Epilepsy Detecting and Halting Mechanism Using Wireless Sensor Networks

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Abstract—**Epilepsy is a condition that affects thousands of people worldwide. In the laboratory setting, it becomes difficult to monitor patients and analyze when the next seizure would recur. Although algorithms have been proposed for deriving when the next seizure is probable, it is difficult to generalize such models for the various types of epilepsy that are occurring every day. A more promising solution is the use of Wireless Sensor Networks (WSNs) that is proposed to simulate small electrodes used in EEG that will be placed on the scalp of the patient as a wearable device along with a portable kit that is capable of monitoring the patient in both ambulatory and resting condition. As much as a detection system is required for epilepsy, a halting mechanism is also needed to prevent such high flow of bio-electrical signals in the brain during seizures. It is estimated that millions of brain cells die during epileptic seizures, which can prove detrimental or even fatal in some cases. In order to overcome this, an IoT-based epilepsy detection and halting system with wireless sensor networks and focal cooling mechanism has been proposed in order to regionally cool the regions of the brain when a seizure is probable or suddenly occurs.**

Index Terms—**epilepsy, seizure detection, seizure halting, wireless sensor networks.**

Original Research Paper
DOI: 10.7251/ELS1822034B

I. Introduction

Wireless sensor networks (WSNs) are a class of wireless networks that use sensors to monitor a specific environment. WSNs have made their way to several interesting applications in healthcare over the last decade [1]. In addition to being of potential use to patients, such systems also find considerable applications for children and elders.

Usually the group of sensors carried or worn by the patient (in the form of wearable sensors) forms the Body Area Network (BAN). The sensors located in the immediate surrounding environment form the Personal Area Network (PAN). Generally, monitoring systems consist of healthcare professionals viewing and interacting with the patient via a Graphical User Interface (GUI) in the form of a mobile application whereas in detecting systems, an algorithm judges the condition of a patient using Artificial Intelligence and Statistical models.

In the healthcare domain, WSN systems commonly comprise the following components: (i) BAN Subsystem, (ii) PAN Subsystem, (iii) Wide Area Networks (WAN), (iv) Gateway to Wide Area Networks (GWAN), and (v) Patients and other users. The BAN subsystem consists of an ad hoc sensor network that is wearable by the patients. Some examples include RFID tags, accelerometers and EEG sensors. Care should be taken so that the sensors do not cause any harm to the patients since they will be required to wear them for prolonged durations. The PAN subsystem consists of the devices in the immediate surrounding environment of the patient. Such a subsystem is also capable of features like location tracking, which may necessitate the use of RFID, Bluetooth, Near Field Communication (NFC) and GPS facilities as well. The Medium Access Control (MAC) layer should be made energy efficient to make the system low-power. All constituents among a subsystem should be interconnected appropriately. The WAN subsystem is needed for remote monitoring scenarios. If the healthcare system is to be implemented globally, satellite networks may also be employed. GWAN is used for the purpose of connecting PAN subsystem and WAN subsystem to the WAN. Finally, as mentioned earlier, the entire system is used by patients or other users like children or elders.

The evolution of IoT (Internet of Things) has resulted in efficiency and better exchange of data using technologies like WSNs and embedded systems. The present work has focused on an IoT-based system involving usage of WSNs for detecting and halting epilepsy. Epilepsy is a condition of the brain defined by at least 2 unprovoked seizures occurring at >24 hrs apart and one unprovoked seizure or probable seizures occurring during the next 10 years [2]. This disease affects thousands of people worldwide and can be fatal in extreme conditions. Epilepsy detection has been an important topic in medical research. The exact cause of epilepsy and how to completely cure it is still an unsolved puzzle. Research has uncovered various types of epilepsy, broadly categorized as generalized epilepsy and partial epilepsy, and specific types including childhood epilepsy, temporal lobe epilepsy and focal epilepsy.

