Multistage seizure detection techniques optimized for low-power hardware platforms

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ABSTRACT

Closed-loop neurostimulation devices that stimulate the brain to treat epileptic seizures have shown great promise in treating more than a third of the 2 million people with epilepsy in the United States alone whose seizures are currently nonresponsive to pharmaceutical treatment. Seizure detection algorithms facilitate responsive therapeutic intervention that is believed to increase the efficacy of neurostimulation by improving on its spatial and temporal specificity. Translating these signal processing algorithms into battery-powered, implantable devices poses a number of challenges that severely limit the computational power of the chosen algorithm. We propose a cascaded two-stage seizure detection algorithm that is computationally efficient (resulting in a low-power hardware implementation) without compromising on detection efficacy. Unlike traditional detection algorithms, the proposed technique does not explicitly require a “training” phase from individual to individual and, instead, relies on using features that result in distinct “patterns” at the electrographic seizure onset. We tested the algorithm on spontaneous clinical seizures recorded using depth electrodes from patients with focal intractable epilepsy and annotated by epileptologists at the University of Freiburg Medical Center, via the Freiburg database. The algorithm performs with a specificity and sensitivity of 99.82% and 87.5%, detecting seizures in less than 9.08% of their duration after onset. The proposed technique is also shown to be computationally efficient, facilitating low-power hardware implementation.

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1. Introduction

Rapid developments in the design and miniaturization of implantable devices to treat chronic disorders plaguing society today have provided a much needed supplement to patients who do not respond to traditional pharmaceutical treatments. In the realm of neurological disorders, epilepsy continues to remain one of the most dominant, next only to stroke, affecting more than 2 million Americans annually and close to 2% of the world’s population [1]. Seizures in approximately a third of this patient population remain nonresponsive to any known form of therapy today and therefore are potential candidates for alternative forms of therapy made possible by implantable devices [2–4]. Neurostimulation shows great promise as a means both to control and to mitigate the spread of seizures, from animal studies as well as several early-stage human trials [5,6]. The vagus nerve stimulator is currently the only U.S. Food and Drug Administration (FDA)-approved device that employs the principles of electrical stimulation (of the vagus nerve) to modulate seizure activity, and shows varying levels of efficacy in patient populations across the world [7,8]. Responsive neurostimulation, or the delivery of electrical stimulation triggered by the detection or prediction of an active seizure, has shown great promise in initial stages of evaluation [4]. Although its benefits over continuous or periodic stimulation are still being debated, it presents multiple benefits from a purely engineering perspective. Limiting the electrical stimulation to a temporally specific window (during an active seizure) and increasing the spatial sensitivity by stimulating the seizure focus add value to the implant by increasing battery longevity and also potentially by reducing the possibility of the neurons becoming acclimated to the stimulus. This phenomenon, known as stimulation-induced depression of neuronal excitation (SIDNE), has been extensively studied by McCreery and colleagues [9,10]. Another factor contributing to the complexity in designing such efficient closed-loop feedback systems to control seizure activity is the uncertainty surrounding when to stimulate to maximize efficacy. Although it is understood that most seizures start in a defined region of the brain before generalizing, the paths taken to generalization and the time for the same vary significantly from limited studies that have addressed this subject [6,11].

Seizure detection algorithms integrated onboard implantable devices allow researchers and clinicians alike to better understand the
spatial and temporal dynamics of seizures, by eliminating the need for transmitting multiple channels of neural data across a wireless link, which usually forms the bulk of the power consumption in the implant. By reducing full-bandwidth neural data down to only seizure episodes, it is possible to minimize the bandwidth necessary to wirelessly communicate with an external receiver, thereby dramatically improving battery longevity and practical utility of these implants in a clinical environment. More importantly, the integration of seizure detection algorithms on implantable platforms allows for the easy realization of such closed-loop devices that responsively trigger therapy on detection of an event, without having the need for an external signal processing unit to perform the computation. Although numerous seizure detection algorithms have been proposed in the past few decades, very few of these algorithms were intended for translation into low-power battery-powered implantable platforms, which present significant challenges because of their limited computational capabilities. In the past, our group has focused on this challenge and developed a number of techniques to adapt computationally intense algorithms into simple mathematical blocks that allow for straightforward hardware implementation with minimal computational resources [12–15].

