# A Low Power System with EEG Data Reduction for Long-term Epileptic Seizures Monitoring

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***Abstract*—Long-term monitoring of epilepsy patients require low-power systems that can record and transmit electroencephalogram data over extended periods of time. Since seizure events are rare, long-term monitoring inherently results in large amounts of data that are recorded and hence need to be reduced. This paper presents an ultra-low power integrated circuit implementation of a data reduction algorithm for epilepsy monitoring, specific to seizure events. The algorithm uses line length of the electroencephalogram signals as the key discriminating feature to classify epochs of data as seizure or non-seizure events. It is implemented in AMS 0.18 $\mu$m CMOS technology and its output is connected to a Bluetooth Low Energy transceiver to wirelessly transmit potential seizure events. All the modules of the algorithm have been implemented on chip to use small number of clock cycles and remain mostly in an idle mode. The algorithm, on the chip, achieves 50% of data reduction with a sensitivity of 80% for capturing seizure events. The overall power consumption of the chip is measured to be 23 $\mu$W while the full system with wireless transmission consumes 743 $\mu$W. The results in this paper demonstrate the feasibility of a long-term seizure monitoring system capable of running autonomously for over two weeks.**

***Index Terms*—Epilepsy, seizure detection, wearables, low-power biomedical system, electroencephalography.**

## I. Introduction

EPILEPSY is a major neurological disorder affecting over 50 million people worldwide [1]. It often manifests in the form of spontaneous seizures and has a profound impact on the day to day lives of those effected by it. These seizures, ranging in severity, can cause physical and psychological damage and may even be fatal in some cases [2]. The healthcare costs associated with the monitoring, diagnosis, and treatment of epilepsy are very high. It is estimated that the total indirect costs of epilepsy amount to over 15 billion USD annually in the United States [3]. Similarly, high costs have been reported in the EU [4] and the UK [5]. As a result, access to these expensive procedures and treatments is severely limited.

Diagnosis of epilepsy involves the use of electroencephalography (EEG) for monitoring brain activity [6]. During this, several electrodes are placed on the scalp of a patient in order to detect an abnormal activity in the brain. This provides useful information such as the type and extent of seizure acitivity, that is needed to decide on the right form of treatment. For the purpose of diagnosis, however, monitoring seizure events at the right time is very difficult. Patients are often admitted and monitored for a few days in hospitals in an attempt to *catch* the seizure event on an EEG trace. However, in most cases the onset of an epileptic seizure is not predictable nor does it recur frequently. Therefore, long-term EEG monitoring of epileptic patients is preferred such that EEG data over few months can be collected and observed. Long-term monitoring of epileptic patients has been floated as an idea over the last three decades and potential benefits of this approach in detecting difficult seizure events as well as its clinical use have been discussed in great detail [7]–[10]. Recently, it has also been reported that long term monitoring of epileptic patients would reduce dependence on self-reporting and hence improve diagnosis [11].

While the idea of long-term EEG monitoring has been floated before, it has only been made possible with the recent advancements in technology. The approach necessitates devices that can be used by patients at the convenience of their homes without requiring major lifestyle changes. The concept of wearable EEG has been previously proposed and the constraints associate with the design of such devices discussed [12]. Based on this, it can be concluded that a wearable EEG device for seizure monitoring needs to have the following features: long battery life, low power consumption, light weight, and easiness of use.

While these features impose severe constraints on the design of a wearable device, they are also a springboard for research and innovation. As an example, for long-term usage a battery with large capacity is needed. However, the small size and weight requirements of the device prohibits the use of a battery that is physically large in size. These two competing requirements mean that a small battery must be used without having a negative impact on the usability of the system. The result of this is that the electronics and processing algorithms have to be designed in such a way that they consume small amounts of power while being able to satisfy all the functional requirements.

In the context of long-term epilepsy monitoring, a large amount of data is generated of which very little is useful i.e. the interesting sections of data are the ones where a seizure event is happening and these events are rare. A single channel EEG, sampled at 256 Hz with a resolution of 10-bits, will generate over 2.3 GB worth of data for a period of 90 days. This may either be stored on the system using flash memory or wirelessly transmitted to a receiving device. While on-system storage *may* result in lower power consumption in certain

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cases, wireless transmission of data has several advantages. It allows real-time access to data enabling remote monitoring and also saves space on the circuit board since no flash memory is needed. Additionally, since the receiving device is not constrained by the same low-power requirements, complex algorithms can be implemented on it to parse the EEG data in real-time.

It has been shown that wireless data transmission is a viable option, in terms of power consumption, if data to be transmitted can be reduced [13]. This makes even more sense in the case of epilepsy monitoring where useful data is sparse. The two common approaches of reducing data being transmitted are described as follows.

- *Compress data prior to transmission.* Using this approach, all sampled data is compressed and transmitted. Depending on the compression scheme, a reduction of up to 60-80% can be achieved. On the receiving end, data must be de-compressed and analysed either automatically or manually for the presence of seizures.
- *Discontinuous transmission of interesting data.* This approach relies on an algorithm prior to data transmission such that only data with increased likelihood of containing seizure information is transmitted. This approach has been extensively detailed in our previous works [12], [14] and can result in up to 50% data reduction while preserving most seizure events.

