iSeiz: A Low-Cost Real-Time Seizure Detection System Utilizing Cloud Computing

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Abstract— ***In this paper, we report on a proof-of-concept wearable prototype, called iSeiz, that can detect specific seizure activity, namely generalized tonic- clonic, in epilepsy patients. We first describe the high-level architecture of iSeiz, and then elaborate on its hardware and software features, including its robust and low-computational intensive real-time seizure detection algorithm (SDA), as well as utilization of cloud computing for recoding, analyzing, and comparing seizure data. We conclude this paper by discussing the performance of iSeiz system in terms of its seizure detection accuracy, lifetime, and communication range.***

Keywords — sensor networks, seizure, epilepsy, Amazon Web Services (AWS), cloud computing, e-health, MEMS sensor, accelerometer, gyroscope.

I. INTRODUCTION

Epilepsy affects about sixty-five million people worldwide. According to the World Health Organization (WHO) approximately 80 percent of the epilepsy patients live in developing countries and have very limited access to treatment [1]. In many resource constraint communities, there is almost no care for epilepsy patients and neurologic expertise is nonexistent. Nearly three fourths of people with epilepsy living in low- and middle-income countries do not get the treatment they need.

Epilepsy is a disorder characterized by recurring two or more seizures within a 24-hour period [2]. A seizure is a brief, temporary disturbance in the electrical activity of the brain. It is estimated that there are over 40 different types of seizures; varying in nature, ranging from *going blank* for a few seconds and wandering around, to falling to the ground and shaking severely [7]-[9]. Many seizure cases may start with minor symptoms, prolong, and lead to loss of consciousness or falling. Other seizures may be brief and only last several seconds.

Seizure can result in serious injuries during or after the onset. Up to 50,000 deaths occur annually in the U.S. from prolonged seizures or seizures related accidents [2]. Some seizures, known as *nocturnal seizures* [3]-[5], can occur while the patient is sleep. These seizures can cause sever medical complications or death.

Epilepsy can start at any age, but it is commonly diagnosed in young people under 20 and seniors over 65 [5]. Thus, many epilepsy patients are elderly living alone and quick response and assistance can be lifesaving. Furthermore, in order to provide an accurate account of seizure to assist diagnosis, it is ideal to have a description of seizure severity, how long the seizure lasted, what the patient was doing prior to the onset, etc.

In this paper, we focus on detection of a specific seizure disorder known as *generalized tonic clonic*, also referred to as convulsive seizure (sometimes called *grand mal*). Patients with grand mal seizure generally experience loss of consciousness and violent muscle contractions, resulting in falling down. In such cases, the body may start jerking and shaking (convulse) as the muscles relax and tighten, rhythmically. The condition can last for less than two minutes.

We report on a proof-of-concept wearable prototype that can detect seizure movements from normal movements in real-time in patients with grand mal. Our working prototype, called *iSeiz*, can record seizure duration, as well as its time of occurrence and movement pattern. Such information is particularly important to diagnose seizure. Furthermore, iSeiz can integrate seizure data with physiological data (e.g., body temperature). During the onset detection of epileptic seizures, iSeiz can automatically notify others by sending SMS messages and emails, and activate its alarm system. Another unique feature of iSeiz is its ability to shut off the electric power to individual heated and hazardous appliances, such as an electric stove. Furthermore, the iSeiz system uses cloud computing capability to store, visualize, and analyze the collected seizure data from individual patients. The utilization of cloud computing also allows secure telemetry data sharing among the medical personnel.

Our hope is that the iSeiz system can help epilepsy patients, particularly those living in resource-constrained communities, to again access to better treatment. We also believe that quantifying and visualizing the seizure data can promote collaborative diagnostics, in communities where limited medical expertise is available. Furthermore, the data collected by iSeiz can result in optimizing patient-specific-therapy, and consequently improvement of patient care. Availability of such data can also lead into possible onset prediction.

The rest of this paper is organized as follows: Section II reviews the related works and different proposed approaches to detect epileptic seizures. Section III describes the hardware system architecture and cloud management system of the iSeiz prototype. In section IV, we elaborate on our seizure detection algorithm (SDA). In section V, we describe our test results, followed by the concluding remarks and some prospects for our future work, in Section VI.

