eSeiz: An Edge-Device for Accurate Seizure Detection for Smart Healthcare

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***Abstract*—Epilepsy is one of the most common neurological disorders affecting a significant portion of the world's population and approximately 2.5 million people in the United States. Important biomedical research efforts are focused on the development of energy efficient devices for the real-time detection of seizures. In this paper we propose an Internet of Medical Things (IoMT) based automated seizure detection system which will detect a seizure from electroencephalography (EEG) signals using a voltage level detector (VLD) and a signal rejection algorithm (SRA). The proposed system analyzes neural signals continuously and extracts the hyper-synchronous pulses for the detection of seizure onset. Within a time frame, if the number of pulses exceeds a predefined threshold value, a seizure is declared. The signal rejection algorithm reduces false detections, which in turn enhances the accuracy of the seizure detector. The design was validated using system-level simulations and consumer electronics proof of concept. The proposed seizure detector reports a sensitivity of 96.9% and specificity of 97.5%. The use of minimal circuitry can lead to reduction of power consumption compared to many contemporary approaches. The proposed approach can be generalized to other sensor modalities and the use of both wearable and implantable solutions, or a combination of the two.**

***Index Terms*—Smart Healthcare, IoMT, Wearables, Epilepsy, Seizure, Electroencephalography, Automated Detection, Energy Efficient Systems, Low Latency Systems**

I. Introduction

SMART health care is becoming dominant due to the combined pressures of an increasing and aging population, an increasing demand for excellent care and limited resources. Smart health achieved through wearables has been focused on general wellness, but is now starting to encompass the management of acute disorders. One example of such an effort is the use of smart health care for the automated real-time control of seizures. Epilepsy is a neurological disorder marked by spontaneous recurrent seizures. A seizure is the occurrence of an abnormal hyper-synchronous disturbance of a population of neurons [1], which is manifested in the form of sensory disturbances, convulsions, and frequently leads to loss of conscience.

There are multiple lines of treatment for epilepsy. Anticonvulsant drugs are used as a first line to control seizures, but a significant portion (more than 30%) of patients remain refractory to medication. For patients who are refractory, uncontrolled seizures have a potentially devastating effect on the patient's quality of life. Epilepsy surgery is suitable for some patients with medically refractory seizures, but not if the patient has multi-focal seizures or if the seizure onset area is located in the eloquent cortex [2]. Other possibilities include modification of diet, which may be effective in some children. Wearable and implantable devices constitute an important fourth line of treatment, and one whose use is growing. Automated, closed loop therapy has shown efficacy in managing epilepsy. Responsive neural stimulation (RNS), for example, which is approved by the Food and Drug Administration (FDA) for use in the USA has been shown to reduce the number of seizures experienced by a patient. Automated seizure detection systems are a growing need for the treatment of epilepsy, as early warning can enable a patient to take protective action such as drug delivery or neurostimulation when necessary [3, 4].

There are several ways to diagnose epilepsy by clinical examinations. However, the diagnosis can be best performed by electroencephalography (EEG) due to its high temporal resolution [5, 6]. EEG is a process of measuring electrical activity in the brain. The EEG can be collected in a number of manners, including through the use of a cap, headband, and invasive or subcutaneous sensors. Also possible is the use of other wearable sensors monitoring galvanic skin response and heart rate to detect changes within the autonomic nervous system, which is reflective of seizure onset. The manual seizure detection process is a tedious and time consuming task, which necessitates automated seizure detection systems which can detect seizures quickly. In this paper we propose such an automated seizure detection system in the IoMT framework. The proposed seizure detector has simple design complexity, low sensitivity to noise and simulation results indicate that it can be implemented as a low-power system. Neural activity is monitored continuously. The input signal is analyzed by a detection circuit and potential seizure activity (hyper-synchronization) is detected. Hyper-synchronous pulses are processed by a different algorithm. A seizure is declared if the pulses exceed a certain threshold. The proposed seizure detector consists of a filter, an amplifier, a voltage level detector, and a signal rejection algorithm. An illustration of the proposed system is shown in Fig. 1. The IoT framework associated with the seizure detector enables recording the patients day to day activities and accessing healthcare data from anywhere or at anytime, hence the remote connectivity

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leads to a better treatment.

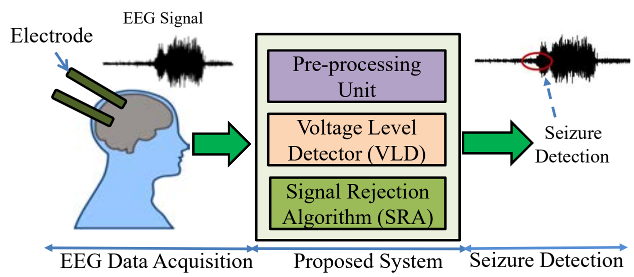

Fig. 1. Seizure Detection Based on EEG data.

The remainder of this paper is organized as follows: Section II emphasizes the novel contributions of this work. Existing relevant research on seizure detection is presented in Section III. Section IV provides an architectural overview of the platform. The proposed seizure detector is discussed in Section V. The implementation of the design block is presented in Section VI. The simulation results are shown in Section VII and conclusions are presented in Section VIII.