While the first approach uses compression algorithms to send all recorded data, the second approach uses intelligent methods to process EEG signals so that only the relevant sections are transmitted. These may include detection of the seizure onset, seizure termination, seizure event itself or just the sections of data with higher likelihood of the presence of seizure events. In this paper, we use the latter approach to develop a light-weight algorithm for identifying data sections with seizure events, which in turn acts as the core method for reducing the amount of data that needs to be transmitted. This data reduction algorithm is then implemented on an integrated circuit and subsequently interfaced with a Bluetooth Low Energy (BLE) [15] transmitter to wirelessly stream EEG data whenever indicated by the algorithm. The choice of the transmitter is primarily dictated by the fact that it provides maximum compatibility with most smartphones and tablets that can act as a receiver. This reduces the overall development cost for such a system while making it easier to use by the patients. Fig. 1 shows an overview of the proposed system. The figure depicts a single EEG channel as an input, which is ideal for wearable use. However, the digital processor shown has been designed to process data from four EEG channels.

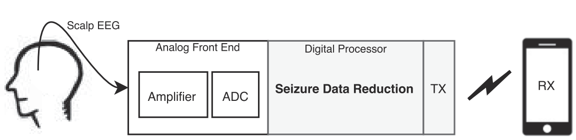


Fig. 1. An overview of the proposed seizure data reduction system.

The work presented in this paper discusses the design and implementation of a wearable epilepsy monitoring system with discontinuous data transmission. Section II presents a review of the different methods relevant to seizure data reduction. In Section III, the data reduction method used in this paper is briefly discussed followed by a description of database and methods used for its verification. Section IV details the circuit-level implementation of the algorithm, explaining the design choices for each module within the system. The results of this implementation, its classification accuracy, and a full system demonstration is presented in Section V.

## II. Seizure Detection and Monitoring Overview

Automatic identification of seizures from EEG recordings is a very active research area as it helps to reduce manual workload, quickly detect seizures, and allows for the possibility of real-time feedback for nerve stimulation applications. Other signals from the brain such as intracranial EEG (iEEG) or electrocorticogram (ECoG) provide more information regarding a seizure thanks to their higher resolution. However, they are invasive, and are generally used with patients at a more advanced stage when they are not responding to medications or prior to surgery. Hence, in this paper, the focus is on real-time data reduction while preserving seizure events using scalp EEG signals. This is achieved by using a light-weight seizure-specific algorithm for compressing data that is implemented on an integrated circuit (IC). An algorithm for IC implementation for a wearable system differs from others due to the processing constraints (discussed earlier). Hence, this section presents a review of only such methods that have either been implemented on an integrated circuit level or designed for wearable applications. For an in-depth review of seizure detection methods, the reader is directed to [16] and [17]

Verma et al. [18] presented one of the earliest complete integrated system on chip (SoC) for seizure detection. Their system followed the algorithm described in [19] to extract features from single-channel EEG. These features were then read out, requiring physical connection to the chip, and classified off-chip using a support vector machine (SVM) classifier. Implementing the same algorithm, Yoo et al. [20] presented an eight-channel EEG-based seizure onset detecion system featuring data acquisition, feature acquistion, and classification - all on the same chip. Additionally, their system included a 64KB RAM to store EEG data whenever a seizure event is detected, and could be read via an external interface. Further improving the system, Altaf et al. [21] presented a 16-channel EEG-based seizure onset and terminal detection system. It included analog circuitry for sampling data from 16 channels, feature extraction engine, and a linear SVM-based classifier for detecting seizure onset and termination events. It also included 64KB RAM on chip to store seizure events, potentially storing events up to 10 seconds in duration (when sampling at 256 Hz with a resolution of 12 bits). In a further modification to this system, Altaf and Yoo [22] used a non-linear SVM classifier to design an 8-channel seizure detection system, including 96KB of on-chip memory to save seizure events .

Salam et al. [23] proposed an implantable seizure onset detector by processing intracranial EEG signals. The advantage of this approach is the availability of much cleaner signals. However the chip would require a surgical procedure to be implanted. In their system, the onset of seizure would be indicated by the output of logic gates which in turn could be used to drive an alarm system. This system was later improved with programmable parameters for extracting seizure onset information and presented in [24]. Chen et al. [25] develop an eight-channel SoC for real-time seizure detection with intracranial EEG signals. Their system was designed to be used for closed-loop seizure suppression using electrical stimulation whenever a relevant event was detected. This system also included an on-chip wireless transceiver to transmit the intracranial EEG signals continuously for real-time monitoring. Another integrated circuit for intracranial EEG-based seizure detection was presented by Shoaran et al. [26]. In this circuit, feature extraction involved computing the line length [27] on a signal compressed using compressive sensing [28]. The advantage of this approach is that low computational resources are needed to process a compressed signal, provided the compression scheme is not too expensive in the first place. Do Valle et al. [29] also presented an 8-channel implantable seizure detector and counter capable of operating in either a diagnosis or counter mode. In diagnosis mode, this system used a sampling rate of 1280 Hz, and required a seizure to be identified by a doctor in order to train the system. In counter mode, it sampled at a rate of 256 Hz, and recorded a seizure event upto 10 seconds in duration on flash memory. An external device is then required to retrieve this data from the implanted chip.

