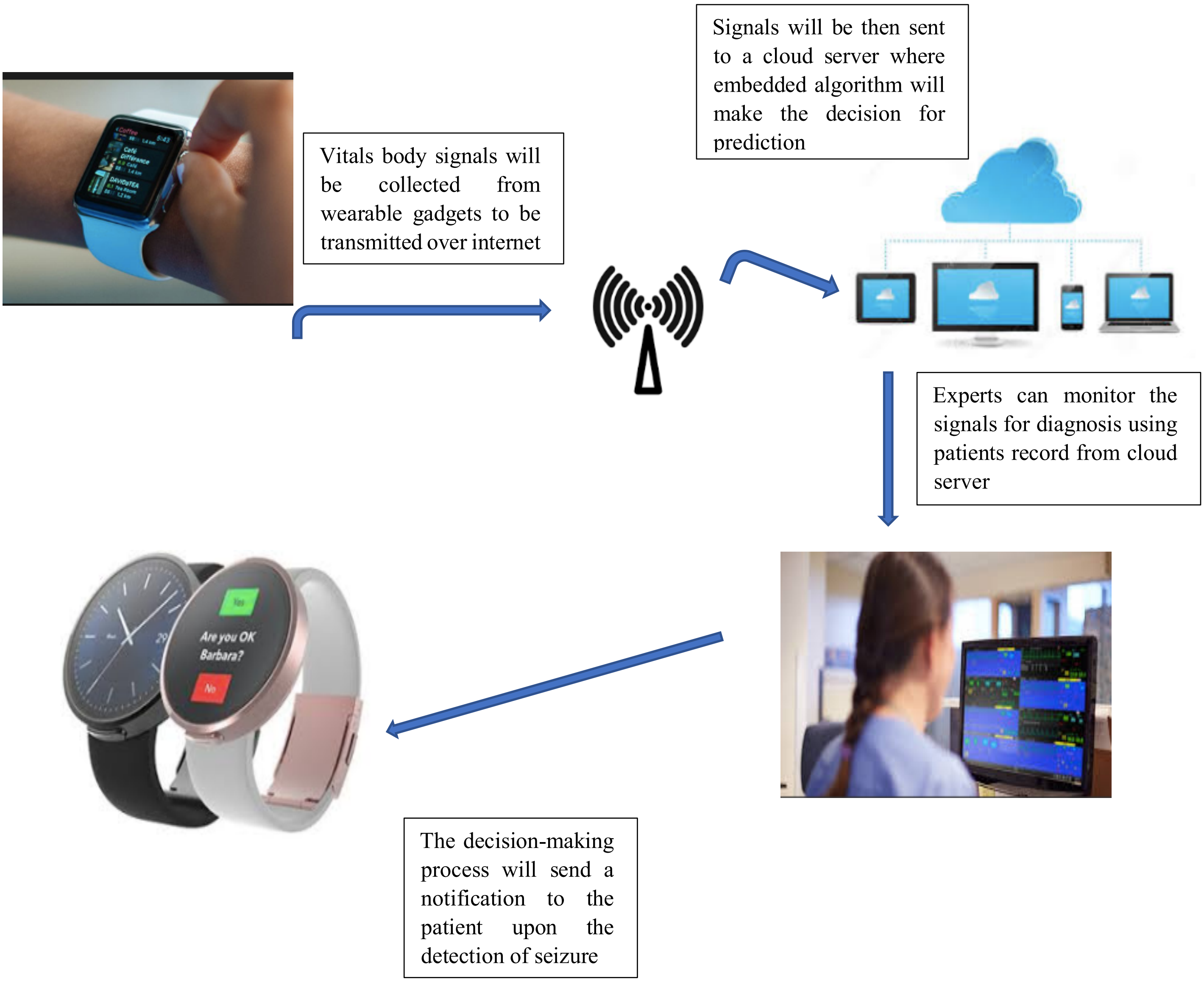

Figure 17. Graphical representation of the seizure prediction model

Source: indiegogo.com, vectorstock.com, usa.philips.com, dreamstime.com, mintel.com

6.2 Decision Making

In this approach, all the techniques being used for seizure predict provide results individually, that means that each technique is capable of making a decision on its own without being dependent on co-techniques. Since, decision is coming independently from

