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An Electroencephalographic Recording Platform for Real-Time Seizure Detection

Bryan L. McLaughlin, Laura J. Mariano, Srinivasamurthy R. Prakash, Alex L. Kindle, Andrew Czarnecki, Mo H. Modarres, Alex Rotenberg, Tobias Loddenkemper, Ali Shoeb, Steven C. Schachter

Abstract— **There are currently no clinical devices that can be worn by epilepsy patients who suffer from intractable seizures to warn them of seizure onset. Here we summarize state-of-the-art therapies and devices, and present a second-generation hardware platform in which seizure detection algorithms may be programmed into the device. Bi-polar electrographic data is presented for a prototype device and future implementations are discussed.**

I. Introduction

Approximately fifty million people worldwide suffer from epilepsy. Thirty percent do not respond to two or more epilepsy medications and suffer from chronic and frequently life-long pharmacologically intractable seizures [1, 2]. For this population of patients, the possible occurrence of incapacitating seizures without warning seriously affects the quality of life and their ability to function normally. Further, this population is especially prone to injury and sudden unexpected death in epilepsy (SUDEP). Clinical options for this group range from surgical removal of the seizure focus if it can be clearly identified, or seizure management by polypharmacy, ketogenic diet, vagal nerve, or brain stimulation. However, the ability to detect the onset of a seizure is necessary to effectively manage the disease. Newer therapeutic devices provide means to intervene when a seizure occurs, either by delivering drugs, or by using neurostimulation [3]. Reliable and rapid seizure onset detection is key to effective intervention. An early warning could also alert patients and caregivers to seek safety or provide assistance in situations where effects of the seizure could be life threatening.

One clinical metric for successful epilepsy treatment, whether in a clinical trial or clinical practice, is a reduction in seizure frequency and severity as reported by the patient [4]. However, patients frequently forget or are not aware of seizures, and recollections of seizure frequency and severity are inaccurate [5, 6]. The testing of new epilepsy therapies are thus constrained to epilepsy monitoring units (EMUs) or monitoring the clinical effects of a therapeutic change [5, 7]. Accordingly, there is an unmet clinical need for continuously tracking patients' seizure frequency and severity. In this paper, we present a prototype ambulatory seizure detection warning system in a behind-the-ear earpiece device.

II. Seizure Detection Platforms

Refractory seizures can be observed electrographically from intracranial or non-invasive EEG. Figure 1 demonstrates a non-invasive ambulatory EEG system with scalp electrodes secured to the scalp and a data recorder positioned in a backpack [8]. In practice, a mechanical fixative is always required to maintain electrode electrical contact and position, and head-caps, netting, colloidon glue, or adhesive tape are typically used.

Investigative research and medical devices have focused on implantable nerve stimulation for the vagus nerve, deep brain stimulation of anterior thalamic nucleus, and Responsive Neuro-Stimulation (RNS) for the cortex among other sites [9]. These devices either respond to detected seizures in a closed loop paradigm or operate in an open loop a scheduled stimulation pattern regardless of timing of seizures. Without exception, these require invasive surgeries and most require electrodes positioned on the brain through a burr hole or craniotomy. There are known surgical complications [10].

A small number of implanted devices detect seizures in real-time, using signal classifier algorithms from *intracranial* electrical recordings. Examples include NeuroVista's seizure likelihood device and NeuroPace's Responsive Neuro-Stimulation (RNS) devices [11]. In the case of RNS, a physician retrospectively tunes detection parameters while in an EMU. NeuroVista's seizure

Figure 1. Scalp electrodes are applied with tape and are connected to an ambulatory EEG recorder located in a backpack.[8]

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B.L. McLaughlin, L. J. Mariano, S. R. Prakash, and M. H. Modarres are with the Charles Stark Draper Laboratory, Cambridge, MA 02139, USA (617-258-4003; email: blm4003@draper.com).

A. Kindle is with Worcester Polytechnic Institute, 100 Institute Road, Worcester, MA 01609

A. Czarnecki is with Northeastern University 360 Huntington Ave., Boston, Massachusetts 02115.

A. Rotenberg and T. Loddenkemper are with Department of Neurology, Children's Hospital Boston, 300 Longwood Ave Boston, MA 02115

S. C. Schachter is Professor of Neurology at Beth Israel Deaconess Medical Center, 330 Brookline Ave Boston, MA 02215

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likelihood device records from cortical electrodes and wirelessly transmits data to a belt worn recorder which performs signal processing of seizure state.

In summary, all of the current electrographic approaches rely upon recorded cortical electrical signals acquired invasively and electrical stimulation applied invasively to abort seizures. However, physicians and researchers are investigating less invasive sensing modalities such as temporal oxygen saturation, electrodermal skin response, body temperature, and actigraphy to identify patterns of the individual sensors that are associated with seizures [12-14]. On one hand, electrographic information is arguably the only signal with predictive information about seizure onset, compared to actigraphy, for example. On the other hand, additional sensors may help reduce false positives in automated seizure detection. Regardless, a reliable, extracranial EEG seizure detection system is an unmet clinical need and is not available.