Sridhara et al. [30] designed a low-power processor based on an ARM Cortex-M3 microcontroller for use in various medical applications. The authors demonstrated its usage for seizure onset detection by using EEG data sampled off-chip and loaded on the SoC using an SPI interface. Although not clear from this paper, there is 32KB of data memory available on the system, part of which could be used to store EEG data. Qian et al. [31] designed a programmable analog front end for sampling EEG data in seizure detection applications. This sytem can be programmed by entering commands via SPI interface. The interface is also used to read the digitised data samples which could then be processed off-chip using a low-power microcontroller. Finally, Yang et al. [32] addressed the need for fast and low-power processing in ICA-based seizure detection algorithms. They presented the design of an ICA processor that would extract features from EEG signals that would subsequently be used for seizure classification.

It can be seen from the brief overview above that the different seizure-related circuits and systems have been designed to target various applications within the broad area of seizure detection. Some of these focus on real-time seizure detection for diagnosis while others aim for real-time treatment of epilepsy through closed-loop instantaneous seizure suppression and symptom alleviation. In this paper, our aim is to develop a system for long-term wearable use to monitor EEG signals and record them for potential seizure events that are reviewed by expert clinicians. From the point of view of patients, in order to make it usable for them, such a system needs to be comfortable and easy to use. Thus it needs to be small in size, light in weight, record as much data as possible without requiring an external device to manually download or read from the chip, and operate over long period of time without requiring frequent battery charging. From the point of view of clinicians, the key issue with long-term monitoring is the huge amounts of data that need to be reviewed by them. We tackle all of these issues in this paper by creating a low-power integrated circuit that has an intelligent data reduction algorithm which reduces the amount of data that is transmitted by discarding most of the background EEG. This approach not only reduces the expert analysis time but also reduces the amount of data to be transmitted thus reducing the power consumption of the transmitter, consequently reducing the size and increasing the operating lifetime of the system. In comparison to the other systems discussed above, our approach is fundamentally different since we are not aiming to carry out automated diagnosis but instead aiming to make the system more usable and also make it easier for neurologists to analyze relevant data and perform the diagnosis.

Long-term usage requires minimum disruption to the patient in order to encourage them to use the system. It is, therefore, important to use smaller number of channels, record as much data as possible without requiring an external device to manually download or read from the chip, and have a system that operates over long period of time. Although reducing the number of channels is not always an option since, in many cases, different areas of the brain need to be monitored, it still makes sense to use lower number of channels and only increase them when needed. Thus, the system presented in this paper focuses on single EEG channel for analysing potential seizure events, although it can accommodate input from four channels. It also transmits data wirelessly whenever an event of interest has occurred. Additionally, it uses Bluetooth Low Energy P2P [15] for wireless communication allowing seamless integration with most modern smartphones and tablets and hence does not require any additional accessory for reading data from the chip. The rest of this paper explains the algorithm that is implemented for data reduction, details the design of each block within the algorithm, and presents the validation of the circuit-level implementation of this algorithm.

## III. Material and Methods

### A. Seizure Data Reduction Algorithm

A block diagram of the seizure data reduction algorithm, to be implemented on chip, is shown in Fig. 2. It shows the different stages of the algorithm that are required to intelligently detect sections of data containing seizures, and thus to be transmitted.

The first stage of the algorithm involves certain preprocessing steps to improve the signal quality that gets processed. At this stage, the first step consists of a high-pass filtering stage with a cutoff frequency of 0.16 Hz [33] in order to remove dc offset from the signal. Next, a third-order Bessel low-pass filter with a cutoff frequency of 10 Hz is used to limit the signal bandwidth in the frequency of interest for seizure detection. The resulting signal is consequently downsampled to 20 Hz which also helps to reduce the processing workload in other blocks further down the pipeline.

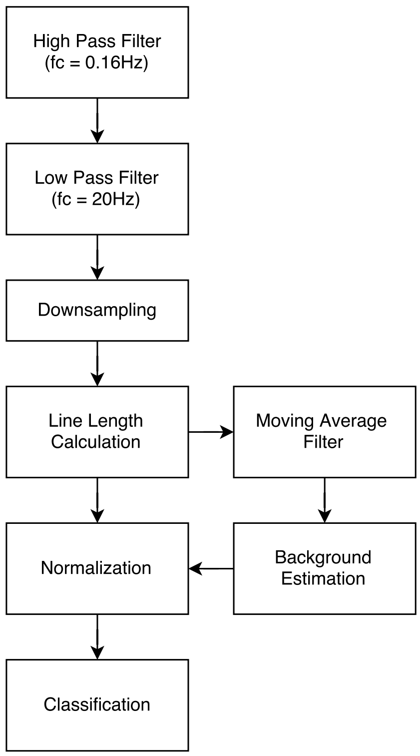


Fig. 2. Block diagram of the seizure data reduction algorithm.