In 2010, we proposed a two-dimensional design space to evaluate seizure detection features on a dual scale of detection efficacy and hardware power consumption, a metric rarely considered when quantifying algorithm performance [13]. Mathematical, algorithmic, and circuit-level design techniques may be applied to trade off computational complexity without impacting detection efficacy significantly, which is easily visualized using the design space proposed [13]. The combination of multiple features is typically used to construct seizure detection algorithms. As Osorio and Frei point out, any method to detect epileptic seizures has to make use of amplitude (or power), frequency, or both metrics in some combination [16]. In this article, we describe a multistage technique to accurately detect the onset of electrographic seizures with a combination of time-domain and frequency-domain analyses with features that are optimized for low-power hardware implementation. The proposed algorithm employs validated hardware-optimized features such as wavelet energy, variance, and coastline and does not require a defined “training” or threshold-setting phase. Most detection algorithms are highly sensitive to chosen detection thresholds, requiring elaborate analyses and ROC plots to evaluate the impact of thresholds on efficacy besides making it harder to optimize on individual patients.

In the next section, we introduce the stages that make up the algorithm and briefly describe the proposed hardware implementation for the same. Section 3 describes the methods used to process and analyze the seizure data to validate the proposed algorithm’s efficacy. Results from testing the algorithm on the Freiburg Seizure database are described in Section 4, which is then concluded with implications for future work surrounding implantable epilepsy prostheses.

2. Seizure detection algorithm

The proposed algorithm is implemented using a cascaded two-stage structure. The first stage is intended to filter the data into the desired band of interest using a discrete wavelet transform-based filtering block. Discrete wavelet transforms (DWTs) preserve both time- and frequency-domain information contained in the signal efficiently while allowing for modular and computationally simple hardware architecture. The wavelet filtering stage is followed by a “feature extraction block” that constantly computes hardware-optimized mathematical features from the filtered neural data to generate a vector pattern. In the case of this algorithm, two linear time-based features (coastline and variance energy) were used based on their capability to accurately identify high-frequency, lower-amplitude morphologies often observed at the electrographic seizure onsets. The feature extraction block returns a vector pattern that is then evaluated by the pattern detector. Given that both features used in this implementation show a marked increase during the electrographic seizure onset window, the pattern detector monitors the vectors for a constant increase over a series of consecutively sampled windows. The magnitude of the increase itself is not taken into consideration, as is the case with traditional thresholding-based detection algorithms. The pattern detector monitors the feature vectors for a consistent increase in both extracted features and detects the onset based on this criterion, in an attempt to mimic human visual inspection of EEG records. Fig. 1 is a block diagram representation of the described seizure detection approach.

2.1. Wavelet filtering

The discrete wavelet transform decomposes the signal into “approximation” and “detail” coefficients corresponding to the lower- and higher-frequency components in each temporal band chosen. In this implementation, a Debauchies-4 (DB4) mother wavelet was used to obtain the approximation and detail coefficients at each decomposition stage of the DWT. In detecting seizures, it is often desired to monitor a narrow band of frequencies for morphological changes captured by extracting features such as variance and energy to accurately demarcate seizure onsets from other shorter, sporadic artifacts more commonly seen in full-bandwidth EEG data. Realizing such accurate narrowband filters typically requires an extremely high order FIR/bandpass filter which makes it infeasible to realize on a low-power hardware platform. The interleaving property of the DWT, which downsamples the signal by half at every stage, allows for the use of relatively wideband filters to circumvent this problem.