EEG, EEG and accelerometer about the status of seizure, therefore, fuzzy logic operations or Boolean operations in this case will be able to provide, compact and exact results. In this approach, the results being provided by all the three techniques will be either 0 or 1, with representing the occurrence of seizure and 0 as no seizure, therefore, For instance, if all the three techniques, namely EEG, ECG, and accelerometer give 0's individually at their respective final outputs, then the final output at the decision-making end will be 0 as well, representing 'no seizure'. Hence, in this case, a simple AND, OR and NOT gates can be implemented to achieve the goal. With 3 techniques, we will have 2^3=8 total outputs. This will give us various scenarios to trigger the alarm and to alert the emergency services or the care taker. Following is the truth table for Boolean variables representing 8 outputs for EEG, ECG and accelerometer.

Table 3. Truth table representing the inputs from EEG, ECG, Accelerometer to trigger the alarm Q

EEG (A)	ECG (B)	Accelerometer (C)	Output (Alarm Q)
0	0	0	0
0	0	1	0
0	1	0	1*

0	1	1	1*
1	0	0	1*
1	0	1	1
1	1	0	1
1	1	1	1

The asterisks (*) with 1's in the truth table corresponds to the double check prior to the activation of alarm. This double check is performed because only two or less than two of the possible techniques are indicating the prediction of oncoming seizure, therefore, a timer needs to be set with these possible combinations before triggering the alarm. The alarm will be triggered if the conditions stay persistent for 10 minutes, if the continuity prevails in the indication of seizure then alarm will be triggered. This precaution will prevent false alerts, which could be triggered as a result of exercise (High pulse rate), head scratching (abnormal motion pattern for accelerometer) etc.

Based on the truth table values, the table can be represented in the form of Boolean expression where Q is the output, and A, B, C are the respective inputs corresponding to EEG, ECG and accelerometer.