The filtered EEG signal is then used to extract a single time-domain feature known as the *line length* [27], that is highly useful in discriminating between seizure and non-seizure events [34]. It is also advantageous since it has a low computational complexity and is thus suitable for use in low-power and wearable systems. In this algorithm, the line length is continuously computed for the downsampled signal in non-overlapping epochs of 2 seconds as follows:

$$F(e) = \sum_{k=1}^{S} |w(k-1) - w(k)| \tag{1}$$

where $F(e)$ is the line length for an epoch $e$, $w$ is the downsampled signal, and $S$ is the total number of samples in a 2-second epoch.

Since the energy level in the EEG signal varies considerably between different people, it is important to normalize the line length in order to make it subject-independent. Normalization is performed by dividing the computed line length with an estimation of the background activity, $z(e)$. This is computed by applying a moving average filter on the $B$ previous line lengths, as shown below, while $\lambda$ is a decay constant and $z(e-1)$ is the background estimate calculated for the previous epoch.

$$\begin{aligned} z(e) =& (1-\lambda) \times \text{Moving Average}\{F(e-1) \cdots F(e-B)\} \\ &+ \lambda \times z(e-1) \end{aligned} \tag{2}$$

The background estimate, $z(e)$, is calculated over the last 64 epochs (approximately 2 minutes). The line length is normalized by dividing the feature $F(e)$ with the background estimate $z(e)$, resulting in the normalized feature $A(e)$.

$$A(e) = F(e)/z(e) \tag{3}$$

Finally, the normalized feature is compared against a detection threshold $\alpha$. This threshold is a variable parameter in this algorithm that can be modified in order to tune the overall sensitivity.

$$DF_n(e) = \begin{cases} 1, & \text{if } A(e) \geq \alpha \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

If $A(e)$ exceeds this threshold, the epoch $e$ being processed is classified to contain a seizure event and a flag is raised to transmit this signal. Otherwise, the epoch data is discarded and no signal gets transmitted. If more than one EEG channels are used, the processing pipeline remains the same, however a decision stage is used to collate the classification results from individual channels.

### B. *Database*

The performance of the data reduction algorithm has already been validated in a study consisting of 168 hours of EEG data obtained from 21 adult subjects, sampled at a frequency of at least 200 Hz [14]. This data was obtained from recordings at the Epilepsy Society (UK), Katholieke Universiteit Leuven (Belgium) [35], [36] and Freiburg University Hospital (Germany). While the algorithm performance has already been validated, its on-chip implementation necessiates certain changes that can accumulate error during various numerical computations. Hence, its performance after implementation will be re-validated using the same dataset.

## IV. Hardware Implementation

Fig. 3 shows the six main blocks of the seizure data reduction algorithm: 1) high pass filter; 2) low pass filter; 3) line length calcuation; 4) moving average filter; 5) classification; and 6) wireless transmission; together with other supporting blocks. In a complete system-on-chip implementation, an analogue front end would be needed to digitize the EEG signals at some point either before the filters or after, depending on the chosen architecture. The hardware implementation described in this paper does not include an analogue front end. A review of front end systems suitable for this application can be found in [37].

In Fig. 3, the digitized EEG signal is first processed using a series of filters. Following this, the line length is continuously computed until the sample count reaches 400 (equivalent to 2 second epoch with a sampling frequency of 200 Hz). A moving average filter is used to compute the background activity which subseqeuently normalizes the line length. This normalized value is compared with a detection threshold, alpha, which can be can be varied by passing the relevant control bits from an external interface. The output of the chip is connected to a Nordic nRF52832 Bluetooth Low Energy (BLE) transceiver [38] via an SPI interface. A control signal from the chip to the MCU acts as an enable signal for the microcontroller (MCU). While an epoch is being processed it

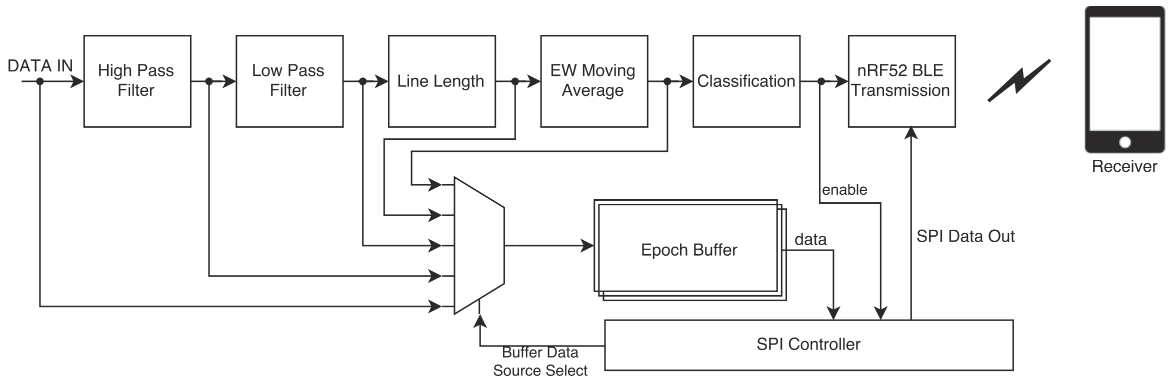


Fig. 3. Top-level block diagram of the algorithm implementation on chip showing the main modules.

is also buffered in a set of registers so that it can be transmitted if deemed as potential seizure at the classification stage.