In the past, our group has reported a low-power hardware implementation of a DWT filter used in an application to detect electrographic seizures from implanted depth electrode recordings from kainate-treated rats [15]. In their study, Markandeya et al. used Mallat’s algorithm to implement a cascaded DWT architecture that relies on a novel multiplier-less FIR filter realization using approximation of coefficients to eliminate the need for any hardware multipliers [17]. The architecture of the wavelet engine employed in this algorithm is described in Fig. 2.

The algorithm presented in this article employs a three-stage DWT engine with the same architecture described in Fig. 2. By employment of the multiplier-less filter design techniques described by our group in [18], Mallat’s architecture is adapted to obtain third-order wavelet decomposition of the raw neural signals, allowing for an extremely narrowband filter realization without a prohibitively high order. Most of the electrographic seizure activity was observed in the third approximation band (corresponding approximately to the 0.5–16 Hz band). In hardware, this is realized by employing multiplier-less filters as described by the authors in [15].

2.2. Feature extraction

The filtered data are then passed through a pattern detection stage that identifies electrographic seizure patterns much like visual inspection, by trending extracted features. In this algorithm, a combination of variance and coastline features are used to determine the onset of a seizure event. The variance and coastline features have previously

![Fig. 1. Block diagram of the proposed seizure detection technique.](image-url)
been reported to have potential in identifying electrographic seizures and are described by Eqs. (1)–(4) [13].

2.2.1. Variance

\[
\text{VAR}_k = \frac{1}{N} \sum_{i=1}^{N} (x[i + (k-1) * N] - \mu_k)^2
\]

(1)

\[
= \frac{1}{N} \sum_{i=1}^{N} x[i + (k-1) * N] - \mu_k^2
\]

(2)

where

\[
\mu_k = \frac{1}{N} \sum_{i=1}^{N} x[i + (k-1) * N]
\]

(3)

and \( k \) stands for the \( k \)th window, respectively.

2.2.2. Coastline

\[
\text{CL}(k) = \sum_{i=1}^{N} \text{abs}[x[i + (k-1) * N] - x[i-1 + (k-1) * N]]
\]

(4)

In this implementation, we employ an adapted version of the variance feature, described by the equation

\[
\text{VAR}_k = \frac{1}{N} \sum_{i=1}^{N} (x[i + (k-1) * N] - \mu_{k-1})^2
\]

(5)

This allows for its hardware implementation to use only one multiplier, significantly reducing the power consumption. The impact of this approximation is verified to be negligible to the efficacy of the feature itself, as captured by its relative location on the two-dimensional design space described in [13].

Fig. 3 shows the impact of this approximation on the feature’s efficacy (top) and hardware power consumption, based on the implementation shown below it.

Fig. 4 plots an electrographic seizure event annotated with identified onset along with the filtered version and the variance and coastline features extracted from the same. As seen in Fig. 4, both the coastline and variance features show a marked increase during seizure onset. The pattern detector is designed to accurately identify these changes, defined to detect seizures of a specific morphology. To reduce false detections from sporadic fluctuations in the extracted feature vectors due to the noisy nature of the data, a smoothing block is employed that computes a moving window average of the extracted feature vector, much like a median vector. In hardware this is implemented using a circular first-in–first-out (FIFO) buffer with a length that is a power of 2, allowing for easy division of the summed result. Fig. 5 illustrates a block diagram that realizes this functionality on hardware. In this algorithm, we use a combination of coastline and variance features extracted from the wavelet band-pass filtered neural signal to flag a detection. A sustained increase in both the smoothed coastline and variance features over consecutive computed windows triggers a detection, eliminating the need to set a threshold that is traditionally associated with seizure detection algorithms in the literature.