III. Algorithms For Seizure Detection

A key performance metric for the success of a seizure detection algorithm is its ability to recognize the onset of a seizure event with minimum latency. Rapid and accurate detection are a requirement for delay-sensitive therapeutic interventions and alarm systems. In addition, accurately recognizing the end of a seizure epoch allows the system to report the number, frequency and duration of seizures. The system we are developing directly integrates the detection algorithm with the signal acquisition hardware, allowing for real-time monitoring of the EEG signals for signs of seizure onset. This "Intelligence-at-Sensor" design approach has been described in a few studies (see [15-17] for example) but is still relatively under-utilized in EEG-based applications. In this approach, computational complexity and resource demands of the algorithm have to be balanced against the complexity, power, and usability of device hardware.

The detection algorithm we are developing utilizes machine learning techniques to design a decision function that can classify a segment of multi-channel EEG data as either "seizure" or "non-seizure". This algorithm is an implementation of a subject-specific approach to detector design. EEG, video, and other physiological data from the patient are recorded in a clinic or EMU, and are examined by a neurologist to identify seizure and non-seizure signal segments. These exemplars are used to train a classifier that is optimized for recognition of each patient's unique electrographic seizure signature. It has been shown that subject-specific onset detection algorithms outperform non-specific versions in terms of latency, sensitivity, and specificity [18, 19].

Our implementation uses a Support Vector Machine (SVM) classifier [20] trained on spectral and temporal features extracted from the annotated signals recorded in the clinic. This particular classifier has demonstrated state-of-the-art performance in several seizure detection algorithm applications [15, 19, 21, 22]. The training of the algorithm will be performed offline due to the computational complexity of the SVM optimization routine; however, it has been shown that the resulting decision function can be ported to the hardware platform and applied to incoming data in real-time with minimal power consumption [18].

Real-time extraction of features for the classifier is the most computationally demanding algorithm component that will be integrated into the device. Candidate features that can be used to infer the presence of seizure activity include spectral energy in a range of frequency bands and coefficients of wavelet decomposition [18, 19, 22]. Algorithms for computing these feature vectors lend themselves to efficient implementation on dedicated hardware using an FPGA and a low-power microcontroller.

To leverage contextual sensor uniqueness for seizure detection, we anticipate the earpiece will contain sensors for additional physiological signals such as ECG, pulse oximetry, acceleration, etc. However, it remains to be determined which sensors and EEG electrodes carry the most value for the classification algorithm. Channel selection will reduce overall computational load and minimize the analog and digital power costs associated with processing data from each channel. The selection of a reduced set of sensors and features can be customized to each subject. While the in-clinic recording of the training data is conducted using a high density array of electrodes, an off-line statistical analysis of the algorithm performance using subsets of sensors and features will identify the optimal configuration for each patient.

IV. Earpiece Platform For Real-Time Seizure Detection And Electronic Seizure Diary

In this work, we are developing a prototype hardware platform in a behind-the-ear style package, whereby scalp electrodes may be attached as shown in Figure 2. The proposed earpiece recorder contains the analog front-end and portable signal processing hardware required to detect seizures from recorded EEG. Future versions would notify the patient with an audible alarm, and transmit the data to a networked handheld device, caretaker, or computer terminal for analysis.

Fig. 3 and Fig. 4 show a block diagram and printed circuit board of the second generation seizure detection hardware platform. A Texas Instrument ADS1298, 8-channel bio-electrical amplifier is operated at a sample rate

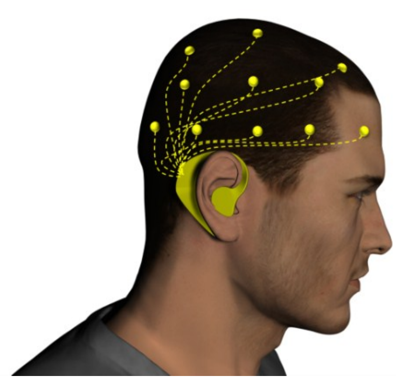

Figure 2. Proposed 10-20 ambulatory EEG recorder with seizure detection, electrographic data storage, and a patient warning alarm.

