Rule-Base Wearable Embedded Platform for Seizure Detection from Real EEG Data in Ambulatory State.

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Abstract—**This paper describes a classification method is presented using an empirical Rule-base System to detect the occurrences of Partial Seizures from Epilepsy data, which can be implemented in any embedded system as a wearable detection system. The system distinguishes between 'Normal' and 'Seizure' state using on-the-fly calculated features representing the statistical measures for specifically filtered signals from the raw data. It was noticed that for a large number of cases, the seizure waveforms manifest higher energy components during the seizure episodes as compared to the normal brain activity in specific bands of frequencies. Same is also true in the reverse fashion for a separate band of frequency that changes the energy levels from higher to lower when a patient goes from Normal to a Seizure state. This fact has been exploited in this paper and filter has been developed to isolate the seizure band. The rule base has been developed on the calculated measures for the filtered signal from this band-filter and classification is performed on the basis of certain empirical thresholds. Since the complexity of calculations have been deliberately kept quite low, the algorithm is highly suitable for implementation in a small micro-controller environment with near-real-time operation. This gives an enhanced advantage over the existing EEG based seizure detection systems due to their complex pattern classification methodologies. Based on the presented technique, a wearable ubiquitous system can be easily developed with applications in personal healthcare and clinical usage. In this case, the users are not necessarily restricted to the clinical environment in which many devices are connected to the patient externally. The wearable devices allow the user to continue daily activities while being monitored for seizure activities. Once seizure is detected, a number of possible usages can be employed such as alerting the user while driving/holding a baby etc.**

Keywords- Embedded system; Seizure; Wearable system; classification; filters

I. INTRODUCTION

Epilepsy can be described as a brain disorder, in which the nervous system brain cells starts malfunctioning, leading to the generation of sudden burst of abnormal electrical signal impulse activity, which ultimately results in changes or complete loss of awareness. There are recurrent seizures in epilepsy; hence, it is regarded as a disorder. These seizures can be very dangerous and occur with different frequency and, in some cases, can be very serious. Patients with epilepsy can have multiple seizure-episodes in one day.

Over the past two decades, Seizure detection using signal processing techniques and its categorization remained a vital issue for researchers. Researchers have tried to identify different signal characteristics and features within various domains and classify the signal segments based on the identified features. Adult's seizure is more prominent than neonates (newborn) seizure. Neonatal seizure is more chaotic and although some methods have been suggested for the detection of such events, the problem still remains open. Therefore various automated spike detection approaches have been developed. Exact localization of partial epilepsy area is necessary condition for successful surgical treatment and its description from functionally applicable regions. The physiological aspects of seizure generation, the treatment and monitoring of a seizure are important issues that need to be considered. With better predictability of seizures will lead to a better cure for the seizure disorder.

The advantage of wearable monitoring systems is that it will facilitate and enable ubiquitous monitoring and active personalized health management of the health conditions of a seizure patient [1]. Most of the algorithms can only detect EEG seizure signal in a controlled environment. In this paper, different signal from different seizure case have been detected in various practical scenarios and have been used with Rule-based detection of partial seizure. This will lead to the development of a more generalizable, fast processing solution as a low cost wearable EEG monitoring and predicting system for the people with partial seizure disabilities [2]. Wearable health care gadgets will definitely play an important role in shaping the future of personalized health care. For the prediction of seizure, brain signal decrypt devices are used to search for the pointers to seizure [3]. When it comes to real-time monitoring of the EEG signals, commercially available Epoc BCI headsets can be used [4]. If the localization of the seizure signal generation point is located well in advance, then we can reduce the number of probes for the detection of seizure, which in turn simplifies and reduces the cost. Advanced tools and systems like single neuron based electroencephalography, electrocorticography, Image processing-Virtual computing [5-6] etc. have been used. In all the methodologies mentioned above require huge computational capabilities and would be very difficult to implement in near real-time ubiquitous system, moreover it will add cost especially if we intend to develop cost effective systems. In ambulatory setting, the commercially available EEG ambulatory recording system are not optimized when it comes to initiating rehabilitations or alarm activation and to prevent seizure spreading [7]. Hence in this proposed system, we introduce low cost EEG partial seizure detection and prediction system by using Rule-based system to classify and detect partial seizure and to notify in on the fly. A system is developed to overcome limitations such as near-real-time operation which is realized by developing simple processing algorithm that can be implemented in a simple microcontroller, communication with nearby clinics if case is critical and for appropriate control action.