A feature extraction block is typically employed in an implementation that allows for the clinician to use multiple features to identify specific seizure morphologies that may be patient specific. In the past, we have presented a thorough analysis of a selected set of time-and frequency-domain features, optimizing them for low-power hardware implementation. A fully programmable, low-power feature extraction microchip was fabricated on the TSMC-65 nm CMOS process that implemented the algorithms described in [13]. The microchip may be employed with the proposed algorithm to select a set of features used in the pattern identification block, to broaden the capabilities of this technique and improve its specificity. Fig. 6 shows a layout screen capture of the designed microchip incorporating the described hardware-optimized features. The chip has been fabricated on the TSMC 65-nm bulk-Si process with an area of 0.068 mm², consuming an average power of 95 μW from a 1-V power supply. The microchip implements mathematical features
such as coastline, variance energy, energy, and nonlinear energy on the same processor with programmability to turn on desired features.

3. Data analysis methods

Data were obtained from the online database owned by the Seizure Prediction Project Freiburg, Germany [19]. The database consisted of invasive long-term EEG recordings from 21 patients with medically intractable focal epilepsy. Informed consent was obtained from each patient, and the retrospective analysis of data was permitted by the ethics committee, Medical Faculty, University of Freiburg. Each of the 21 patients had seizures that primarily originated in either the hippocampus or the neocortical regions of the brain. However, some patients had seizures that originated in both the hippocampus and

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![Feature extraction for a typical electrographic seizure](image1)

**Fig. 4.** Feature extraction for a typical electrographic seizure: (a) Plot in time of ~120 seconds of data containing an electrographic seizure marked with the onset and the end of the seizure marked with a red line. (b) Output of the wavelet filter. (c, d) Plot of coastline and Hjorth variance features on the same time scale as data with a sharp increase marked with the dashed arrow at seizure onset.

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![Top: Hardware implementation of the moving window average of the extracted feature vector. Bottom: Effect of the moving window average vector implemented in software in eliminating potential false positives from sporadic fluctuations in the coastline feature vector due to spikes/noise.](image2)

**Fig. 5.** Top: Hardware implementation of the moving window average of the extracted feature vector. Bottom: Effect of the moving window average vector implemented in software in eliminating potential false positives from sporadic fluctuations in the coastline feature vector due to spikes/noise.
the neocortical region of the brain. EEG data were recorded using a Neurofile NT digital video EEG system with 28 channels and a 16-bit analog-to-digital converter operating at a sampling rate of 256 Hz for most patients (512 Hz for some, where noted) and was bandpass filtered between 0.1 and 128 Hz. In addition, a 50-Hz notch filter was also implemented to reduce the noise.

The database consisted of at least 24 hours of continuous interictal recordings for 13 of the 21 patients. For others, multiple recordings were combined to obtain a total duration of 24 hours of interictal data. In addition to the interictal recordings, multiple 1-hour-long files containing seizures were available for each patient, with the number of the files depending on the number of seizures from each patient, where the number of seizures varied from 2 to 5. Each recording was obtained using six electrodes, at least three of which were located proximal to the identified seizure focus. The algorithm was evaluated by parallel running it on the three focal channels and performing a logical “OR” of each of the detection signals to obtain the final detection signal. This study focuses on data from five patients who were selected purely on the basis of number of seizures. Characteristics of the patients investigated in this study are given in Table 1. For details on the other patients not evaluated in this study, the reader is directed to [20].

4. Results

Analysis was performed on data obtained from five patients with intractable focal epilepsy as explained in Section 3. For each patient, 24–25 hours of interictal data and 4–5 hours of ictal data containing spontaneous seizures were available. Data amounting to approximately 146 hours were analyzed. The average data obtained from each patient were approximately 29.2 hours (± 0.45 hours), with 29 hours being minimum and 30 hours being maximum. No further processing or modifications were applied on the recorded data besides breaking the large continuous data into smaller snippets ~1 hour each for ease of processing (no chunks of data were eliminated as a result of this). The Freiburg EEG database had seizures annotated and the annotated scores were used for analysis. A total of 24 seizures were observed in the five patients. The mean seizure duration was observed to be 1.89 minutes (± 0.61). Details of patient data are summarized in Table 2; the reader is also directed to [20] for the complete surgical procedure and protocols used in obtaining data.