II. Previous Works

Over the past several decades many researchers have relied on utilizing Electroencephalograms (EEGs) to diagnose and detect the epileptic seizure conditions. By extracting appropriate features from the EEG signal it is possible to identify epileptic seizures [6]-[7]. However, it has been suggested that the EEG signal features resulted from detection of an epileptic seizure has limited sensitivity and can result in many false alarms [8], [21]. Furthermore, such procedures are typically complex and can mainly be performed in clinical settings.

Many convulsive seizure conditions, such as tonic clonic, are associated with abnormal rhythmic movements. Hence, Inertia Measurement Units (IMU), such as accelerometer sensors, have been proposed as viable solutions to track body motions. With the advent of wearable sensors and Wireless Body Area Networks (WBANs), many projects have focused on developing wireless accelerometer-based patient monitoring systems. Such systems are designed to continuously monitor patient's activities and detect the onset of epileptic seizures [8]-[11]. Often, gyroscopes and magnetometers are used in conjunction with accelerometers to improve body motion tracking [8]- [12]. Various authors have focused on utilization of 1-D accelerometers [23]-[24], whereas others have proposed seizure detection using 2-D accelerometers [14]-[15], [25]. Authors in [26] use multiple 3-D accelerometers located on the wrists and head of patients to detect seizure.

There are also a number of commercial products that are designed to track epilepsy patients and notify the family or caregivers in the event of detecting a seizure activity. For example, Smart-Monitor [16] is capable of sending an alarm in the event of detecting abnormal movements. Samialert [17] is an infrared camera-based seizure detection system with notification capability. It can send the collected seizure data to an iOS products. Emfit [18] is a bed monitoring system that monitors patient movements throughout the night and notifies family members or caregivers in the event of detecting abnormal movements. The bed monitor consists of two sensors that are placed underneath the mattress. The Seizalarm [19] is a phone app that notifies others when abnormal body movements are detected.

In this work, we report on development of a low-cost, low-power, long-range wearable wireless sensor system to detect the onset of epileptic seizures. The key contributions of this work are two folds: (1) utilization of cloud computing for recoding, analyzing, and comparing seizure data from a large patient population; (2) development of a robust and low-computational intensive real-time seizure detection algorithm (SDA). Utilizing a cloud-based data management system can promote collaborative diagnostics, leading to a greater understanding of seizure dynamics, and eventually obtaining better treatments for epilepsy.

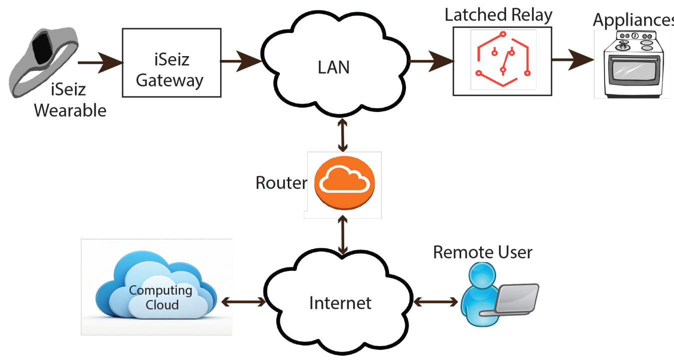

Fig. 1. High-level architecture of iSeiz system.

III. System Description

In this section, we first describe the hardware design of the iSeiz system, and then we describe its cloud architecture.

A. Hardware Design

Fig. 1 depicts the overall architecture of the iSeiz system. The system includes the wearable bracelet (iSeiz wearable), central gateway module (iSeiz Gateway), and appliance control module (latched-relay), used to shut off individual appliances.

Details of each subsystem are depicted in Fig. 2. The wearable hand bracelet module monitors body's abnormal movements due to seizure onset. The micro-controller (uC) on the wearable module is a low-cost *Feather M0* microcontroller [13]. The Feather M0 is based on a 48 MHz ATSAMD21G18 ARM Cortex M0 processor, requiring 3.3V power supply. The chip has 256K of FLASH and 32K of RAM and it includes a built-in USB. The Feather M0 uses an RFM96 Long Range Radio (433 MHz) radio module. This radio module consumes considerably lower energy compared to Bluetooth, Bluetooth Low Energy (BLE), WiFi, or ZigBee. The radio was interfaced with the microcontroller using SPI and in order to improve the range, we designed an onboard quarter-wave antenna.