II. Experimental Setup

The detection of normal state and seizure state of a patient is based on the data from a real-time Epoch EEG sensors or an EEG data depository. From the data set, both seizure and normal signals are individually analyzed for best results. The proposed system has a LilyPad-microcontroller from Arduino [8] as the wearable processing system; its small scale is also an advantage for this prototype. This microcontroller is connected to a Bluetooth module from Roving networks [9]. This allows for the notification to the mobile device via the Bluetooth and ultimately the information will be send to the hospital or nearby clinic for immediate response, EEG signal acquisition and monitoring since the seizure EEG signals at the time of occurrence are very critical to make an evaluation by the neurologists.

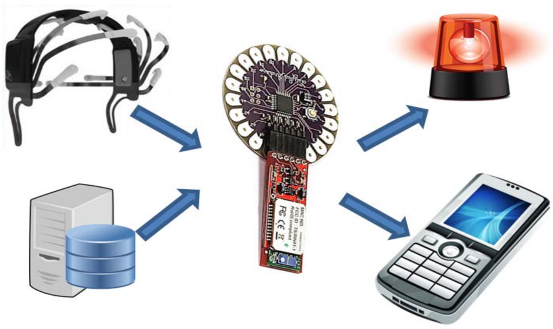


Figure 1. Overall System with all the functional blocks.

In Figure 1, a generalized system is shown in which a commercially available EEG headset is used to acquire EEG signals from the patient or from partial seizure EEG database to generate using a simulator for validation of the seizure detection and experimentation in the lilypad microcontroller.

For the initial test of the system, the data used here for the seizure patients are from the CHB-MIT EEG scalp data depository [10]. This database consists of EEG data of 22 patients from children's hospital at Boston, USA. The database consists of 129 files with one or more seizure amounting to 129 cases with one or more seizure. The file format is as '.edf'. Here the sampling rate of the signal per second is 256. And the resolution is 16 bit. This raw EEG data is selected from the data depository of each of the patient randomly; therefore we have each EEG data set from the 24 patients. For all the patients, the first channel (FP1-F7) has been selected in the initial stage with the signal of 30 seconds; for example for the dataset 'chb01_03.edf' of patient-1, it is stated that the seizure point in the dataset of that particular patient is at 2996 seconds after the data has been acquired, until 3036 seconds and returns to normal state; therefore in our system, the normal signal is until 2966 second time line of the dataset. This have been keep as the reference in order keep the seizure signal clean from the normal signal and to divide the signal processing stages in the microcontroller like acquisition, processing and seizure notifications. Once this time slot of the signal have been fixed, the signal is passed on to the hardware Seizure signal simulator and generator [11] for testing the algorithm and evaluating the efficiency of the microcontroller to process the EEG signal and to initial a trigger on detection of seizure.

III. Proposed Algorithm

Initially to test the algorithm, a 'Test Bench' was developed using LabVIEW environment (Figure 2). The signals were obtained from the database of the EEG signals which contains the seizure signal signatures. Numerical controls are given in the front panel to select the start time in seconds and stop seconds in seconds. As a preprocessing procedure on the signal, the signal is passed to a filter. After designing various filters, the band pass type filter with a lower cut-off frequency of 25 Hz and a higher cut-off frequency of 35 Hz was designed to give better results when it comes to seizure patient data. A typical Infinite Impulse Filter (IIR) with Elliptic topology of order M has a transfer function of the following form:

$$H(z) = \frac{b_0 + b_1 z^{-1} + \ldots + b_N z^{-N}}{1 + a_1 z^{-1} + \ldots + a_M z^{-M}} = \frac{\sum_{k=0}^{N} b_k z^{-k}}{1 + \sum_{k=1}^{M} a_k z^{-k}} \quad (1)$$

Where a_k and b_k are the filter coefficients which are listed in Table I.