The described algorithm was implemented on MATLAB, and the scored data files were processed individually to record algorithm detections. These were then compared with the scored seizure onsets by a second MATLAB script that computed the false-positive rate, sensitivity, detection delay, and specificity of the algorithm. As described in Section 2.1, third-order wavelet decomposed coefficients were used at the input to filter data. The third approximation band captured the activity of interest (seizure onsets) while minimizing higher-frequency artifacts. The approximation coefficient was directly upsampled and employed in the algorithm without having to reconstruct the original signal using an inverse DWT. Markandeya et al. describe the hardware architecture that facilitates this operation [15]. For this study, the Hjorth variance and coastline features were implemented to detect an electrographic seizure. A detection was flagged only if a consistent increase was seen in both the Hjorth variance and coastline parameters over seven windows of data, with each window consisting of 256 data points. Our analyses also indicated that using a larger or smaller window size impacted only detection delay and not the sensitivity significantly.

Table 1
Characteristics of the five patients who were evaluated in this study.

<table>
<thead>
<tr>
<th>Patient ID</th>
<th>Sex</th>
<th>Age (years)</th>
<th>Seizure type</th>
<th>H/NC</th>
<th>Origin</th>
<th>Electrodes</th>
<th>Number of seizures analyzed</th>
<th>Interictal duration (h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>M</td>
<td>14</td>
<td>SP, CP</td>
<td>NC</td>
<td>Frontal</td>
<td>g,s</td>
<td>5</td>
<td>24</td>
</tr>
<tr>
<td>2</td>
<td>M</td>
<td>44</td>
<td>CP, GTC</td>
<td>NC</td>
<td>Temporo/occipital</td>
<td>g,s</td>
<td>5</td>
<td>24</td>
</tr>
<tr>
<td>3</td>
<td>F</td>
<td>41</td>
<td>CP, GTC, H</td>
<td>NC</td>
<td>Fronto/ temporal</td>
<td>d,s</td>
<td>4</td>
<td>25</td>
</tr>
<tr>
<td>4</td>
<td>F</td>
<td>50</td>
<td>SP, CP, GTC</td>
<td>H</td>
<td>Temporal</td>
<td>d,s</td>
<td>5</td>
<td>24</td>
</tr>
<tr>
<td>5</td>
<td>M</td>
<td>13</td>
<td>SP, CP</td>
<td>NC</td>
<td>Temporal</td>
<td>g,s</td>
<td>5</td>
<td>25</td>
</tr>
</tbody>
</table>

SP, simple partial; CP, complex partial; GTC, generalized tonic–clonic; H, hippocampal origin; NC, neocortical origin; d, depth electrode; g, grid electrode; s, strip electrode.
The algorithm was provided with the time stamps of seizure events for files containing seizures to calculate metrics like false positives (FP), true negatives (TN), true positives (TP), detection delay, average detection rate (ADR), and sensitivity (SEN) and specificity (SPC) of the algorithm. The numbers obtained from each file were averaged out to determine the overall detection efficacy of the algorithm for each patient. The definitions of the above metrics were taken from previously published literature [13]. In this study, the false positives were defined to be the percentage of time during baseline where detections were flagged by the algorithm, where baseline activity was considered to exist where the data showed no electrographic epileptiform activity. True positives and false negatives, on the other hand, were defined as the number of detections or misses out of the total number of seizures present in a data set. The detection delay was defined as the time interval between electrographic onset of the seizure and a detection triggered by the algorithm. In this study, the detection delay was normalized by dividing it by the total duration of the seizure to result in a normalized percentage time after electrographic onset that the seizure is detected. Such a metric makes the number more easily comparable with others in the literature, as seizure durations may greatly vary both within and across patients. To define the average detection rate, sensitivity, and specificity of the algorithm, we used the equations

\[
ADR = \frac{\text{SEN} + \text{SPC}}{2}
\]

\[
\text{SEN} = \frac{\text{TP}}{\text{TP} + \text{FN}}
\]

\[
\text{SPC} = \frac{\text{TN}}{\text{TN} + \text{FP}}
\]