II. Novel Contributions of The Current Paper

An accurate and energy-efficient seizure detection system is proposed in the IoMT framework. The detection of EEG abnormalities is a challenging task because of the its high complexity. Existing algorithms show promising results for seizure detection, though accuracy and power consumption remain critical issues. The novel contributions of this work address these issues as discussed below:

The proposed signal rejection algorithm (SRA) estimates the seizure onset by accurately eliminating unwanted bursts of pulses and noise. The unwanted signal rejection continues in a time frame up to the threshold point A threshold number of hyper-synchronous pulses within a time frame defines a seizure onset. The continuous rejection of unwanted signals leads to a reduction in false detections, which in turn enhances the performance of the seizure detector. In common with current IoMT trend, the proposed system provides the advantages of remote healthcare monitoring and consultation. The patient's EEG data are continuously stored and analyzed on the cloud and a notification is sent to the physician if a seizure occurs. Physicians can take required actions based on the healthcare report from the cloud.

Simulation results of an ideal prototype show low power consumption. Combined with the system's increased detection accuracy, it is suitable for use as a wearable or implantable device for seizure detection and epilepsy treatment.

III. Related Prior Research

Table I provides a comparative presentation of relevant existing research and development in consumer electronics and illustrates the contributions of each work to smart healthcare. An IoMT based smart healthcare system has been proposed in [7] which collects the patient's medical data including blood pressure and heart rate, and sends them to a physician through the cloud, providing remote healthcare service. An architecture of remote electrocardiogram (ECG) monitoring with a wireless sensor network has been proposed in [8–11] in which portable sensors transmit data to an ECG server which are then sent to hospitals and physicians for evaluation. An extensive survey has been conducted in [12] which reviews the concepts, applications, current research trends, challenges, opportunities and significance of the IoMT in smart health care. U.S regulators have recently approved the first medical grade smart watch, a novel consumer electronics product for neurological health, which measures abnormal activity during an epileptic seizure and sends alerts to a physician for proper action [13]. While this product has shown promising results for the detection of generalized clonic-tonic seizures, significant research remains to be conducted for the detection of partial seizures. The proposed system advances consumer electronics by bringing seizure detection and control to the smart health care system.

Several seizure detection algorithms such as wavelet decomposition [15], phase coherence [16], and signal synchronization have been proposed. The implementations of these algorithms are only confined to powerful desktop computers and are not applicable to wearable or implanted devices. Considerable research has been focused recently on developing implantable devices [17–19]. An algorithm based on events [17] distributes EEG datasets into events of identical size. A seizure state is defined by a threshold voltage associated with EEG abnormalities. Detection relies on positive and negative thresholds but can false detection is possible. A method based on support vector machines (SVM) [20] exhibits excellent detection accuracy but numerous support vectors are required to differentiate bewteen a seizure and normal states. This results in increased power requirements and high cost. A complex detector [21] requires an ASIC to meet sensitivity requirements. A detection technique based on a CMOS preamplifier [19] provides good seizure detection accuracy at the cost of high power. Due to poor CMOS noise immunity, noise related issues degrade its performance [22]. In the current work, to mitigate the noise problem, the detection method proposed is energy efficient and more immune to noise.

The wavelet transform has the capability of capturing the non-stationary behavior of EEG signals using time-frequency localization. A wavelet transform-based seizure detection method [23] has been introduced which provides a sensitivity of 76% and a detection latency of 10 sec. A fast and accurate approach [24] of seizure detection has been proposed in the edge-IoT framework that utilizes a naive Bayes classifier for feature classification. The edge-IoT framework offers a reduction in latency compared to the cloud-IoT and enhances the detection accuracy for short duration intracranial icEEG. A patient-specific seizure classification method [25] has been presented, which uses an SVM as a classifier and achieves a sensitivity of 96% and a mean detection latency of 4.6 sec. An alternative approach to EEG is proposed [26], which uses a single wrist-worn accelerometer device for monitoring and detection of convulsive seizures in a noninvasive way. The use of the accelerometer sensor reduces resource and labor associated with the existing EEG based detection system. In the temporal synchronization based approach [27], the recurrence pattern of

TABLE I
EXISTING CONSUMER ELECTRONICS WORKS ON SMART HEALTHCARE.

Existing Works	System Details	Application to Smart Healthcare	Characteristics
Ivanov, et al. 2012 [9]	Cooperative wireless sensor network (WSN) with wireless body area network (WBAN)	Healthcare monitoring includes ECG, blood oxygen level, and body temperature	Energy efficient and cost effective
Spinsante, et al. 2012 [10]	An integration of WSN framework, bluetooth, and digital TV	Remote health monitoring and smart sensor	Simplistic and cost effective
Dey, et al. 2017 [8]	Wireless sensor network (WSN) and Zigbee technology	ECG home healthcare monitoring	Improvement in device integration, reliability, and latency
Lee, et al. 2018 [14]	Analog front end circuit and Digital signal processor	Arrhythmia monitoring	Enhancement in accuracy and low power consumption
Raj, et al. 2018 [11]	ABC-LSTSVMs	ECG health monitoring	Improvement in accuracy
Proposed System	Signal rejection algorithm (SRA) and IoMT	Remote EEG health monitoring and detection of seizure	Accurate with potentially low power consumption (based on simulation results)

seizure and non-seizure behavior is represented by a complex model and reports a average latency of 6 sec. In the local mean decomposition (LMD) based seizure detection approach [28], the raw EEG signal is decomposed into several product functions (PF) and then the extracted features are given to the classifier for seizure detection.