The multi-sensor breakout board in the wearable module includes three separate devices: L3DG20H (triple-axis gyroscope), LSM303DLHC (triple-axis accelerometer and a compass), and BMP180 (combination of a barometric sensor and a temperature sensor). A rechargeable Lithium Ion Polymer battery was used to power the bracelet.

As shown in Fig. 2, the wearable bracelet has two buttons: OK and PANIC. The user (patient) can use the OK button to override any false alarm, indicating that he/she is ok. The OK button can also be pressed after the seizure activity has stopped. The PANIC button can be used to request help.

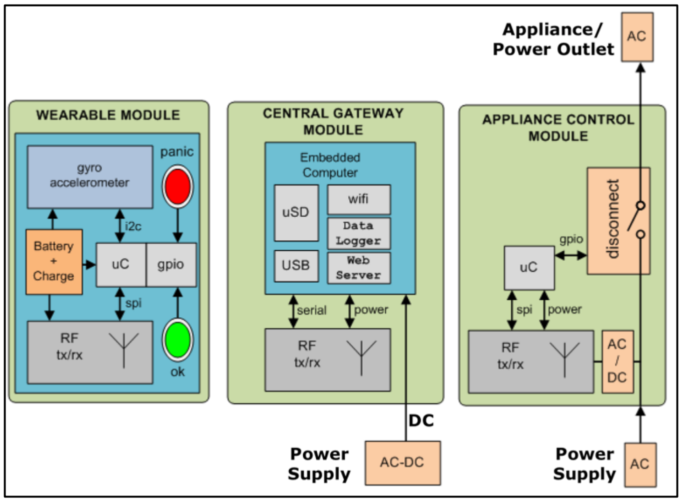

Fig. 2. Detailed architecture of iSeiz sub-systems.

The bracelet aggregates and transmits the data received by the IMU sensors to the Gateway module. Each transmitted data packet, *D<k>*, includes the following fields (*k*): *TMP, Ax, Ay, Az, Gx, Gy, Gz, SeF, STA_OK* and *STA_PA*. Below, we briefly describe each data field.

The *TMP* field indicates the body temperature. The field *Ai* represents the three measurements reported by the triple-axis digital accelerometer: *Ax, Ay,* and *Az*. The measured rotations around the three axes (*x, y,* and *z*) are represented by *Gi*. The *SeF* bit is set when the seizure algorithm has detected a seizure activity. The status of OK and PANIC switches is reflected in bits *STA_OK* and *STA_PA*, respectively.

The Central Gateway Module (CGM) consists of a Raspberry Pi Model 3 (RPi). The RPi utilizes a QUAD Core Broadcom BCM2837 64 bit ARMv8 processor running at 1.2GHz. The board is connected to the Internet using an onboard WiFi module. As shown in Fig. 2, the RF link between the gateway and the wearable is achieved using an RFM96 module. Each received data packet from the iSeiz wearable module, *D<k>,* is checked for the following fields: *SeF, STA_OK* and *STA_PA*. If *SeF* is set, indicating an onset, the Gateway will enable its alarm and send a request to the Appliance Control Module (ACM) to take an action (e.g., turn off the appliances). Another function of the Gateway is to forward the received data packets to the cloud. We will discuss this in sub-section III.B.

The CGM uses broadcasting to communicate with all ACMs in the event of seizure onset detection. Fig. 3 depicts the timing diagram of the signals exchanged between the three modules. Note that in our protocol each transmission is confirmed by an acknowledgement. This figure shows the exchange of data packets between the wearable and the Gateway when the seizure condition is detected. Upon receiving a seizure detection signal (*SeF*), the Gateway module waits for 10 seconds before activating ACMs, or activating its own alarm. This reduces the possibility of any false triggering.

B. Cloud-Based Architecture

The cloud-based architecture of the iSeiz system is particularly important to reliably handle a large number of devices and remote users. The cloud architecture is also critical to securely store and distribute patient's medical data. Furthermore, having a readily accessible database of onset epileptic seizure occurrences can be particularly helpful in studying and learning the onset patterns in different patients.