Epilepsy is most commonly detected using the technique of EEG (Electroencephalography). The graphs are then analyzed by doctors or healthcare professionals who determine the type

Manuscript received 18 December 2017. Received in revised form 22 April 2018 and 26 May 2018. Accepted for publication 5 June 2018.

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of epilepsy and the associated course of treatment. In some cases, MRI and CT imaging is also used. However, in most cases, EEG graphs show continuing occurrences of seizures or only slightly decrease using medications. Most medications even cause harmful side effects. In other words, it is difficult for doctors to determine the exact type and origin of seizures from a single EEG report. It is even more challenging to predict the occurrence of the next possible seizure and immediately halting it. Common approaches to reduce epileptic seizures include using one or a combination of medications, surgery, brain stimulation and focal cooling [3].

During an epileptic attack, seizures may happen due to sudden misfiring or incorrect connections in neurons in the brain. This results in sudden increases in electrical voltage in the neural cells. Each epileptic attack damages hundreds of brain cells that can be very harmful for the patients. As a result, it is important to halt or at least reduce the intensity to prevent such damages.

In the present work, a model has been proposed that uses WSNs to monitor and detect epileptic seizures as well as a mechanism using focal cooling to halt the seizures.

The rest of this paper is organized as follows: Section II gives an overview of previous related work. Section III discusses about the proposed method. Section IV highlights the implementation and results. Section V concludes the paper and suggests possible future work.

II. Related Work

Previously, several methods have been proposed for seizure detection. Lay-Ekuakille et al. [4] have developed a system using WSNs to detect epilepsy from joint EEG-ECG-Ergospirometric signals. It consists of a wireless ECG and EEG systems. It uses a $K4b^2$, which is a device worn by patients for pulmonary monitoring purposes. It can be worn while the patient is in motion and operates on battery power. Generally, the wave ranges for a normal EEG have been observed to be as follows [5]: (i) alpha (8-13 Hz), (ii) beta (13-30 Hz), (iii) delta (0.5-4 Hz) and (iv) theta (4-7 Hz). Along with acquiring the ECG and EEG signals, authors have then measured the Heart Rate Variability (HRV) before and after exercise, while simultaneously observing the corresponding changes in the Average Message Transmission Time (AMTT). Amplitudes over 45 and 100 microvolts imply suspected cases of epilepsy. The authors have noted that a simulator can enhance their results and that the method can be improved if WSNs can be related to the foci.

Otoum et al. [6] have developed Epilepsy Patients Monitoring System (EPMS) using WSNs. More specifically, they have proposed an SMAC (Sensor Medium Access Control) based system in order to reduce the power consumption of the system. They have designed the system using MICAz sensor motes (developed by Crossbow Technology). The EPMS consists of five sensor nodes that acquire the seizure information and pass it on to the coordinator. The coordinator then sends the information to the receiver. They have evaluated the performance of their system using NS2 simulator. Their SMAC protocol has shown lower average delay in packets compared to the ZigBee protocol. Their future work suggests allowing patients more freedom of movement by incorporating GPS and routing protocols.

Sareen et al. in [7] have proposed a mobile framework to predict seizures from EEG data. They acquired the EEG signals using Emotiv EPOC headset containing 14 sensors. They have extracted the desired features using fast Walsh-Hadamard transform (FWHT) and Higher Order Spectral Analysis (HOSA). Then k-means has been used to obtain a classification accuracy of 94.6%. They have tested their model in Amazon EC2 cloud. The data stored in the cloud is also used to connect to other family members and doctors in case of medical emergencies. A drawback of their work is they are only predicting seizures and not proposing any first hand technique of combatting the seizures by the time medical help arrives.

Salem et al. [8] have proposed a Discrete Wavelet Transform (DWT) and Ant Colony Optimization (ACO) based approach with WSNs for detecting seizures. They have acquired the data by placing electrodes on the scalp of the patient and acquiring the data and forwarding it to a transceiver and storing the data on a Local Processing Unit (LPU). They have identified the ictal period (during which a seizure is occurring) as being characterized by a discharge of polymorphic waveforms of varying amplitude and frequency that exhibit continuous spikes. Their model has shown a detection rate (DR) of 100% and a False Alarm Rate (FAR) of 9%. The shortcoming of this model is that the data is being processed after recording, that is, it is not being implemented in a real-time scenario.