In our previous work [29], an energy efficient seizure detector was proposed. The system needs both software and hardware validation with extensive EEG data. In the current extended article, an accurate and energy efficient seizure detector is proposed in the IoMT platform. The proposed eSeiz in the present work has been extensively validated, and uses a signal rejection algorithm (SRA) for seizure detection.

IV. THE PROPOSED SEIZURE DETECTOR IN THE INTERNET OF MEDICAL THINGS PERSPECTIVE

Due to increased and aging population, traditional healthcare systems are not able to provide the necessary services to everyone. Smart healthcare utilizes limited resources in an efficient way to fulfill everyone's needs [12, 30]. The IoMT in smart healthcare is an integration of universal communication and connectivity where all the necessary components can be connected together [7]. The proposed device is divided into three components, as shown in Fig. 2.

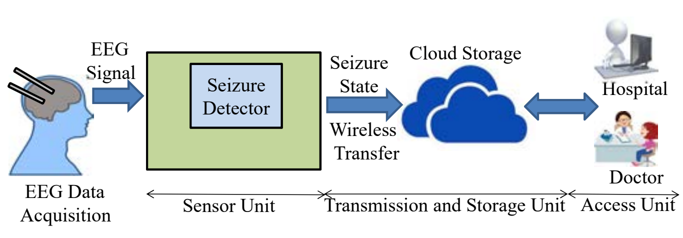

Fig. 2. Proposed eSeiz in the Internet of Medical Things (IoMT).

A. Sensor unit

The sensor unit consists of an EEG pre-processing unit and a seizure detector . The input EEG signal is analyzed by the pre-processing unit. The seizure detector continuously monitors the seizure state of the epileptic subject. The information relating to the patient's seizure state is then sent to remote storage through a wireless transfer.

B. Transmission and storage unit

The transmission unit acts as an interface between the sensor unit and cloud storage. The main function of the storage unit is to store and manage the patient's data. Cloud storage is preferred as it enables data to be accessed from anywhere and provides automatic redundancy.

C. Access unit

This unit allows health professionals like physicians, health practitioners, and hospitals to access data from the cloud. The information relating to a patient is continuously stored in the cloud. In the case of a seizure, a notification is sent to the corresponding physician for proper action. The physician will check the patient's medication history as well as documented seizures and prescribe the required dosage for the treatment of epilepsy. The data is also accessible by the patients which allows them to be updated with current health conditions [7].

V. THE PROPOSED NOVEL SEIZURE DETECTOR

The proposed seizure detector (SD) monitors the brain activity at the seizure onset area. Fig. 3 shows a characterization of seizure onset. The architecture and flowchart of the proposed detector are shown in Fig. 4 and Fig. 5, respectively. The input EEG signals are filtered and submitted to an amplification unit. The amplified signals of desired range are then passed through a voltage level detector (VLD). The resulting hyper-synchronous pulses from the VLD are then submitted to the signal rejection algorithm (SRA) unit. The SRA unit eliminates unwanted signals and noise. The elimination of unnecessary signals continues until the number of hyper-synchronous pulses surpasses the threshold value. Seizure detection is characterized by the following equation:

$$V_{SE}(n) = \begin{cases} 1, & \text{seizure, for } V(n-i) = 1 \cdots \text{ and } V(n) = 1 \\ 0, & \text{no seizure, otherwise,} \end{cases} \quad (1)$$

where $V(n)$ is the EEG sample at time sample n and $i = 1, 2, 3, \cdots, N$, with N being the threshold number of samples.

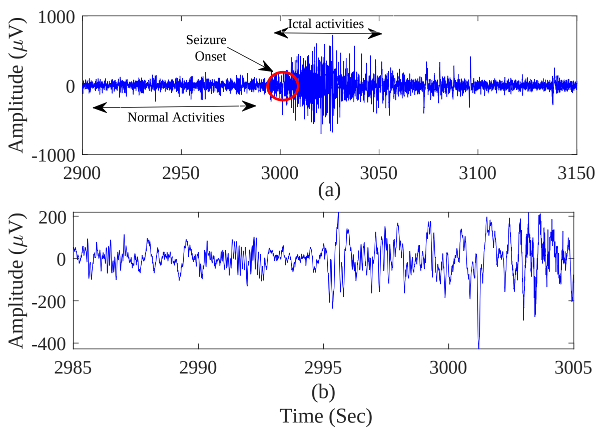

Fig. 3. Seizure Activity Characterization in the Time Domain (a) Invasive Electroencephalography (EEG) of an Epileptic Seizure (b) Zoom Inset 6-10 seconds.