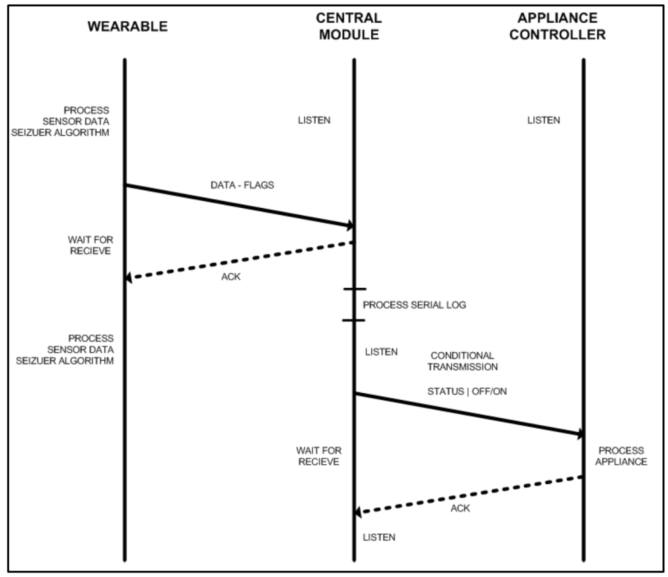

Fig. 3. The timing diagram of the signals exchanged between the three modules.

In this project, we used Amazon Web Services (AWS) IoT [20] as our cloud computing platform. The AWS IoT is a managed cloud platform that can be connected to different iSeiz systems, each assigned to an individual patient. Fig. 4 shows the cloud architecture of the iSeiz system using AWS IoT. In this architecture, individual iSeiz Gateway modules send their data packets to the device gateway of AWS IoT using Message Queuing Telemetry Transport (MQTT) protocol. The MQTT is a lightweight messaging protocol, which is based on *publish-subscribe* method and it is designed for low-bandwidth, high-latency applications. The Amazon IoT Device Gateway acts as an MQTT *message broker*. The broker receives the *published* topics, in this case seizure data, from each gateway module and then sends (pushes) the results out to different *subscribers* interested in receiving a specific patient's data [27]. Each connected iSeiz gateway device has its own specific credentials in order to access the message broker. All traffic to and from the AWS IoT are encrypted over Transport Layer Security (TLS).

As shown in Fig. 4, AWS can offer a number of services, including AWS SNS, AWS Dynamo DB, AWS Lambda, AWS RDS (MySQL), and AWS EC2. Below, we briefly describe these features, known as *cloud services*, and elaborate on how they are used by the iSeiz system.

AWS SNS is mainly used for notification. If the *SeF* and *STA_PA* bits are set, the SNS can send an SMS message or email to the designated phone numbers or subscribers, respectively.

AWS Dynamo DB service offers a NoSQL database. Alternatively, it is possible to store the incoming seizure data using MySQL (AWS RDS) in order to support complex relational queries. In this project, we used the Dynamo DB service as it is believed to be the appropriate choice to ensure database scalability, performance, and reliability. We note that AWS also offers other database services, such as Amazon SimpleDB, and Amazon S3, that can be utilized, depending on the required data size, latency, read and write access, etc.

AWS Lambda service is mainly used for creating a real-time seizure data analytics. Using this service, we can receive the raw seizure data from each individual patient, remove the errors and outliers, and then create a metric that can potentially offer greater insight into patient's epileptic disorder. The data from various patients can be compared and studied in terms of seizure duration, frequency, body temperature, and activity levels prior to the onset.

AWS EC2 (Elastic Compute Cloud) provides a virtual web server. Using this service, we are able to select a configuration of memory, CPU, instance storage, and the boot partition size that is optimal for the seizure system. In our project, we used EC2 as the primary way to host a secure web service for remote users (e.g., medical personnel).

We developed the web site for the iSeiz system using **Dijango** software framework. Dijango offers interactivity and high-security web applications [22]. The main reason we used Dijango was to ensure secure access to each individual patient's data set.

IV. Signal Processing Algorithm

The seizure detection algorithm (SDA) is based on detecting abnormal hand movements due to grand mal seizure (convulse). The algorithm is implemented in the wearable's microcontroller (uC) in order to increase the detection time and accuracy.