TABLE I. FILTER COEFFICIENTS USED IN THE DESIGN OF BPF USED IN THIS PAPER

k	a	b
0	1	0.000178255694492592
1	-7.2389849777012	-0.00090578903505654
2	25.700530898206	0.00214398141078075
3	-57.8465640338915	-0.00296858412824248
4	90.821947636071	0.0022455821142596
5	-103.547781340888	8.67361737988404 e^{-19}
6	86.7495661423678	-0.0022455821142596
7	-52.7750900354483	0.00296858412824248
8	22.3959428748316	-0.00214398141078075
9	-6.02547646697156	0.00090578903505654
10	0.795172110112095	-0.000178255694492592

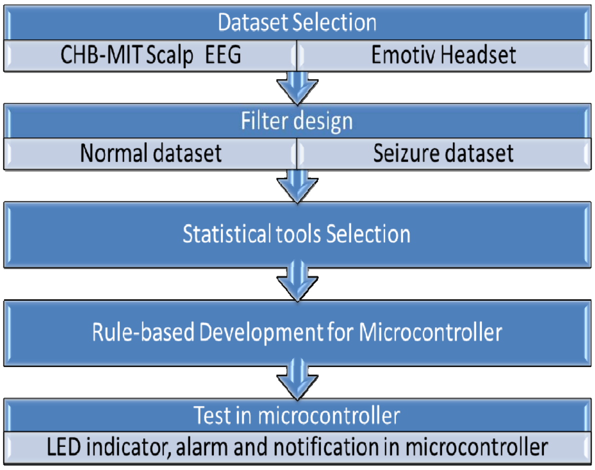
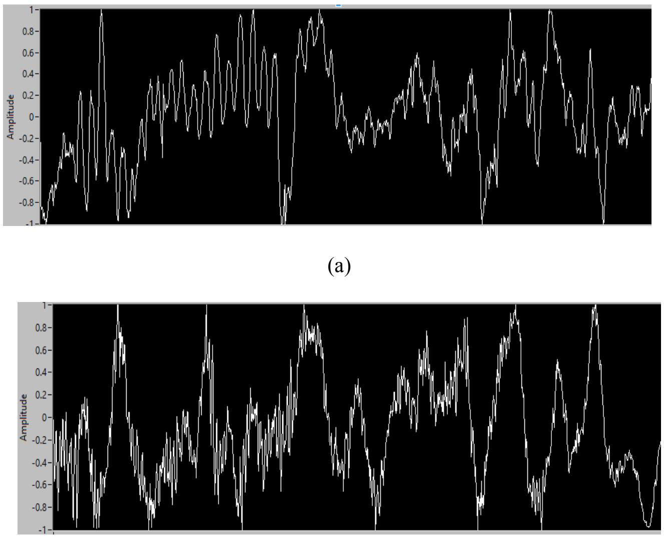


Figure 2. Flowchart of the Wearable Computing System for the Seizure Detection.

Figure 2 shows the overall flowchart of the wearable computing system for the seizure detection. The test bench consists of signal display areas for the raw EEG signal, the filtered signal and the statistical data waveforms. The test bench has an additional option of generating the EEG signals as actual analog voltage values from these EEG files using an external Data Acquisition Unit (DAQ) with analog outputs. These voltage signals can be given to the microcontroller unit directly to emulate the real patient's EEG input and to apply the signal processing utilizing the presented algorithm in this paper. The front panel also has alarm indicator for an event of seizure in the EEG signal. In addition to these features, it also indicates the time stamp of the seizure trigger in the EEG signal. This capability can be used with the actual trigger information given by the neurologists for the waveform under study in order to confirm the detection incident.

The raw EEG data is filtered through the designed filter (Table I) as a standard procedure in the algorithm for all the 24 patients' dataset. This is done for the 30 seconds raw data window for normal (as benchmark) and seizure data set. Several statistical measures were calculated and compared between the filtered signal and the frequencies corresponding to the non-seizure region, i.e. the band from 0 to 25 Hz. These measures include: Skewness, Arithmetic Mean, Kurtosis, Mode, Root Mean Square, Median, Standard Deviation, Sum of Values and Variance. A threshold-based decision on certain statistical measures made the classification possible using a simple Rule Based technique. Signals obtained from the test bench are shown in Figure 3 separately for more clarity.

Figure 4 and Figure 6 show the spectra of a normalized EEG signal. These show the RMS values of the signal (linear form) with flat-top window. The averaging is done on the signal with ten samples in all the iterations. In Figure 5 and Figure 7 show the spectra of the filtered signal for the same raw data as in Figure 4 and Figure 6. In all cases x-axis represents frequency in Hz and all the y-axes represents amplitude of the frequency components in volts.