Borujeny et al. in [9] have proposed an algorithm using WSNs and k-nearest neighbors (kNN) for detection of epilepsy using accelerometry and have proved that it gives better performance compared to using neural networks. For the purpose of acquiring signals, they have used MICAz wireless motes. Three 2D accelerometer sensors are placed on the left thigh, left arm and right arm of the patient. The system is also capable of monitoring the patient and sending the location of the patient to the family members or hospital staff when a seizure occurs. However, the system is capable of detecting epilepsy only when the acquired signals show at least 50% of seizures.

Kramer et al. [10] have designed a system that works to detect seizures and alert close family members of an epilepsy patient. The motion sensing unit comprising an accelerometer and transmitter were fitted in the form of a bracelet on the patient's wrist. They have developed an algorithm using time and frequency domain analysis to map the motion of the subject with previously gathered ictal data obtained from video EEG. Their system correctly identifies 91% of the captured seizures. They have suggested refining the algorithm to have above 95% accuracy and test it on larger populations.

Jeppesen et al. in [11] have developed a portable device capable of seizure detection that uses Near infrared spectroscopy (NIRS). For recording the signals, they have used two PortaLite wireless NIRS devices. They have then evaluated the changes in levels of oxygenated- (HbO), deoxygenated- (HbR) and total-hemoglobin (HbT). Their method has shown that the levels change by 6-24% during seizures. They have suggested individual tailor-made seizure detection for patients in the future.

Yilmaz and Dehollain [12] have used a wireless approach for data transmission for the purpose of monitoring intracranial epilepsy. They have used inductive coupling which is performed with the same frequency as that of the power transfer. Implantation is necessary in order to sense the signals and full-duplex communication has been established between the implant and the external unit. The authors have suggested using energy-per-bit connections between the uplink and downlink channels for future designers.

Conradsen et al. in [13] have suggested a wireless surface electromyography (sEMG) device that can be used for recording epileptic seizures. Their system was capable of detecting 4 out of 7 seizures with a false detection rate of 0.003/h. However, in some instances the model was unable to record data and the authors have suggested testing sEMG on the biceps instead of the tibia.

El Menshawy et al. [14] have developed an algorithm for automated detection and analysis of epileptic seizures using signal processing techniques. Using MATLAB, they have also used feature extraction to reduce the vector space. They have stated that the limitation is that their approach has no error detection mechanism and absence of domain ontology for EEG.

TABLE I
Survey Table

Reference	Proposed Work	Limitations	Year
Lay-Ekuakille et al. [4]	EEG, ECG and HRV analysis	WSNs not related to the foci	2013
Otoum et al. [6]	EPMS and SMAC for monitoring	Does not allow patients enough freedom of movement	2015
Sareen et al. [7]	Mobile framework using FWHT and HOSA in cloud	Only predicting seizures	2016
Salem et al. [8]	DWT and ACO approach with LPU	It is not implemented in a real-time scenario	2014
Borujeny et al. [9]	kNN based detection model with accelerometer sensors	Detects only >50% of seizures	2013
Kramer et al. [10]	Bracelet for ictal data analysis using accelerometry	Not tested on larger populations	2011
Jeppesen et al. [11]	NIRS and changes in HbO, HbR and HbT levels in blood	Seizure detection is not tailor-made for different patients	2015
Yilmaz and Dehollain [12]	Inductive coupling and full-duplex communication between internal implant and external sensing unit	No presence of energy-per-bit connections between uplink and downlink channels	2014
Conradsen et al. [13]	sEMG placed on tibia for detection of seizures	Unable to record data in some cases; Not tested on biceps of patient	2012
El Menshawy et al. [14]	Automated detection using signal processing and feature extraction	No error detection mechanism; Absence of domain ontology	2015

III. Proposed Method

In the proposed method, the data is first acquired using WSNs. The EEG signals are recorded and processed simultaneously. This proposed system will work with inputs of both non-seizure as well as seizure data.