Results obtained by analyzing continuous data recorded from the five patients were recorded in a tabular format and are summarized in Table 3. All results in Table 3 were obtained by running continuous data obtained from five patients with focal intractable epilepsy. The data included seizures as well as baseline EEG activity. A total of 24 seizures were observed in the five patients, of which 21 seizures were detected by the proposed algorithm. The average sensitivity and specificity of the algorithm for all patients were 87.5 and 99.82%, respectively, and it detected the electrographic onset within 9.08% of the seizure duration. Fig. 7 is a box and whisker plot that quantifies the percentage delay to detection for each patient. Table 2 also reports duration of each seizure observed for each patient. Seizure durations followed by asterisks in Table 3 were missed by the algorithm.

5. Discussion

The proposed detection algorithm detects morphologies of electrographic seizures characterized by high-frequency, lower-amplitude onsets progressing to larger amplitudes with a downward shift in the dominant frequency. The average sensitivity and specificity were found to be 87.5 and 99.82%, respectively. The normalized detection delay was 9.08%, and the algorithm spent an average of 0.2% of the time in false warnings. Average duration of seizures showed significant variation both within and between the five patients, as expected. This is one of the main reasons we define detection delay as a normalized percentage of time after electrographic onset. The algorithm was tested on a database hosted by the University of Freiburg [19], and detected 21 of 24 seizures from – 146 hours of continuous data analyzed from five patients. We observed that all of the seizures missed by the detection algorithm showed uncharacteristically sudden changes in morphology unlike all the other scored seizure events. The designated wavelet band failed to accurately identify these onsets, causing the feature vectors to change sporadically instead of showing a progressive pattern as was the case with the detected seizures. Algorithms are typically “thresholded” or tuned to fit a particular patient’s seizure morphology, while we do not perform any such “training” on this proposed algorithm. It is possible that a careful choice of features based on a patient-specific morphology would significantly impact sensitivity. Fig. 8 depicts one of the three seizures that were missed by the proposed algorithm along with the plots of its associated Hjorth variance and the coastline features.

The sensitivity reported was obtained by dividing the number of seizures detected by the total number of seizures identified in the patients (cumulatively 21/24). This results in a highly discretized distribution for sensitivity (can only take values that are multiples of 1/24). In the literature, some algorithms have been evaluated on a window-to-window basis, resulting in a more continuous distribution of possible sensitivity values.

False positives were also evaluated as “percentage time spent” rather than an absolute number, as recommended by Mormann et al. [21], because this removes the dependency on window size which could significantly impact the reported false-positive rate. For instance, a window size of 500 on 1000-sample data would result in only 2 false positives.

Table 2

<table>
<thead>
<tr>
<th>Patient ID</th>
<th>Sex</th>
<th>Age (years)</th>
<th>Number of seizures</th>
<th>Total duration of data (h)</th>
<th>Total duration of seizure time (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>M</td>
<td>14</td>
<td>5</td>
<td>29</td>
<td>7.77</td>
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<td>M</td>
<td>44</td>
<td>5</td>
<td>29</td>
<td>7.87</td>
</tr>
<tr>
<td>3</td>
<td>F</td>
<td>41</td>
<td>4</td>
<td>29</td>
<td>14.43</td>
</tr>
<tr>
<td>4</td>
<td>F</td>
<td>50</td>
<td>5</td>
<td>29</td>
<td>10.13</td>
</tr>
<tr>
<td>5</td>
<td>M</td>
<td>13</td>
<td>5</td>
<td>30</td>
<td>6.98</td>
</tr>
</tbody>
</table>