A. Hyper-synchronous Signal Detection Circuit

The proposed circuit in Fig. 6 consists of a band pass filter, an amplifier, and a voltage level detector (VLD). The filter eliminates the unwanted signals and noise associated with the scalp-EEG signals and only keeps signals of the desired frequency range. The low amplitude neural signals need to be amplified prior to analysis. The desired level of the signals is achieved by the amplification unit. The VLD analyzes the amplified signals and detects hyper-synchronous pulses. The threshold values (V_{max}, V_{min}) of the VLD are determined from the analysis of known seizure instances. The detection of the hyper-synchronous signal is based on the following equation [19, 29]:

$$V_{vld}(n) = \begin{cases} 1, & \text{for } V_{max} > V_{mod}(n) > V_{min} \\ 0, & \text{otherwise,} \end{cases} \quad (2)$$

B. Signal Rejection Algorithm (SRA): Detection of seizure onset from hypersynchronous signals

The hyper-synchronous signals from the VLD are analyzed and spurious pulses are eliminated using the SRA. The elimination of unwanted signals is performed by:

$$V_{SE1}(n) = \begin{cases} 0, & V(n-2) = 0 \text{ or } V(n-1) = 0 \\ V(n), & \text{otherwise.} \end{cases} \quad (3)$$

The spurious pulse is further eliminated using:

$$V_{SE2}(n) = \begin{cases} 0, & V(n-1) = 0 \text{ and } V(n) = 1 \\ V(n), & \text{otherwise.} \end{cases} \quad (4)$$

The seizure onset is characterized by [19, 29]:

$$V_{SE}(n) = \begin{cases} \text{Seizure,} & V(n-2) = 1 \text{ and } V(n-1) = 1, \\ & \text{if } V(n) = 1 \text{ or } 0 \\ 0, & \text{otherwise.} \end{cases} \quad (5)$$

Neural signals are continuously monitored and seizure is detected from the hyper-synchronous pulses (V_{vld}). Within a time frame, the unwanted pulses are eliminated if their amplitude is lower than the threshold value. A seizure onset is declared when the SRA completes the n-th iteration. If the number of hyper-synchronous pulses is greater than the threshold number, a seizure is declared according to equations (3), (4), and (5).

VI. Consumer Electronics (CE) Proof of Concept of the Proposed eSeiz

The EEG signal is initially preprocessed and filtered. The low amplitude neural signal is then amplified using an adjustable gain amplifier. The maximum and minimum voltages of the VLD define the hyper-synchronous signal. Using the proposed SRA, the seizure onset is identified when it occurs. The design flow of the proposed seizure detector is shown in Fig. 7. System-level prototyping of the proposed eSeiz is performed as a first step towards CE prototyping. The system level model of the proposed system is shown in Fig. 8. EEG signals are fed into the system. A band pass filter eliminates unwanted noise and extracts all seizure onset information. The adjustable gain amplifier enables signals to be amplified to the desired level. Hyper-synchronous signals are detected by the VLD. If the voltage is within the range, the function outputs a 1, otherwise it is zero.

The maximum and minimum voltage of the VLD is determined by heuristic analysis of the amplified signal. For an epileptic subject with and even of seizures n, the V_{max} and V_{min} values are computed from $n/2$ seizure instances. If n is odd, the V_{max} and V_{min} values are obtained from $(n-1)/2$ seizure instances. The average optimal values have been adjusted by trial and error and are then applied to unknown seizure and non-seizure instances. The hyper-synchronous signal which is obtained from VLD is given to the SRA unit. In the first iteration of signal rejection, if a sample is either '0' or '1' and the previous two samples are '0', the algorithm outputs a 0. In the next iteration, if the previous sample is '0', the algorithm outputs a '0'. For seizure onset formation at the $(n-k)$th iteration, if the previous sample is '1', the algorithm results a '1'. In the n-th stage, the algorithm define a seizure onset if the number of hyper-synchronous pulses, which is denoted by '1', exceeds the threshold value. The optimal value of threshold, n and k can be achieved by heuristic analysis of the known seizure and non-seizure instances. The SRA technique is illustrated in Table II, where the signals have been analyzed for seizure onset and non-seizure onset instances.

Power estimation is generally performed using two approaches: pattern-dependent and pattern-independent. The power consumption of the proposed system is computed using the pattern-independent approach [31]. Different EEG signals

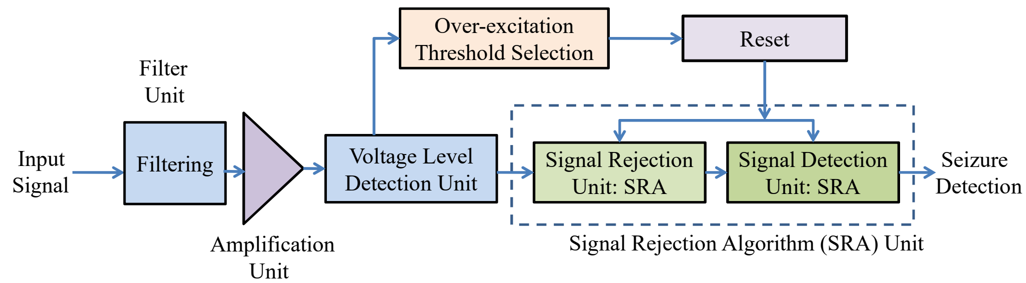

Fig. 4. Architecture of the Proposed Seizure Detector.