(a)

(b)

Figure 3. EEG Signals as seen by the developed test bench; (a) Normal state EEG Signal of the patient (Normalized Signal), and (b) Seizure state EEG Signal of the patient (normalized Signal)

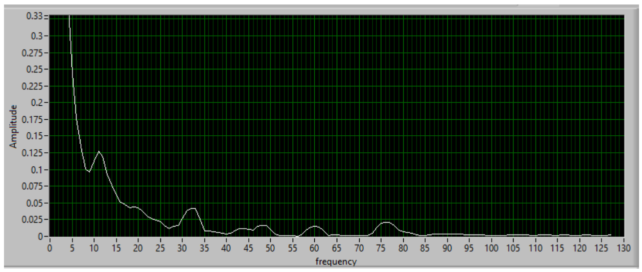


Figure 4. Spectral Waveform of the EEG signal (Normal Case)

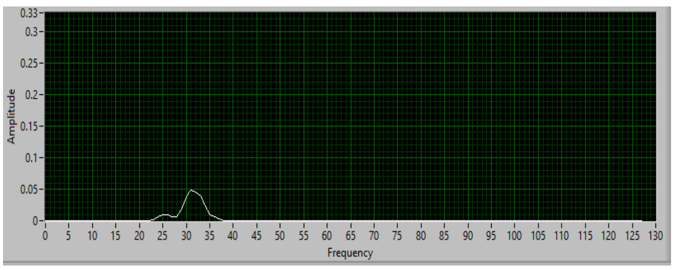


Figure 5. Filtered Spectral signal for the classification using statistical Computation.

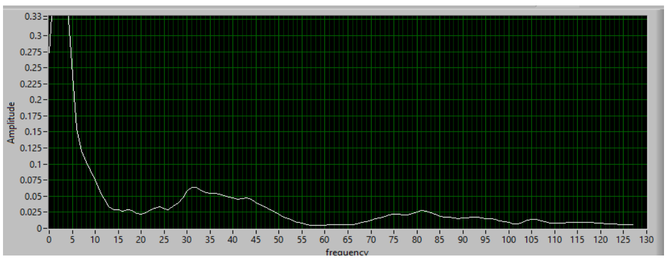


Figure 6. Spectrum of the EEG signal (Seizure Case)

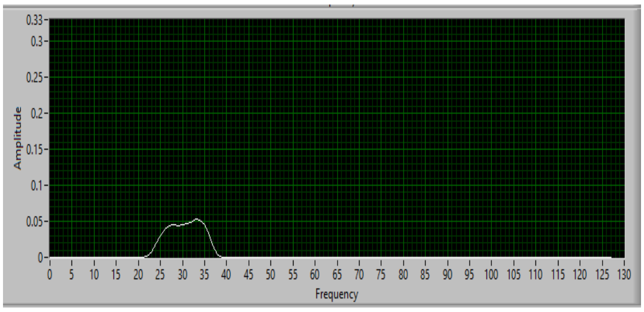


Figure 7. Filtered Spectral signal for the classification using statistical Computation.

IV. Feature Selection

The proposed technique has been designed to be implemented with an embedded and wearable form factor; hence, there is a need for measures or Features that can be calculated quite quickly and recursively as well as the whole algorithm to be as simple as possible. Also, for the selected classes of the output, two features were isolated from the above list since they showed maximum differentiation of the two output classes and were found to be sufficient for the required classification. This was deduced based on the following procedure:

From the EEG data set, after passing through the statistical tools, both the Kurtosis and Summation property of the signal showed some distinguishable dynamics when it reached the point of Seizure. The low frequency components of the EEG signal were vanished or dropped out (as in Figure 6). At the same point, the Kurtosis of the EEG signal showed a spontaneous rise in the value whereas the Summation showed a sudden drop in the value as shown in Figure 8.

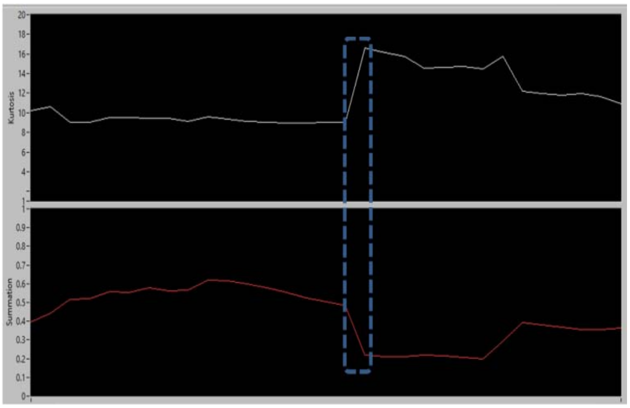


Figure 8. The dotted region shows the place where Seizure class discrimination is seen quite obviously of the Kurtosis and Summation respectively.