An independent component analysis is performed on the data in order to extract the channel spectra for quantitative analysis. The unwanted artifacts are then rejected by visualizing the 2-D component maps and individual activity power spectra of each of the components. Once this step is completed, the peak and amplitude (peak-to-peak) are calculated for each of the remaining channels.

The data points are then plotted for both seizure and non-seizure data. The classification boundary is then used for detection of the seizure data. Additionally, focal cooling mechanisms can also be included in this system for halting the seizures whenever they are detected. The proposed methodology is shown in Fig. 1. The entire proposed methodology consists of the following steps:

1. Data Acquisition from Epilepsy patient using WSN electrodes: Data is acquired from the patient through wireless electrodes.
2. Input Seizure/Non-seizure data: The data (seizure/non-seizure) is input into the system.
3. Perform ICA: Independent Component Analysis is performed to evaluate the spectra of the EEG. ICA is also later used to perform artifact rejection.
4. Plot Channel Spectra: The channel spectra are plotted to find the frequencies at which peaks occur in seizure and non-seizure data.
5. Plot Activity Power Spectrum for each component: The activity power spectrum is also a useful parameter for visualizing peak and amplitude of seizures occurring in every individual Independent Component (IC).
6. Rejection of Artifacts: Rejection of artifacts is done to eliminate all unwanted signals which may give erroneous results in the model. This is done manually based on the ICA, channel spectra and activity power spectra.
7. Calculate peak and amplitude from Activity Power Spectrum: After rejection of artifacts, the activity power spectrum is considered only for the useful components.
8. Plot obtained data points: The data points are plotted using the peak and amplitude values obtained.
9. Classification boundary for seizure detection: A classification boundary is set for classifying seizure and non-seizure data.
10. Focal Cooling for Halting: Based on the classification, focal cooling is used to lower the temperature of the electrodes which can help in controlling and possibly halting the seizures.

IV. Implementation and Results

The EEGLab Toolbox [15] in MATLAB has been used for the purpose of this simulation. Data was obtained from the PhysioNet [16] database on CHB-MIT Scalp EEG [17]. This dataset contains both seizure and non-seizure EEG data of ep ilepsy patients.

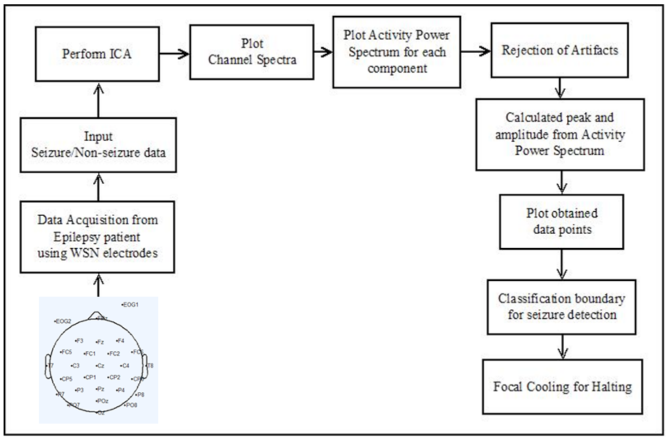

Fig. 1. Proposed Methodology.

A. Data Acquisition

The data considered from subject chb21 was evaluated for both non-seizure data and seizure data. The EEG signals were acquired using 28 electrodes. The locations of all the electrodes on the scalp are shown in Fig. 2.

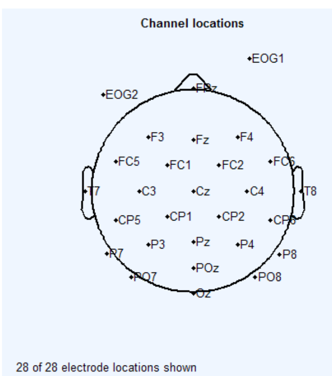

Fig. 2. Locations of 28 channels (WSN electrodes).