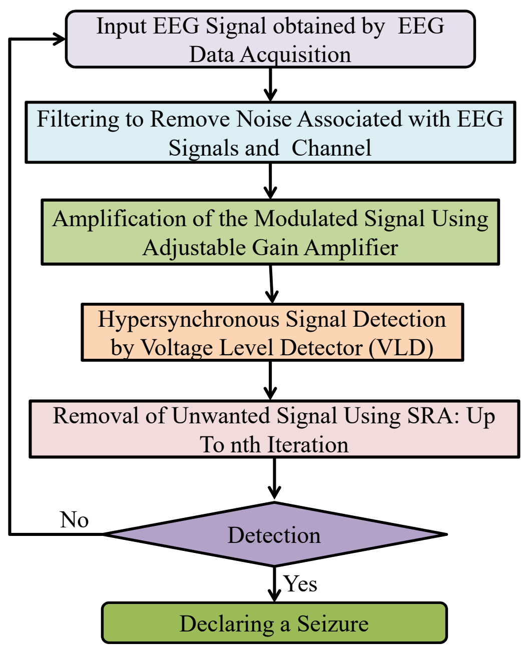

Fig. 5. The Proposed Steps for the Seizure Detection in eSeiz.

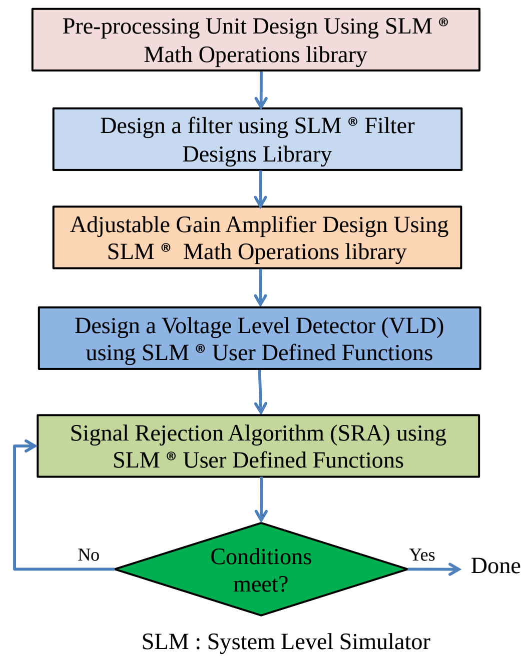

Fig. 7. Design flow of the proposed eSeiz.

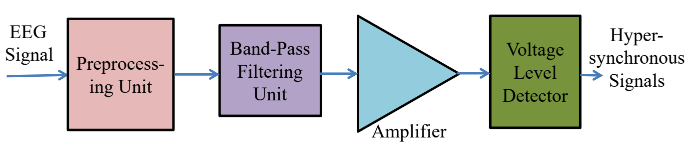

Fig. 6. Hyper-synchronous Signal Detection Circuit.

TABLE II
SIGNAL REJECTION ALGORITHM (SRA) TECHNIQUE.

Location	Normal EEG	Seizure Onset
VLD output	0 1 0 0 1 1 0 0 0	1 1 1 0 1 1 1
SRA (1^{st} iteration)	0 1 0 0 0 1 0 0 0	0 1 1 0 1 1 1
SRA (2^{nd} iteration)	0 1 0 0 0 0 0 0 0	0 0 1 0 0 1 1
SRA (3^{rd} iteration)	0 0 0 0 0 0 0 0 0	0 0 1 1 0 1 1
SRA (n^{th} iteration)	0 0 0 0 0 0 0 0 0	0 0 1 1 1 1 1
Seizure Detection	0	1

of identical size are applied to the design and the average of the computed power defines the power dissipation. The proposed seizure detector is viewed as a black box and current and voltage values are obtained form current and voltage sensors available in the system level simulator libraries. A hardware-in-the-loop simulation approach was followed for the CE prototyping of the proposed system. A vendor-provided hardware support package was used in the system level simulator and the proposed model was run on the actual board. EEG data and seizure information are continuously stored on the eSeiz channel in the open IoT cloud. A Liquid Crystal Display (LCD), which is attached to the board, displays information about seizure state. If any seizure occurs, a notification is sent to the designated user through the cloud. The EEG data and seizure state are sent to open cloud storage, while the system concurrently receives dosage information prescribed by the physician. The proposed system consists of two channels: the eSeiz channel and the EEG channel .The information on seizure state is stored in the eCeiz channel whereas continuous EEG data are saved in the EEG channel. Both patients and medical professionals have access to the IoT cloud as well as