Fig. 5 depicts the details of the SDR algorithm. The algorithm uses the received data from the gyroscope and the accelerometer sensors. In order to remove any erroneous data points and noise introduced by the sensors, each of six data sets is passed through a moving average (smoothing) filter with a window size of 250. The filtered data points (*ax, ay, az, gx, gy, gz*) are then used to calculate the RMS values:

$$(i)_{RMS} = \sqrt{ix^2 + iy^2 + iz^2}/3\ , \qquad (1)$$

where *(i)* represents the RMS value for the accelerometer measurements *(a)* or gyroscope measurements *(g)*. For each new window *n*, the calculated RMS value is compared with the previous RMS value, *n-1*. If the difference is larger than a designated threshold value (TH_{i_RMS}), then the counter, $Count_i$, is incremented:

$$if\ |i_{RMS}(n) - i_{RMS}(n-1)| > TH_{i\_RMS} \\ \rightarrow Count_i++; else \rightarrow Count_i = 0. \qquad (2)$$

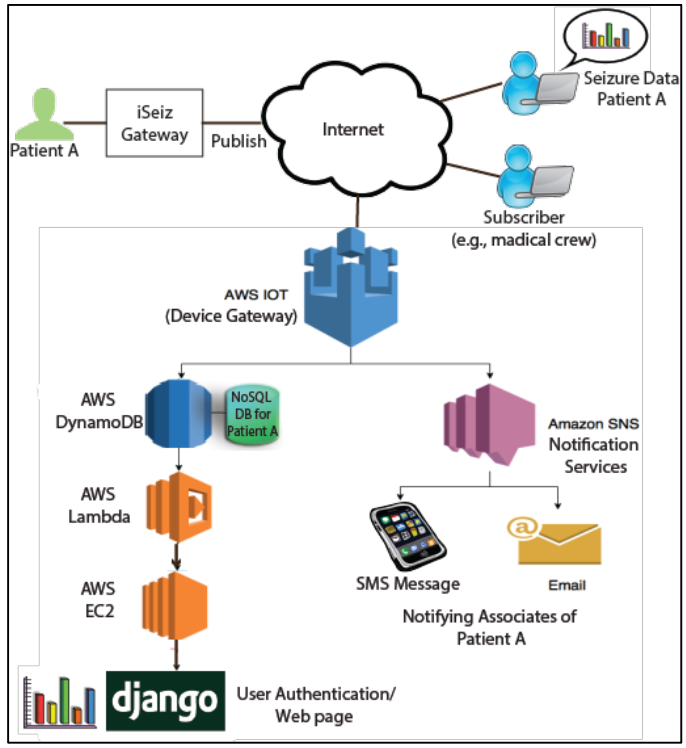

Fig. 4. AWS cloud architecture of the iSiez system.

We refer to $Count_i$ as the *persistent interval (PI)*. The SDA declares seizure condition if $Count_i$ value is larger than a set value, TH_{i_c}. We note that the algorithm requires two separate TH_{i_RMS} values, one for the accelerometer *(i=a)* and another for the gyroscope *(i=g)* data points. In our approach, we assumed $TH_{a\_c} = TH_{g\_c}$.

Clearly, the performance of the algorithm depends on the selection of TH_{i_RMS} and TH_{i_c} threshold values. These thresholds may be different from one patient to another.
We set TH_{i_c} to be equal to 20, indicating 20 consecutive moving windows. This is a good compromise between ensuring fast detection time and reducing any false triggering.

We note that using the proposed threshold-based SDA, various repetitive activities and hand movements can result in false positives. However, such cases can be ignored using the OK button on the wearable.

V. Experimental Setup and Results

In this section, we present the performance results obtained from the iSeiz system. We note that at this point we have very limited clinical test results and our SDA has only been tested on two patients. More clinical results are needed to evaluate the performance and accuracy of the seizure detection algorithm.

PCB Design: Fig. 6 depicts the bracelet's PCB design. The quarter-size PCB footprint (25 mm x 28 mm) was designed using Eagle software and manufactured by OSH Park [28]. The actual bracelet case is shown in Fig. 7. The wearable case was designed using Autodesk Fusion 360 CAD software and built by a 3D printer using polyactic acid (PLA) filament, a thermoplastic aliphatic polyester, commonly used in 3D printing. The overall cost of the hardware was calculated to be about $150.