Table 3

<table>
<thead>
<tr>
<th>Patient ID</th>
<th>Total number of seizures</th>
<th>Number of detections</th>
<th>Average time spent in FP (%)</th>
<th>Seizure duration (s)</th>
<th>% Time to detection (delay)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5</td>
<td>4</td>
<td>0.1598</td>
<td>109,119,117,95,26</td>
<td>12.21</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>4</td>
<td>0.2924</td>
<td>39,168,86,88,91</td>
<td>4.01</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>4</td>
<td>0.3005</td>
<td>71,359,287,149</td>
<td>3.29</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>5</td>
<td>1166</td>
<td>171,94,97,88,158</td>
<td>13.74</td>
</tr>
<tr>
<td>5</td>
<td>5</td>
<td>4</td>
<td>0.00523</td>
<td>91,68,70,68,122</td>
<td>12.15</td>
</tr>
</tbody>
</table>

Note. Missed seizures are marked by asterisks.
positives at the most, whereas an algorithm with a window size of 10 could result in as many as 100 false positives. Interpreting the results of a binary decision algorithm on a complex data set such as epileptic EEG is not trivial and makes it hard to draw comparisons to performance of algorithms reported on different data sets.

Fig. 8 is snapshot of a missed seizure, with the onset zoomed in the inset. Although the coastline feature is able to accurately track this onset, the variance energy feature does not track it until much later in the progression of this short seizure, resulting in no detection. Choosing the right features to extract from wavelet-filtered data determines the efficacy of the technique, if it is to be optimized specific to a patient. In the work described here, we did not perform any patient-specific training. The ASIC described in earlier sections allows for the caregiver to program any combination of hardware optimized features and employ it as a low-power hardware feature extraction module.

The algorithm offers a number of benefits including low-power hardware implementation in a custom application-specific integrated circuit (ASIC) and moves away from the traditional thresholding approach that requires subject-specific training datasets. The automated “pattern-detector” approach mimics visual inspection used to score seizures and is shown to perform with comparable efficacy to traditionally thresholded algorithms. A multi-algorithm feature extraction processor has been designed and fabricated on 65-nm silicon by our group and is currently under laboratory testing for implementation in battery-powered low-power implant platforms. The proposed algorithm may be implemented on the processor by selecting the features required (coastline and variance energy) from the programmable module. This custom processor also allows for the implementation of multiple morphology detectors by using a different set of feature extractors for identifying various rarer morphologies of electrographic seizures sometimes seen in the same patient. The features chosen have been thoroughly evaluated for both performance and hardware efficacy, and optimized for ultralow-power operation. The development of computationally simple yet efficacious and programmable algorithms such as the one described in this article allows for rapid translation of these algorithms into implantable, battery-powered platforms. Besides their application in designing closed-loop treatments for epilepsy, such low-cost algorithms also provide significant benefits as data compression tools running onboard multichannel neural data acquisition devices that are commonly reported in the literature today [22–24].

Developments in silicon chip design combined with microelectrode fabrication techniques now make it possible to record spatially and temporally selective neuron activity from multiple recording sites simultaneously, while wirelessly communicating with an external receiver [22,24]. Such implants allow researchers and clinicians alike to better understand the spatial and temporal dynamics of seizures, to improve the efficacy of alternative therapeutic interventions such as electrical stimulation. Wireless transmission is usually the most power-consuming part of such implantable devices, which has a direct impact on battery longevity and, thereby, its practical utility when translated into the clinical environment. The integration of seizure detection algorithms onboard these implants reduces the amount of data required to be transmitted externally to only time stamps/chunks with detections, allowing for monitoring from multiple channels while still being powered by a battery [24]. Developments in algorithm hardware co-design pave the way for next-generation deep-brain implants that have potential to revolutionize our understanding and treatment of chronic neural disorders.

**Conflict of interest statement**

This work was made possible by funding in part from Cyberonics, Inc., the pioneers of the vagus nerve stimulation therapy. Dr. Raghunathan was with the Center for Implantable Devices, Purdue University and is currently employed as a Senior Research Scientist at Cyberonics, Inc. Dr. Irazoqui is the Director of the Center for Implantable Devices, Purdue University, and consults with Cyberonics, Inc.

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