The EEG signals that have been acquired using this setup are shown in Fig. 3.

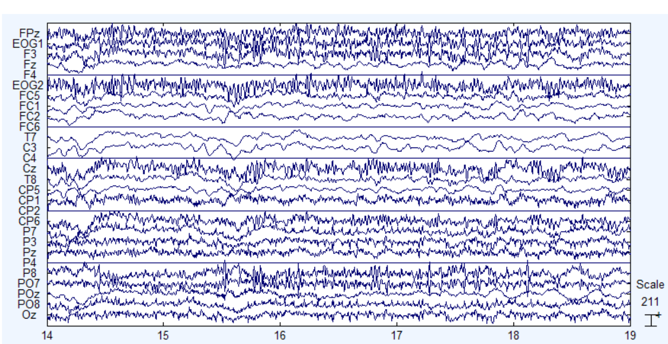

Fig. 3. Acquired EEG signals.

B. Independent Component Analysis (ICA)

In order to evaluate the spectra of the EEG, an ICA (Independent Component Analysis) was first performed on the given data. A rank of 21 was used for ICA in this experiment. ICA in EEG data is used to distinguish the particular regions of the brain contributing to robust EEG signals. The 2-D component maps of all the ICA components of non-seizure and seizure data are shown in Fig. 4 and Fig. 5 respectively.

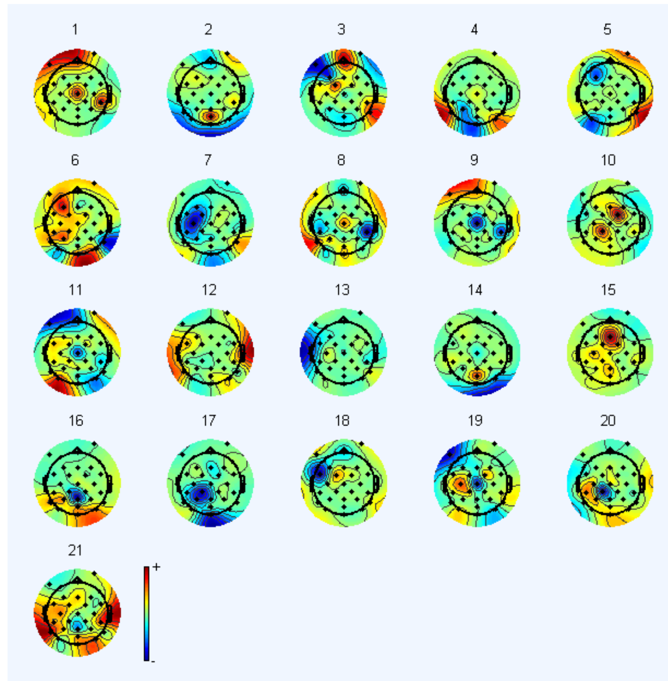

Fig. 4. 2-D Component plots of non-seizure data.

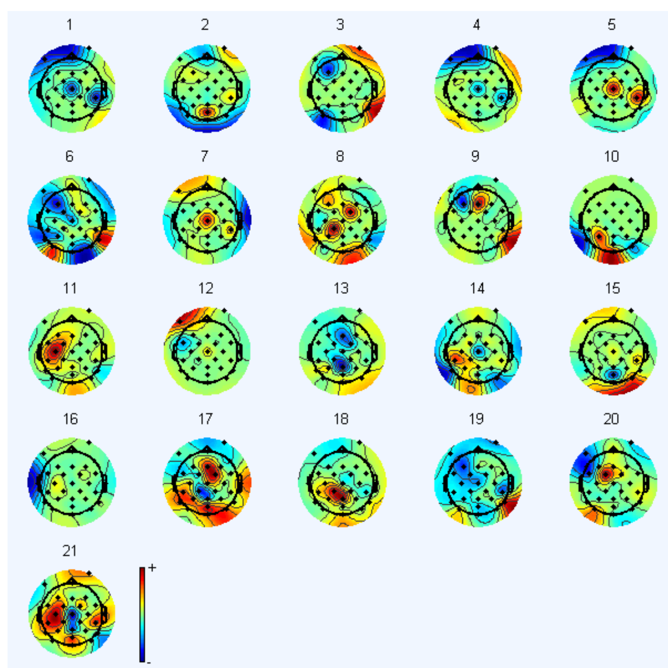

Fig. 5. 2-D Component plots of seizure data.