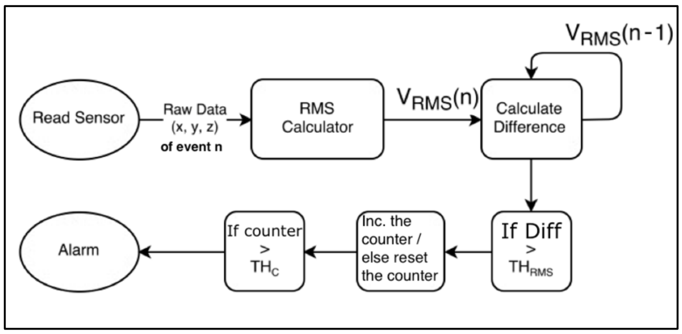

Fig. 5. Detainls of seizure detection algorithm.

Response Time: In our tests the exact notification time to send an SMS message (or email) to remote users within the U.S. highly depended on the network status. However, we never observed higher than 4 seconds of delay. Within the LAN, as shown in Fig. 1, the total measured delay to shut off electrical appliances following the detection of seizure was 100 ± 12 milliseconds.

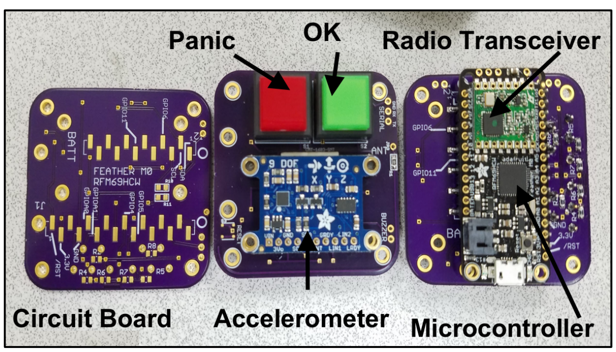

Fig. 6. PCB design for the bracelet.

Seizure Detection Algorithm: The iSeiz bracelet was tested on two female patients with severe mal gran seizure epilepsy; we refer to them as P_A and P_B. In each case the device was securely strapped on the right hand of the patient. The data from both IMU sensors, was sampled by the microcontroller every 250 milliseconds, and only the filtered RMS data was transmitted to the Gateway module. For each patient, we recorded the received data for two consecutive days in order to evaluate the system performance.

Fig. 8 shows the recorded RMS accelerometer reading for P_A. The top part of this figure depicts the off-line spectral centroid of the RMS data, a_{RSM}, for about 100 seconds as defined in (1). Note that referring to the results from the spectrogram analysis, it is evident that the P_A is experiencing some abnormal movements; in the figure the brightness indicates the presence of an abnormal rhythmic hand movement. The off-line spectral centroid is used to demonstrate the characteristics of the accelerometer data when seizure is detected.

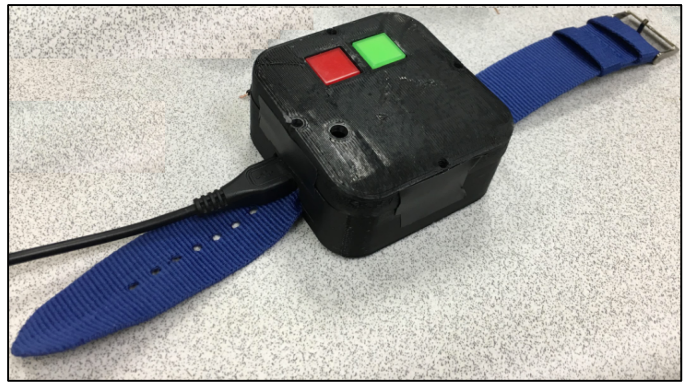

Fig. 7. iSeiz wearable bracelet prototype (4cm x 4cm x 2cm) being charged.

Fig. 8 also depicts a snap shot of a_{RMS} recorded from P_A. We note that obtaining a_{RMS} and using it as the onset detection parameter, as suggested by (2), is significantly faster and less computationally intensive, compared to using FFT.