Q= A’BC’ + A’BC + AB’C’ + AB’C + ABC’ + ABC

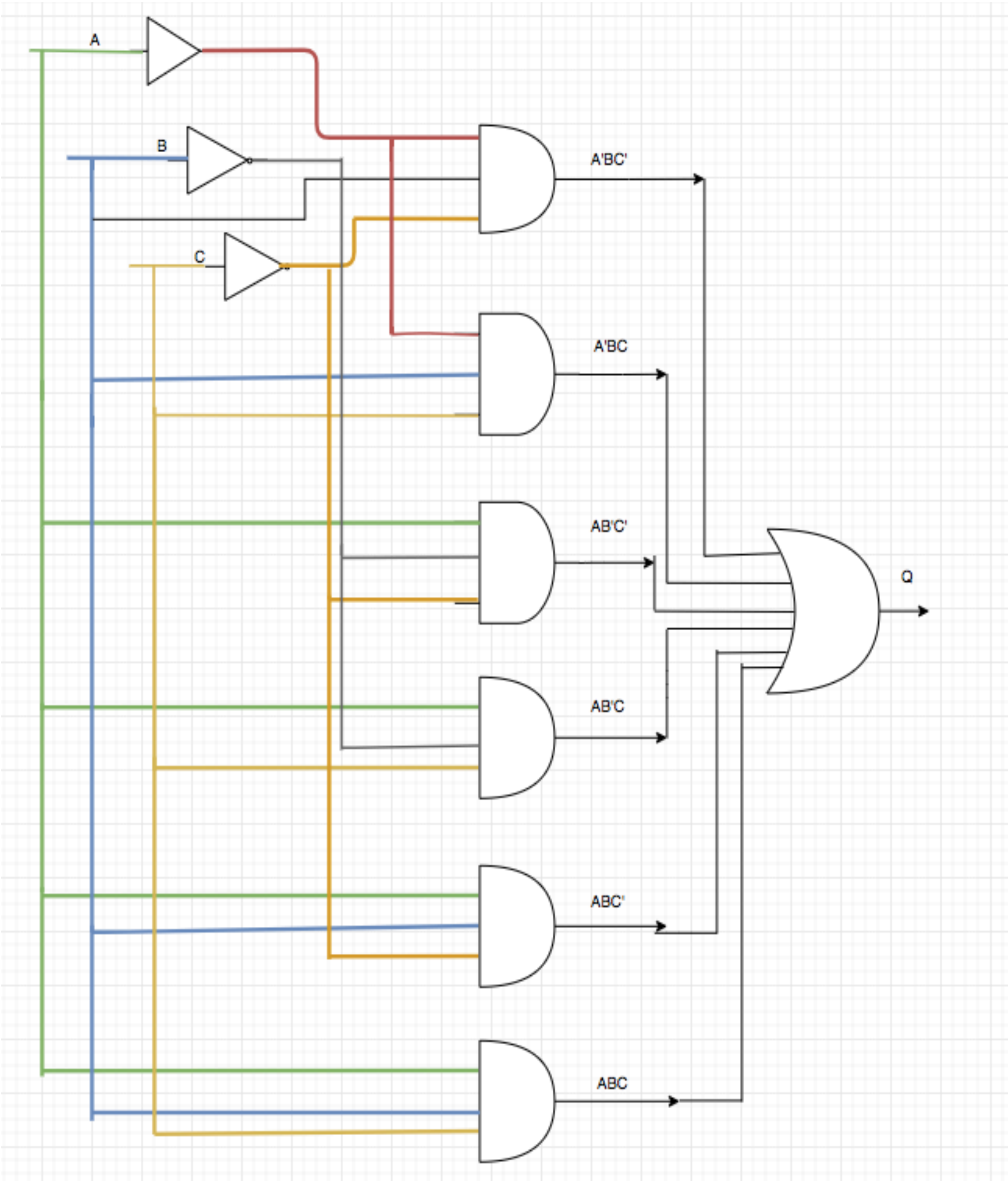

Figure 18. Logic gate representation for Boolean values

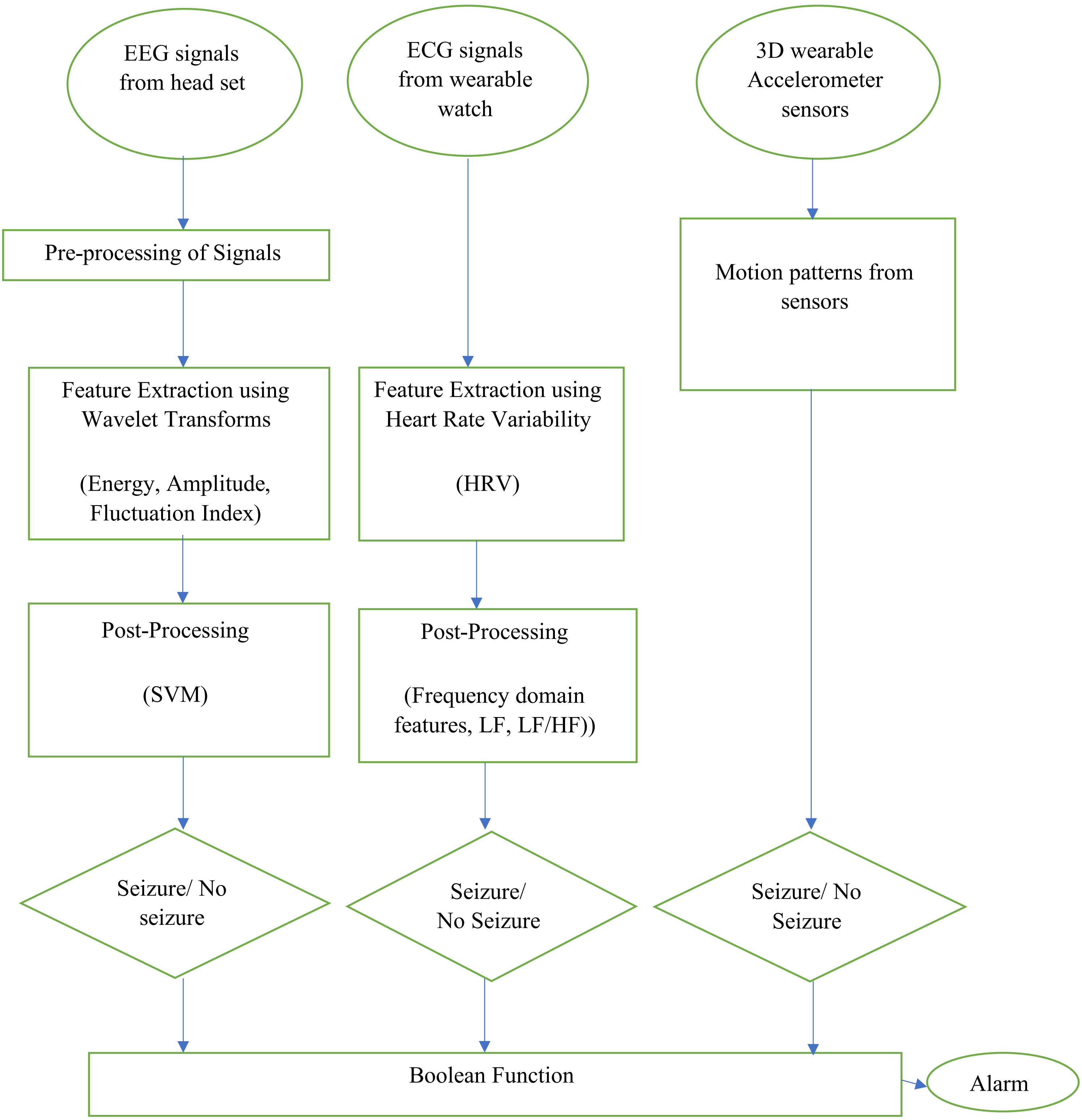

Figure 19. Flow chart Representation for prediction of seizure followed by the alarm trigger

7. FUTURE WORK

A lot of work in the field of prediction and detection of seizures is already underway to ease the lives of the patients and to reduce the risk factors involved in living with epilepsy. The more techniques are used to detect and predict the onset of seizure the more reliable and accurate the system turns out to be. Hence, this approach can be accompanied with the use of infrared cameras or thermal cameras to detect the movement and position of patient in the inhabited place. Some of these techniques are already in place in the toilets of elderly home and hospitals. Moreover, approaches to predict and detect nocturnal seizures can also be accompanied with the existing ones to improve the working model for the prediction of epileptic seizures. Sensitivity of devices also need to be worked on, since the signals vary from person to person, so devices have to trained properly to adjust to the subject's signals in order to avoid missing the detection or to make any false alerts. This predictive model uses ECG with limited number of electrodes, better results can also be achieved by using a headset with a greater number of electrodes keeping battery's performance in view.

8. CONCLUSION

The epileptic seizure itself is not as harmful as its unpredictable nature could be. The unpredictability of this neurological condition not only compromises the safety of patient but also of the people surrounding him. Therefore, there is a dire need of systems that can be used to predict the onset of seizure to minimize the safety risks. The predictability will also help the neurologist to take the activities into account which patient was performing when the seizure occurred. This will assist the doctors in learning about any particular event that may have triggered the seizure. Moreover, these signals are not only used to predict the onset, but they will be logged in records to form a seizure diary which will in turn give the epilepsy experts an insight on frequency of occurrences of seizures, time of seizure, situation the patient was in when he encountered the seizure.