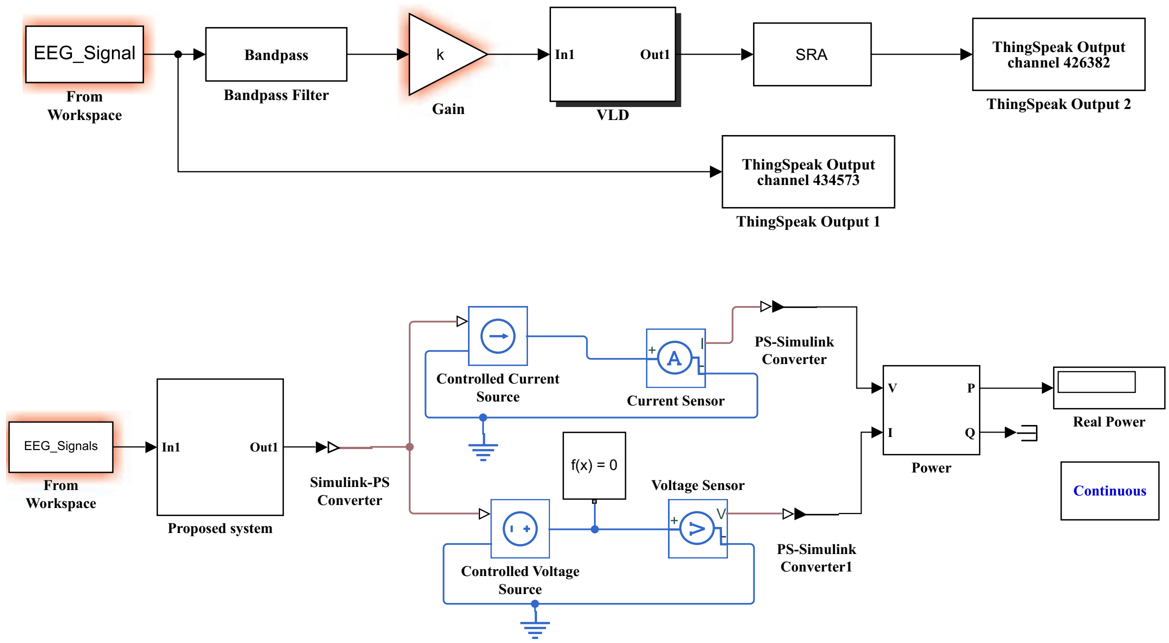

Fig. 8. System-Level Simulator Model of (a) Proposed Seizure Detector. (b) Pattern-Independent Power Measurement Setup.

the database using a REST API [24]. Fig. 9 shows the CE prototyping of the proposed eSeiz. It should be pointed out that this prototype serves simply as a proof-of-concept and is not suitable for consumer electronics mass production. It is not optimized and consumes substantially more power than a final product would. For these reasons, in this discussion we examined the power consumption from a simulation point of view since this will be much closer to an optimized, consumer-ready device.

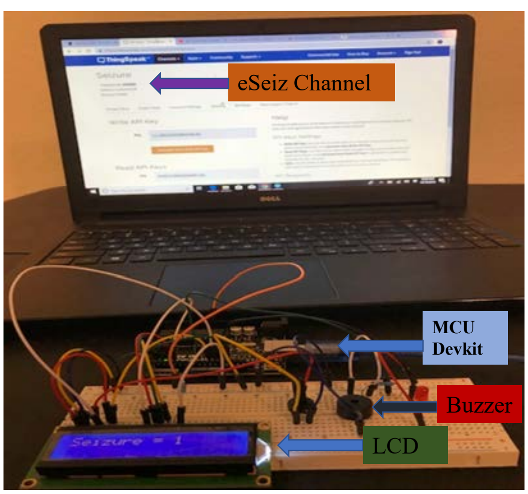

Fig. 9. CE Prototype of the Proposed eSeiz Device.

VII. Experimental Results

The continuous and long term EEG recordings are taken from the CHB-MIT scalp EEG database [32], [25], which consists of EEG recordings from pediatric subjects. This work uses common EEG data from the following anonymized subjects: chb01, chb03, chb05, chob08, chb11, chb17, and chb19. EEG recordings were obtained at 256 samples per second with 16-bit resolution. The EEG electrodes were placed according to the International Federation of Clinical Neurophysiology 10-20 placement system. Initially, the EEG signal is passed through a band pass filter of frequency range between 3 Hz to 29 Hz, which is then amplified to a certain level. The amplified signal is applied to the VLD. The seizure onset information is extracted using the VLD. The maximum (V_{max}) and minimum (V_{min}) voltages are computed by heuristic analysis of the known seizure instances. As a good number of non-seizure signals fall in the VLD category, the VLD produces a number of unwanted pulses. The output of the VLD, namely hyper-synchronous pulses (V_{vld}), are fed into the SRA. The SRA eliminates unwanted pulses in every iteration. The SRA iterations continue until the number of hyper-synchronous pulses surpass the threshold number. The unwanted pulses are being eliminated as SRA completes the n-th iteration. The time frame (T_f) is in the range of milliseconds to seconds. For patient-specific detection, the values of T_f , V_{max}, and V_{min} can be varied accordingly. It is also reported that some unwanted signals with amplitude of the VLD range trigger a false detection. In order to solve this problem, the statistical energy [24] in each time frame is calculated for the known seizure and non-seizure instances and an optimal value is determined by a heuristic approach, as discussed earlier. The optimal threshold value of energy in each time frame is considered. Even if an instance is incorrectly detected by SRA unit, further analysis using the threshold energy provides correct detection. The average amplitude of the seizure pattern at onset is between 150 mV and 450 mV. The frequency range for epileptic discharge is between 3 and 29 Hz. The