Hence, the proposed Rule based system consists of:

- Two statistical methods as inputs, which are the Kurtosis (K) and the Summation (S) of the filtered signal.
- A simple rule that represents the heuristic combinational model with historical understanding of the human users in the domain under study.

As a result, in the case of normal signal, the high frequency peaks 'F_h' which fall in the range of 10Hz, 32Hz, 47Hz, 60Hz, 73Hz were visible; whereas in Seizure these frequency components was diminished. This can serve as a visual indication of whether a seizure is present or absent.

V. Embedded System Implementation

The 8 bit low cost Atmel microcontroller has a maximum clock frequency of 20 MHz, which performs the above mentioned calculations for averaging, features, and decisions in near-real-time. It also has a 32 Kilobytes of onboard storage which is capable of storing the 10-20 seconds of raw EEG signal from a single probe. External interrupts can be used for enabling the three external or internal timers of the microcontroller, which supports better iteration for the filter and the statistical blocks. This timer helps in multiplying the EEG sample and the filter coefficients at an equal interval even if the microcontroller tries to execute other commands. When acquiring the data from EEG probe, ADC [12] resolution of 10 bits with a maximum speed of up to 15 kilo samples per second were used. These values are sufficient for the detection of seizure either by using simulators or in real-time.

The pseudo code of the main logic of the program is shown Figure 9. The microcontroller initializes/clears the states in run-time in order to have sufficient room for a faster decision making values and their availability. In the code 'K' represents Kurtosis of the filtered signal and 'S' represents the Summation of filtered signal. Once the decision has been made by the microcontroller, the waveform and seizure states will be transmitted to the mobile device via the Bluetooth SPP (Serial Peripheral Protocol) module.

```
Void [Seizure]{
IF (K0>=10 && S0 <=0.4)
then critical_code==00
endIF
IF (K0<10 && S0>0.4)
then critical_code==1
endIF
Enable Bluetooth Client Transmitt on Port [available]
        IF ( critical_code == 00)
        DO Nothing
        Patient_Condition == Normal
IF (critical_code == 1)
                RECEIVE ECG_Data FROM Bluetooth Port
                AFTER X1 seconds UNTILL X2 min.
                PLOT eeg_graph
                TAKE Snapshot
TRANSMIT eeg_picture_segmants
Patient_Condition == Seizure Alert: Needs Attention
                ALERT CALL AND MESSAGE AND EMAIL
                Caregivers (Doctors, Kin, Healthcare Unit)
                LOCATE Nearest DEFIB UNIT and Seek Help
                Broadcast LOCATION
                Patient_Condition == Critical Attention
                                                      }
```

Figure 9. The The Pseudo Code for EEG Microcontroller Alert System.

TABLE II. RULE-BASE FOR OUTPUT CLASS INDICATION

K	S	Output Class
HIGH	LOW	SEIZURE
LOW	HIGH	NORMAL
HIGH	HIGH	NORMAL
LOW	LOW	NORMAL

Centered with respect to the visual interpretation, heuristics [13] and statistical data [14], a simple rule is developed for as the microcontroller to detect normal or seizure state. Table II shows the rule for the microcontroller: if Kurtosis High and Summation is Low then Seizure state is highly likely to happen for the patient; if Kurtosis is Low and Summation is High Normal state is highly likely. As an empirical reference, 'K' is high if it is greater than 10 and 'S' is high only of it is greater than 0.4 After the rule-based classification is made, and when a clear differentiation is made, the data is passed from the microcontroller to the remote server or to a user mobile console for notification of the seizure disorders for monitoring and logging purpose.

VI. RESULTS AND CONCLUSION

Here about 95% exact recognition of normal and partial seizure form the data set was achieved. Other data of patient can be included for classification and identification by using rule based system. In this work, a heuristic control is offered as an extension to achieve economically viable classification technique to distinguish real-time within the EEG data set of the signal. This system can be a classification engine or a prediction system for people with specific type of seizure disabilities. This algorithm is being incorporated into a wearable form so that the patient can be monitored wirelessly on the fly, 24/7 along with other day to day activates.

By this system, we can expand even to detect other types of clinical signals like the ECG and Sp02 levels apart from EEG. Since overall methodology in this paper is unique, the results are useful and interesting since it can distinguish the important unique signature of data in signal , which can be used to predict the later state in the signal, then detect and then to notify.

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