The purpose of this comparative study and the fusion of three different techniques involving different body zones is to cater for the need of efficiency in real time processing of signals as well as accurate predictions. Furthermore, the devices being used to monitor brain signals and other body vitals are designed to keep the comfortability of the patient in view. The patient, of any age can wear them and the design is aimed to reduce the hinderance with their day to day life. With the help of using more than one techniques for the prediction of a seizure, chances of errors and false alerts are minimized, however, it might take a toll on the battery life of the equipment's being used. In order to avoid missing the onset of seizure, the batteries need to be working properly. Besides, the sensitivity of the accelerometer matters a lot in this predictive approach, there are high chances of alarm being getting triggered because of activities like head scratching, taking off shirt etc. therefore, here the timer will kick in to continue monitoring the event, moreover, it will also be cross checked with other techniques in order to reach a final decision on predictive approach. Accelerometer is particularly useful for the people with tonic-clonic seizures as they have sudden jerking and shaking whereas patients with partialized seizure might not show shaking, in this case, EEG and ECG will continue to detect even without any jerking which will go unnoticed by accelerometer. On similar basis, ECG can detect anomaly in heart rate with exercise, running etc. and EEG can indicate anomaly in brain signals in stress, in such circumstances when one technique triggers a false positive alarm, the final alarm will not be triggered unless comparing the results obtained from other techniques via Boolean function. This scheme makes the entire system more reliable, accurate and reduces the chances of triggering false positive alarms.

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