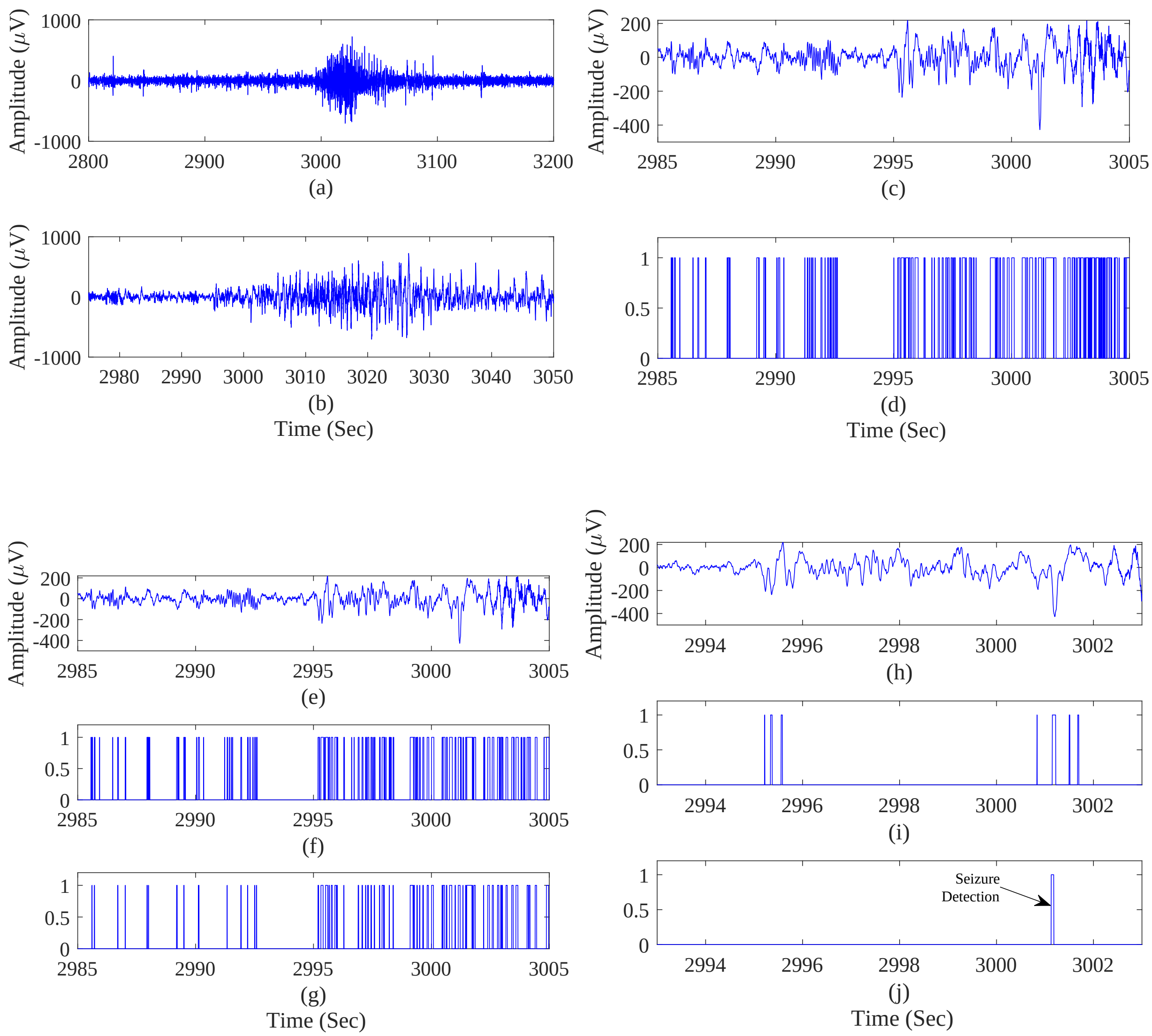

Fig. 10. Transient analysis (a) Input EEG signal of 2800-3200 seconds (b) EEG signal of 2975-3050 seconds (c,e) Zoom 2985-3005 seconds of input signal (d) Output of VLD at 2985-3005 seconds (f) Output of SRA after 1st iteration (g) SRA output after the 2nd iteration (h) Zoom 2993-3003 seconds of input signal (i) SRA output after the $(n-k)$-th iteration (j) SRA output after the n-th iteration.

performance of the detector is measured using sensitivity, specificity, and latency. The sensitivity and specificity of the classifier were evaluated as follows:

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{6}$$

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}} \tag{7}$$

The latency is defined as the delay between the expert marked seizure onset and the seizure onset marked by the seizure detector.

Figure 10 shows the analysis of the EEG signal and detection of seizure for epileptic subject 1 (chb01), in which seizure starts at 2996 sec. and ends at 3036 sec. The time frame for chb01 is selected as 500 ms. Fig. 10(a), 10(b), 10(c), 10(e), and 10(h) represent EEG epochs of different duration. The output of the VLD contains unnecessary and unwanted pulses, as depicted in Fig. 10(d). The SRA eliminates the unwanted signals in every iteration. Fig. 10(f) and 10(g) are the output of the SRA after the first and second iterations, respectively. Fig. 10(i) shows the initiation of seizure detection after the $(n-k)$-th iteration, which reports a smaller number of pulses in the non-seizure area. After the n-th iteration, the SRA eliminates all the pulses in the non-seizure area and processes pulses in the ictal area and declares a seizure. The seizure instance of epileptic subject 11 (chb11) has been studied in Fig. 11. Fig. 11(a) shows the time domain characterization of the EEG epoch of 290-310 sec. The seizure instance originates at 298 sec and ends at 320 sec. The outputs of the VLD and SRA (after the $(n-k)$-th iteration) are shown in Fig. 11(b), and 11(d), respectively. Finally, the resulting signal after the n-th SRA iteration as well as the detection of seizure is presented in Fig. 11(e). Overall, the detector misses one seizure instance