The following sections explain the hardware implementation and the architecture of the individual processing blocks in detail.

### *A. High Pass Filter*

The high pass filter used in the algorithm is a simple first order IIR filter with the following difference equation.

$$y[k] = 0.9975x[k] - 0.9975x[k-1] + 0.9950y[k-1] \quad (5)$$

where $x$ and $y$ are the input and output samples, to and from the filter, respectively. For the hardware implementation of this filter, three multiplication operations are needed. However, since the filter coefficient for $x[k]$ and $x[k-1]$ are the same, the result of the multiplication with $x[k]$ can be stored and used in the next cycle. Hence, overall, two multipliers and two adders are used for this filter, together with two registers with a depth of four that are needed to store the values of the previously multiplied input and the filtered output sample from up to four channels of input data. Both multipliers are implemented to perform 16-bit integer multiplication since the filter coefficients are represented as 16-bit fixed-point numbers. The filter is gated at the input and starts its computation only when a valid sample is available for each channel. When its operation is complete, the result is registered and a control signal raised to indicate the availability of valid data at its output.

### *B. Low Pass Filter*

The low pass filter is a third order Bessel filter which is realized as a cascade of first and second order filters, as shown in the equations below.

$$\begin{aligned} u[k] &= 0.1000y[k] + 0.1000y[k-1] + 0.7423u[k-1] \\ v[k] &= 0.1000u[k] + 0.1999u[k-1] + 0.0999u[k-2] \\ &\quad +1.5452v[k-1] - 0.6283v[k-2] \end{aligned} \quad (6)$$

This filter involves several more arithmetic operations than its predecessor in the processing pipeline. Hence, it is implemented as a multi-cycle operation such that the multipliers and adders can be shared between clock cycles. This implementation uses three multipliers and two adders with multiplexers at their input to select the correct filter coefficients and data input based on the clock cycle. Similar to the High Pass Filter, this filter also uses registers with a depth of four to accommodate data from up to four input channels.

When a valid sample is available at its input, this block is enabled and the first stage of filtering is performed in the first clock cycle. This intermediate result is buffered and used in the next two cycles to complete the process. At the end of the third clock cycle, a valid signal is raised to indicate that data is ready to be used. Additionally, since the signal is downsampled by a factor of 10, a counter is used to set the valid signal at the output after every 10 samples only.

### *C. Line Length Calculation*

The line length for each epoch is calculated as the sum of the absolute differences between the subsequent samples in the epoch, as described in Eq. (1). This is implemented in hardware using an accumulate operation where the difference gets added to a registered value, that is inialized with zero at the beginning.

Fig. 4 shows a block diagram of the line length calculation block, implementing the following equations.

$$\begin{aligned} p[k] &= v[k] - v[k-1] \\ q[k] &= abs(p[k]) \\ F[e] &= sum(q[k].....q[k-n]) \end{aligned} \quad (7)$$

where $F[e]$ is the line length for an epoch $e$ and $n$ is the number of samples in the epoch.

At the start of the calculation for each epoch, a register is initialized to zero. At the same time, another register to hold the previous sample value is also reset to zero. When a valid data sample is available at the input, the absolute difference between the new sample and the previous sample is computed and added to the value already stored in the `line_length` register, for each channel. The new sample is also used to replace the value in the register holding the previous sample for the corresponding channel, so that it could be used in the next iteration. After the values are updated a counter is

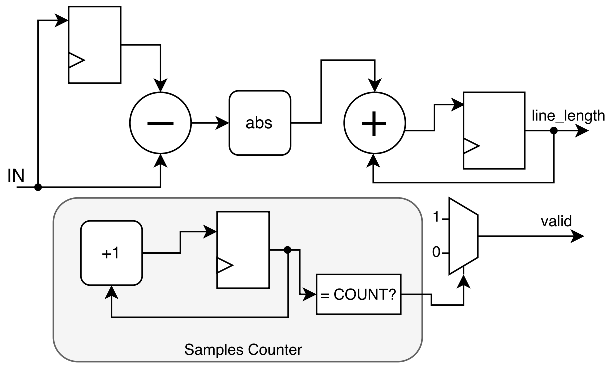


Fig. 4. Block diagram of the Line Length Calculation module.

incremented to track how many samples in the given epoch have been received and processed. Once the required number of samples for an epoch are processed, a valid signal is raised indicating that the line length value in the register is ready to be used.

The architecture used in this implementation allows the line length calculation as soon as a new sample is received rather than having to wait for all the samples in an epoch (which would also require more registers to buffer the filtered epoch).