C. Channel Spectra

Once ICA has been performed, the spectrum of the EEG can be plotted to visualize the frequencies at which peaks are occurring and hence, quantitatively detect the possibility of seizures [18]. The channel spectrums for non-seizure and seizure data are shown in Fig. 6 and Fig. 7 respectively.

D. Activity Power Spectrum

The single channel activity power spectrum is then plotted for all the ICA components in both non-seizure and seizure data. Like the channel spectrum, the activity power spectrum also provides insights into information about peaks occurring in seizure and non-seizure data. One such activity power spectrum is shown in Fig. 8.

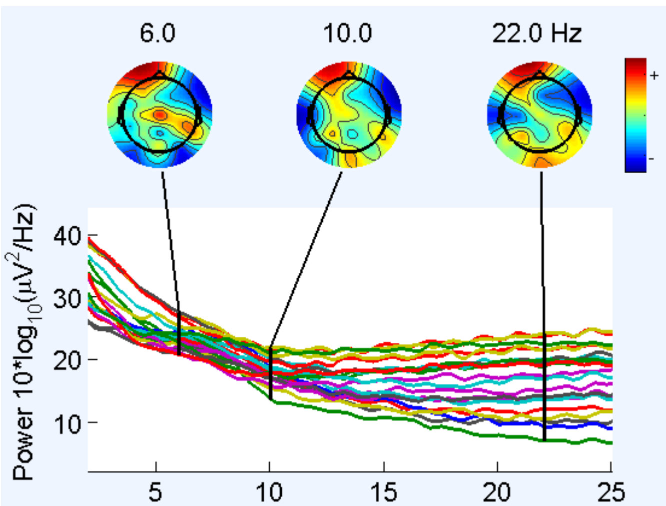

Fig. 6. Channel spectrum in non-seizure data.

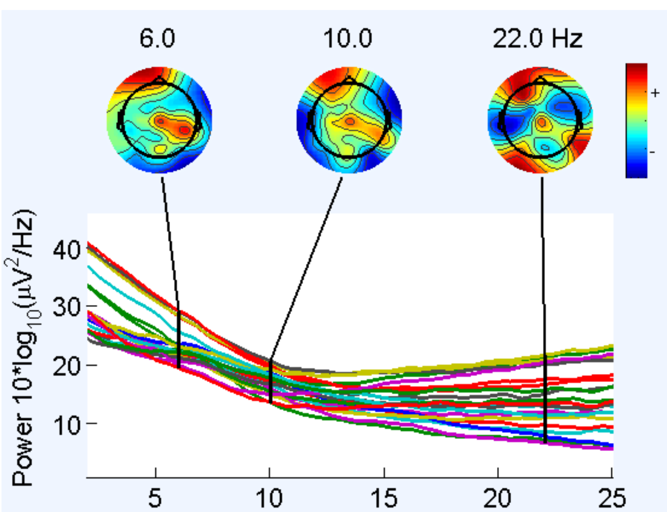

Fig. 7. Channel spectrum in seizure data.