of 500 samples per second, giving a data rate of 13,500 bytes per second, including overhead. The ADS1298 communicates with the ACTEL Igloo Nano AGLN250 over a 4 MHz SPI interface. The FPGA can both process this data internally for seizure detection and retransmit it to the MSP430 for data logging. The MSP430 configures the ADS1298 over SPI through the FPGA, setting options such as the number of channels to record, the amplifier gains for each channel, the sample rate, and other initialization parameters. The MSP430 also logs all EEG data in a binary format in a flat file system on the microSD card using the SD SPI command set. Additionally, this EEG data can be streamed to an attached computer, where custom software will convert the binary format into formatted text for storage or processing. This custom software is also required to access the contents of the microSD card due to the custom file system. The FAT32 file system was explored so data could be imported using an arbitrary card-reader and windows mass storage device interface. However, the additional complications of implementing a full file system in an embedded environment mitigated the benefit, so a custom file format is used for embedded power optimization. Future versions may leverage a custom low-noise amplifier chip, a different version of the TI ADS family, and additional amplifier channels. This prototype system costs less than $100 in parts, and has a battery life in excess of 24 hours in record-only mode; seizure detection power consumption has not yet been quantified. The electrodes are not the focus of this project, and are simply standard wet electrodes. They are detachable from the device and could

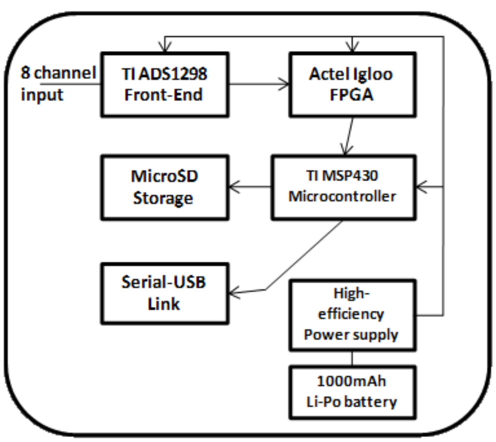

Figure 3. Block diagram of an 8-channel prototype seizure detection printed circuit board.

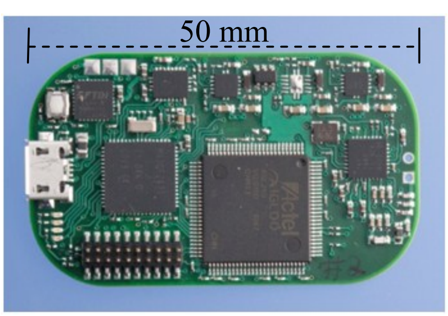

Figure 4. A second generation 8-channel EEG recorder and seizure detection printed circuit board.

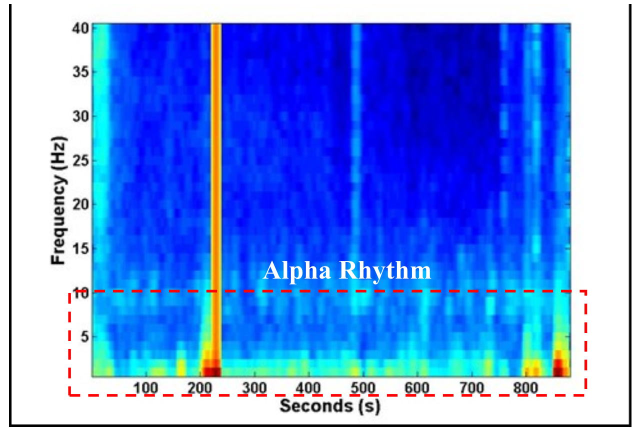

Figure 5. A spectrograph of bi-polar frontal lobe EEG data recorded from the prototype EEG recording platform using scalp electrodes.

be changed, if some superior alternative appeared. A ground electrode can be affixed behind the ear with the device. While it is not yet implemented, the ADS1298 supports electrode-off detection, which can be implemented to measure lead impedance.

Fig. 5 shows a time-frequency plot of a bi-polar frontal EEG recording performed on a patient sleeping. At t=0 and t>800 seconds, the electrographic recordings are broad spectrum, indicating alertness. A noticeable alpha rhythm is also present when the patient is asleep.

V. Conclusions and Future Work

We have developed a novel device for recording and storing EEG from a behind-the-ear device platform and verified an alpha rhythm using the device using eight recording channels. We envision several future implementations of the seizure-detection earpiece. Firstly, the platform firmware will be configured with a real-time patient specific seizure detection algorithm so that the device may be used on ambulatory patients. Ongoing work is being performed to reduce PC-based seizure detection algorithms into FPGA firmware. Secondly, the earpiece could contain sensors that detect physiologic changes associated with seizures (e.g., heart rate, pulse-oximetry, head-turn). The earpiece could wirelessly communicate with, for example, an actigraphy watch that provides electrodermal skin response information. The number of sensors, increased algorithm complexity, and duty cycle of powering sensors may have to be optimized to keep the overall battery size of the earpiece practical. Thirdly, we envision that the device will wirelessly trigger an abortive therapy such as VNS. Finally, we recognize that the current system relies upon gelled scalp disk electrodes which have constrained the use of EEG to single or few-day use. Thus, the classic short-term EEG recording limitation remains. To overcome this, we are developing a wireless version of the platform with invisible electrodes positioned underneath the scalp. Similar to a cochlear implant, electrodes would be cosmetically invisible under the scalp, and the behind-the-ear seizure detector could be worn for chronic seizure detection.

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