### D. Moving Average Filter

The moving average filter is used to calculate the background estimate, $z(e)$. For its implementation, an exponentially weighted moving average (EWMA) filter is used. This approximates the response of the linear moving average filter very well and has no negative impact on the performance of the algorithm. A further benefit of using this filter is that it is much simpler to implement in hardware and obviates the need for a buffer to hold all the previous line length values. The EWMA filter is represented by the following equation.

$$M[e] = M[e-1] + \gamma(F[e] - M[e-1]) \tag{8}$$

where $M$ is the output of the filter and $\gamma$ is the weighting parameter. In this case, $\gamma$ is set to be $1/64$.

The corresponding hardware implementation of this filter is shown in Fig. 5. It requires just one shifter which performs the divide-by-64 operation, one adder, and one subtractor. An additional register is used to store the output value, from each channel, that is needed in the next iteration when the previous value of the filter output is needed.

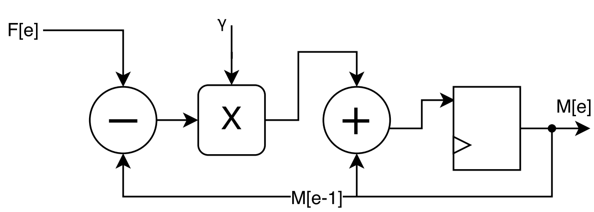


Fig. 5. Block diagram of the EWMA Filter module.

The output of the EWMA filter together with its previous value, are used to estimate the background activity using a decaying memory, as shown in Eq. (2).

### E. Classification

The final stage of the algorithm is classification which involves assigning an epoch with a seizure or non-seizure label. For this, the line length calculcated as $F[e]$ is normalized by dividing with the background estimate $z[e]$, and the resultant value compared against a detection threshold $\alpha$.

$$\frac{F[e]}{z[e]} > \alpha \tag{9}$$

The threshold $\alpha$ is a fixed value that is used for classifying potential seizure events. It is not a patient-specific parameter and, instead, controls the sensitivity of the algorithm i.e. it determines how much of data is to be transmitted. Hence, it is implemented to be a variable parameter that can be selected at the start to allow user control based on desired accuracy.

Fig. 6 depicts the classification stage where a multiplexer is used to select $\alpha$ from sixteen different values of stored in the ROM by writing to a register via the SPI interface. Eq. (9) is rearranged so that a fixed point multiplier can be used rather than a divider and a comparator is used to determine the result of the following result.

$$F[e] > \alpha \times z[e] \tag{10}$$

If the epoch being compared is classified as a seizure, a control signal is asserted high. This indicates the epoch buffer to begin serial transmission of data, and remains high until the epoch has been written out to the MCU. If four EEG channels are used, the control signal is asserted high when the epoch is classified as seizure in at least two of the input channels.

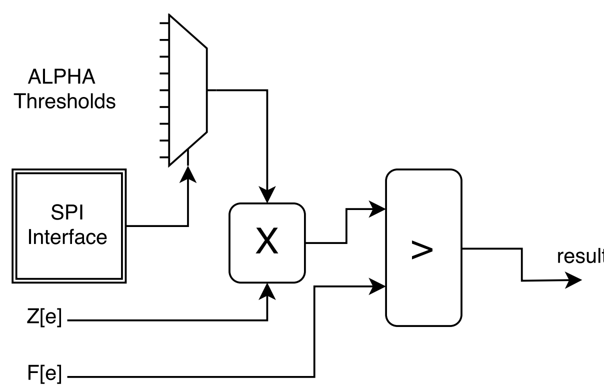


Fig. 6. Block diagram of the Classification module.

### F. Epoch Buffer

The epoch buffer is simply a register bank to store the samples of the epoch that is currently being processed. This is to ensure that this data is available if the epoch is classified as a potential seizure and can therefore be wirelessly transmitted. If the detection stage returns a non-seizure classification, data in the epoch buffer is discarded. Additionally, the input of the epoch buffer is multiplexed such that it can store either raw data or the output from any one of the stages in the processing pipeline. The epoch buffer stores samples from one EEG channel only. If multiple input channels are used, the channel from which samples need to be stored can be selected by the user.

## G. SPI Interface

SPI is a synchronous serial communication interface popularly used in embedded systems and microcontrollers to transfer data between devices. Typically, it consists of one master device and one or more slave devices. The master device configures the communication clock frequency and initiates the transfer of data. SPI has spearate lines to transmit and receive data. When a bit of data written by the master, it is received and read by the slave which then responds by writing a bit of data to the master. Hence there is always two-way synchronous communication between the devices.

In this work, an SPI module has been added to the seizure data reduction chip to enable communication with the BLE transceiver. This module has been designed to act as a slave while the BLE transceiver will act as the master device. It writes and reads the most significat bit (MSB) first. Reading happens on the first clock edge (low-to-high transition), while writing happens at the following edge. While these parameters are fixed on the slave, the master device (which is a microcontroller in this case) is configurable and can be adjusted to match the communication requirements. Additionally, the module is used only when there is data to transmit and is disabled to save power when no transmission is needed.

The SPI module on the chip is used to transmit data in the epoch buffer to the nRF52832 microcontroller. It also receives data from the microcontroller to configure what needs to be written into the epoch buffer, select the detection threshold $\alpha$, and to enable debug mode where a known sequence of data is written into the epoch buffer.