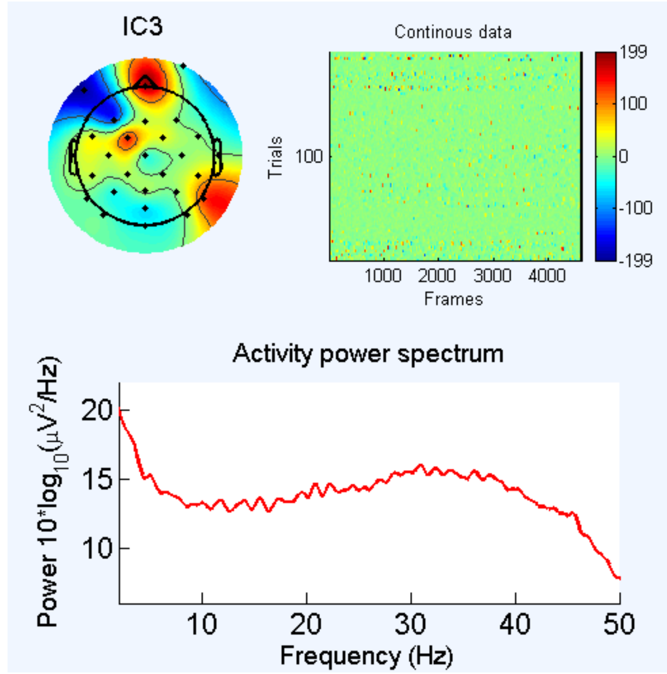

Fig. 8. Activity power spectrum for single component.

E. Artifact Rejection

Artifacts are unwanted signals due to eye blinking, heartbeat, muscle activity and so on that result in unwanted signals in EEG data. In order to retain only the brain signals, it is important to reject the artifacts using ICA. In this case, artifact rejection was done manually by visualizing each component.

F. Detection of Seizure Data

After the process of artifact rejection, only those components were retained that contributed to brain activities. From each graph, the peak and amplitude (peak-to-peak) was calculated. A separate set of data points were then obtained for non-seizure and seizure data. The points were then plotted as shown in Fig. 9 and a classification boundary (the line that was deemed best-fit) was set for detecting and separating seizure data from non-seizure data. This provides a suitable model for a particular subject (patient) and future prediction can be done based on the peak and amplitude.

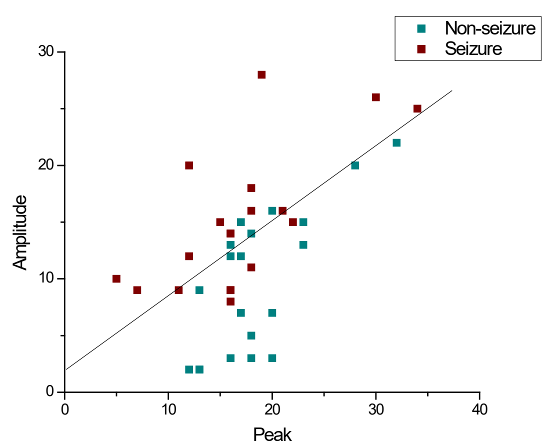

Fig. 9. Classification boundary for detection of seizure data.

An average classification accuracy of 90% and false positive rate of 9% was obtained using the proposed detection system. The proposed system performs at par with previously proposed systems having average accuracy 94.6% [7], detection rate 100% and false positive rate 9% [8], accuracy 91% and false negative rate 9% [10] efficiency 30% [11] and sensitivity 57% [13].

Hence, given any EEG sample, the proposed methodology can be followed and the detection of seizures can be carried out using its activity power spectrum and plotting its data point.

When seizures are detected, a focal cooling mechanism can be incorporated along with the mobile WSN EEG electrodes to cool the focal region in order to prevent impending seizures from arising.

V. Conclusion and Future Work

In this paper, an IoT-based system using wireless sensor networks has been proposed by incorporating machine learning for detection of seizures and a focal cooling mechanism for halting of seizures in epilepsy patients. This system is particularly helpful in the case of mobile EEG, especially in cases of patients with epilepsy who require monitoring even in ambulatory condition. The classification approach for detection of seizures has obtained 90% classification accuracy and 9% false positive rate, which is competent with the previous approaches.

Future approaches with regard to this work include enhancing the system with more advanced wireless electrodes and more advance machine learning algorithms.

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