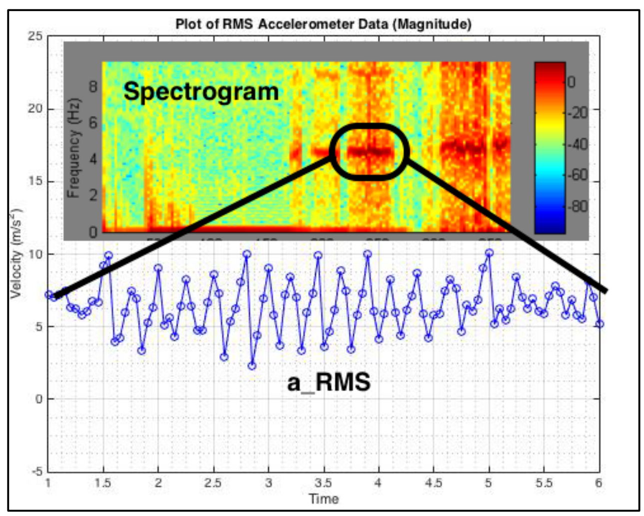

Fig. 8. Accelerometer sensor data recorded for P_A.

Fig. 9 depicts the web graphical representation of the data received from P_B and recorded in AWS database server. Each data point is time stamped and coded ranging from 1 to 8. The description for each code is shown in Table 1. For example, Code 8 indicates that the device is active. Code 7 represents a seizure activity, whereas Code 1 indicates that the OK button was pressed. A persistence Code 7 suggests a true seizure condition. On the other hand, a Code 7 followed by Code 1 suggests false alarm. Multiple cases of Code 7 conditions indicate the length of the seizure activity.

Table II depicts the number of times iSeiz system reported false positive under various simulated test conditions, (e.g., falling, walking) using the Seizure Detection Algorithm with and without the Persistent Interval (PI), as described in (2). An example of a *repetitive action* is using a screw driver or scrubbing a plate. We note that SDA without PI simply refers to the case where the calculated RMS (as shown in Fig. 5) is compared with a given threshold value (TH_{i_RMS}).

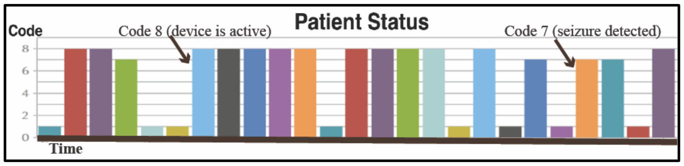

Fig. 9. Patient B (P_B) status as appears on the web site.

TABLE I. CODE DESCRIPTION.

Code	Description
1	OK Button was pressed
2	Panic button pressed
7	Seizure detected
8	Device is active
3-6	Reserved for future.

TABLE II. SUMMARY OF TEST RESULTS.

TASK TYPE	# of False Alarms using SDA with PI	# of False Alarms using SDA without PI
Falling (*n*=40)	2	13
Walking (*n*=30)	0	4
Jogging (*n*=30)	0	3
Sleeping (*n*=20)	0	2
Repetitive action (*n*=32)	1	8

Each task type in Table II was repeated 20-40 times, indicated by *n*. For example, we repeated the *Falling* test 40 times. Using SDA with PI, in two instances the system falsely detected seizure condition. This can be compared with 13 instances of false alarms when PI was not utilized in the SDA. Overall, the results in Table II clearly demonstrate the advantage of implementing the PI. It must also be noted that while performing a repetitive action the SDA/PI incorrectly generated false alarm one time. Our results indicate that during actions such as normal sleeping, walking, or jogging conditions the SDA/PI was never falsely triggered.

VI. CONCLUSIONS

In this paper, we presented a proof-of-concept wearable prototype that can detect specific seizure activity, namely generalized tonic clonic, in epilepsy patients. This work focused on two important areas: (1) designing a robust and computationally low intensive real-time seizure detection algorithm, and (2) utilization of a scalable cloud-based data management system to record, analyze, and visualize the received seizure data. More clinical testing is required to evaluate the reliability and accuracy of the proposed seizure detection algorithm. However, the presented limited results indicate that the algorithm can in fact offer promising results. Furthermore, our proposed approach in utilization of a secure cloud-based database to record seizure data from various epilepsy patients appears to be practical and efficient, particularly for collaborative diagnosis. Our next step is to conduct more clinical tests to evaluate the performance and accuracy of the seizure detection algorithm. Furthermore, it is important to understand the performance of iSeiz if the bracelet is placed on different locations on the body to capture various movements. We also intend to further integrate and miniaturize the wearable part of the system.

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