## H. Wireless Transmission

In order to wirelessly transmit EEG data with potential seizures, a number of different transmission protocols can be used. In this work, however, we opted to use Bluetooth Low Energy (BLE) for two reasons:

1) It allows maximum compatibility with existing devices such as smartphones, tablets, and laptops due to which no special receiver needs to be designed.
2) The BLE standard has been specifically developed for applications that require sporadic transmission transmission making it a natural fit for our algorithm.

For BLE transmission, the Nordic nRF52832 chip is used which includes an ARM-Cortex M4 processor with integrated BLE radio in a small form factor. This microcontroller is programmed to receive serial data from the chip using its SPI interface and to transmit it using the BLE radio. This happens only when there is valid data available at its input interface, indicated by a signal from the chip. At other times the microcontroller stays in a low-power sleep mode waiting for a valid data event to happen at its input, thereby consuming little active power when inactive.

## I. Data Receiver

To receive data from the BLE transmitter, an Apple iPhone 6 is used to act as a receiver. An application has been written to discover the specific BLE peripheral device and establish a connection with it. This application logs the time and stores data in a file whenever it receives EEG samples. A list of seizure events with timestamps is presented to the user to select and view the EEG data for a particular event. In continuous transmission mode, it is possible to save and view the data being received in real-time. It is also possible to simulatenuously upload the received data to a cloud platform which can provide real-time and on-demand access to a healthcare practitioner and thus enable remote monitoring of seizure events.

# V. Results

## A. Classification Accuracy

The classification performance of the algorithm on chip has been validated by using the same database which was used previously in [14]. The database consists of over 168 hours of EEG recording from 21 different patients using 16 channels. It includes 34 marked seizure events with a total duration of 4150 seconds obtained from the Epilepsy Society (UK), Freiburg University Hospital (Germany) and Katholieke Universiteit Leuven (Belgium) [35], [36]. Of these 16 channels, Fp1-A2 is used to test the accuracy of the algorithm on chip. Digitized data from this channel of EEG recordings were stored on a SD card. The test setup, shown in Fig. 7, includes a microcontroller reading stored data from this SD card and passing this on to the chip mimicking the output of an analog-to-digital converter. The output of the chip is also connected to one of the inputs of this microcontroller to record the classification result. Whenever a valid output is available, it is indicated by an output signal from the chip that goes from low to high. This serves as an interrupt flag for the microcontroller to register the output and store it on the SD card. As a result, the sampled label for each processed epoch is stored on the SD card. The final results are then interpreted in two ways. First, the classification results are against the reference results in the database to obtain the algorithm classification performance on chip. Second, the results are compared against the algorithm performance in MATLAB (version 2015a) using the same EEG data as input to ascertain the differences occuring due to integrated circuit implementation. The entire test procedure was repeated for all the recordings using the sixteen different values of $alpha$ (detection threshold).

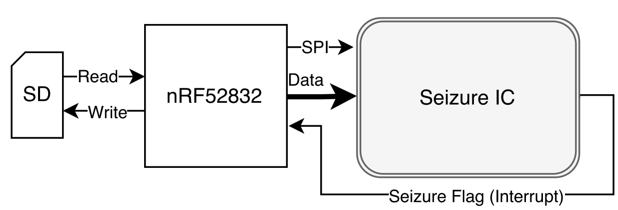


Fig. 7. Test setup where data from a SD card is loaded and used as input to the chip.

The classification performance of the algorithm are explained using the following performance metrics.

**1) Event Sensitivity**, which represents the fraction of seizure events that are correctly identified by the algorithm.

$$EventSensitivity = \frac{TP_{ev}}{TP_{ev} + FN_{ev}} \times 100\% \tag{11}$$

**2) Epoch Sensitivity**, which represents the fraction of 2-s seizure epochs that are correctly identified by the algorithm.

$$EpochSensitivity = \frac{TP_{ep}}{TP_{ep} + FN_{ep}} \times 100\% \tag{12}$$

**3) Specificity/Data Reduction**, which is the fraction of 2-s non-seizure epochs correctly rejected by the algorithm).

$$Specificity = \frac{TN_{ep}}{TN_{ep} + FP_{ep}} \times 100\% \tag{13}$$

In the equations above,

- $TP_{ev}$ is the number of correctly identified seizure events.
- $FN_{ev}$ is the number of seizure events missed by the algorithm.
- $TP_{ep}$ is the number of correctly identified seizure epochs.
- $FN_{ep}$ is the number incorrectly rejected seizure epochs.
- $TN_{ep}$ is the number of correctly rejected non-seizure epochs.
- $FP_{ep}$ is the number epochs incorrectly identified as seizure.

Note that two variants of the sensitivity metric are used here to highlight the performance of the algorithm for both seizure event and epoch detection. These are epoch sensitivity and event sensitivity. For epoch sensitivity, the ground truth is taken to be the total number of epochs enclosing all the seizure events marked by experts. It effectively measures the fraction of total seizure duration correctly identified by the system. In case of event sensitivity, the reference used is the total number of seizure events expertly marked in the test database. For its computation, a detection is condered to be a true positive event if there is an overlap of at least one epoch between the detected event and the corresponding seizure event in the reference.