TABLE III
COMPARISON WITH EXISTING SYSTEMS

Existing Works	Seizure Detection Method	Sensitivity	Specificity	Latency	Power Consumption	IoT Implementation
Verma, et al. 2010 [20]	Amplifier, ADC, digital processor and Support vector machine	>90%	NA	5 sec	120 μW	NA
Shoeb, et al. 2010 [25]	Spatial and temporal feature vector and support vector machine	96 %	$0.083h^{-1}$	3.4 sec	NA	NA
Salam, et al. 2012 [19]	Asynchronous front end detector	100 %	100 %	13.5 sec	51 μW	NA
Yoo, et al. 2013 [33]	Analog Front-End (AFE), Linear support vector machine (LSVM)	84.4 %	96 %	2 sec	1.49 μJ/class (energy efficiency)	NA
Altaf, et al. 2015 [34]	Dual detector architecture (D^2A) classification processor, two linear support vector machines(LSVM)	95.7 %	98 %	1 sec	2.73 μJ/class (energy efficiency)	NA
Fan, et al. 2019 [27]	Spectral graph theoretic features extraction	95.7 %	98 %	6 sec	NA	NA
Our Proposed System	Signal rejection Algorithm (SRA)	96.9 %	97.5 %	3.6 sec	39.5 μW	Open data platform

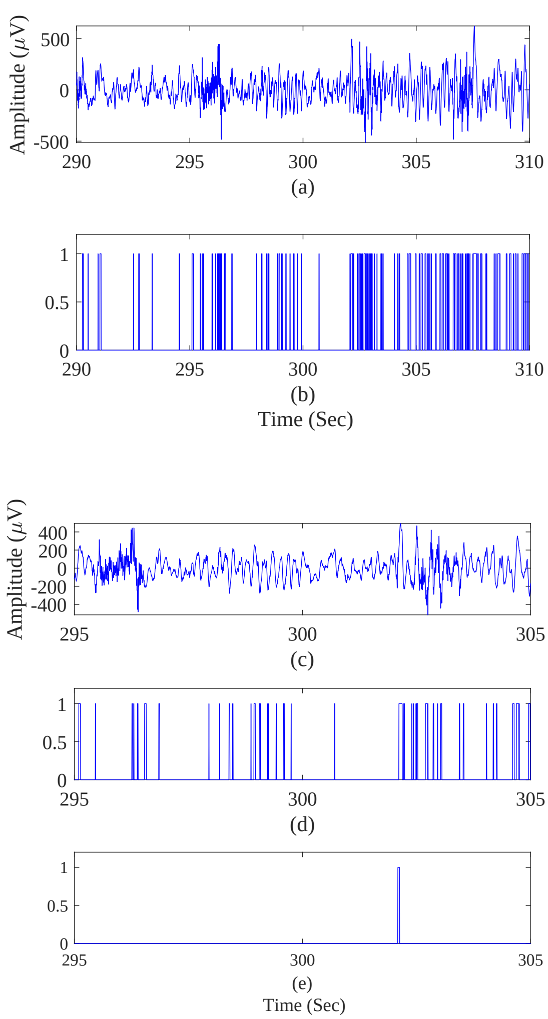

Fig. 11. Transient analysis (a) Input EEG signal of 290-310 seconds (b) Output of VLD at 290-310 seconds (c) Zoom 295-305 seconds of input signal (d) SRA output after the $(n-k)$-th iteration (e) SRA output after the n-th iteration.

TABLE IV
CHARACTERIZATION OF THE SEIZURE DETECTOR

Parameter	Value
Sampling frequency	256 Hz
Seizure Frequency (Minimum)	3 Hz
Seizure Frequency (Maximum)	29 Hz
VLD (Average Maximum Voltage)	150 mV
VLD (Average Minimum Voltage)	450 mV
Sensitivity	96.9%
Specificity	97.5%
Latency	3.6 Sec
Power Consumption	39.5 μW

for the chosen EEG dataset. The sensitivity, and specificity of the seizure detector are measured as 96.9%, and 97.5%, respectively. The average latency of the proposed system is found to be 3.6 seconds. A comparison with existing seizure detectors is provided in Table III. The characterization of the seizure detector is shown in Table IV.

VIII. CONCLUSIONS AND FUTURE RESEARCH

We have proposed an SRA-based automated seizure detector in the IoMT framework. The proposed system was implemented with a system level simulator in an open IoT platform. The proposed signal rejection algorithm (SRA) is useful in eliminating unwanted signals and extracting hyper-synchronous activity from the EEG signals for the detection of seizure, thus enhancing the performance of the seizure detector. Simulation results also demonstrate that the proposed system can potentially be implemented as a consumer electronics product consuming low power, which makes it a suitable candidate for low power wearable applications. In future research, we will miniaturize the proposed system using the latest integrated circuit technologies for wearable biomedical applications and test this solution in an animal model of epilepsy.

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