The specificity is only for epochs and corresponds to data reduction in this case since any epoch correctly classified as non-seizure represents data reduction without any loss. The results from the chip showing the sensitivity against specificity are shown in Fig. 8 for the different 16 detection thresholds (0.2, 0.4, 0.6, 0.8, 1.0, 1.2, 1.4, 1.6, 1.8, 2.0, 2.2, 2.4, 2.6, 2.8, 3.0, 3.2).

These results show that the algorithm is able to detect up to 97% of seizure events with data reduction of 90%. For epoch-based metrics, it achieves data reduction of 50% while preserving 80% of seizure epochs across all seizure events from one EEG channel. In the ROC curve where the event sensitivity is 100%, the corresponding specificity is about 74%. This means that 74% of the epochs were correctly rejected as non-seizure epochs while 26% of the EEG epochs were transmitted. This corresponds to 44.3 hours of data (out of 168h of total recordings) being transmitted including 0.7 hours of seizure data. These results are consistent with those

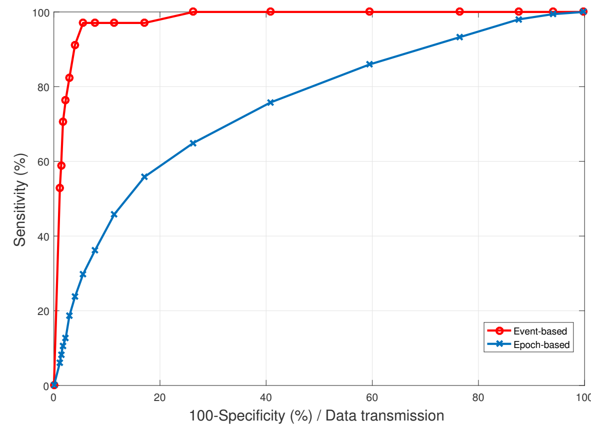


Fig. 8. Classification performance of the algorithm on chip.

previously discussed earlier in [14] where the performance metrics are also explained in further detail.

The classification performance of the chip was also validated against the reference algorithm in Matlab using the full database. Of the 304125 epochs tested with the 16 thresholds (4866000 epochs effectively), only 526 were misclassified on hardware (99.9892% accuracy). These were mainly due to the numerical differences resulting as a consequence of using 16-bit fixed-point as opposed to 64-bit floating-point arithmetic and an exponentially weighted moving average filter instead of the linear moving average filter. Further, only three seizure epochs were misclassified as non-seizure in this comparison. As a result there was virtually no difference in event and epoch sensitivities as well as specificity between the results obtained on hardware and in Matlab. This represents a very robust on-chip implementation after taking into considerations the chip-level trade-offs and fully validates its performance.

### *B. Patient-specific Performance*

The previous section showed the overall performance of the system using data from different patients using a single global threshold. However, the optimal threshold to achieve the best performance for individual patients may be different, as show in the patient-specific results in Table I. This difference in thresholds could be due to a number of reasons including the seizure location, data quality, filter settings on the recording eqipment, etc. For this reason, the proposed system has variable thresholds that can be changed to achieve the desired performance after deciding on the specific trade-off between sensitivity and the amount of data reduction. Further, it should also be noted that while the epoch sensitivity also differs for each patient, the event sensitivity for all patients is 100% i.e. all the seizure events were at least partially detected and transmitted.

### *C. Chip Measurements*

The algorithm is implemented on chip using the AMS 0.18$\mu$m process technology with 6 metal layers and measures 0.26 mm$^2$ in die area. It is powered using a single 1.8 V

TABLE I
PATIENT-SPEICIFIC PERFORMANCE OF THE SEIZURE DATA REDUCTION SYSTEM

| Patient | Threshold | Ep Sen (%) | Ep Spe (%) |
|---|---|---|---|
| 01* | 1.4 | N/A | 90.95 |
| 02* | 1.4 | N/A | 88.87 |
| 03* | 3.2 | N/A | 89.22 |
| 04* | 1.4 | N/A | 85.09 |
| 05 | 1.8 | 93.33 | 89.43 |
| 06* | 1.6 | N/A | 91.4 |
| 07 | 1.2 | 67.08 | 74.91 |
| 08 | 1.4 | 68.89 | 73.27 |
| 09 | 1 | 61.9 | 63.54 |
| 10 | 1.2 | 76.31 | 76.44 |
| 11 | 1.2 | 86.5 | 74.88 |
| 12 | 0.8 | 56.25 | 40.81 |
| 13 | 1.2 | 92 | 73.93 |
| 14 | 1 | 75 | 61.6 |
| 15* | 1.4 | N/A | 89.59 |
| 16* | 1.4 | N/A | 86.19 |
| 17 | 1 | 77.08 | 69.77 |
| 18 | 1.2 | 72.49 | 60.21 |
| 19 | 0.8 | 72 | 57.69 |
| 20 | 0.6 | 79.71 | 65.79 |
| 21 | 1 | 59.09 | 69.87 |

Ep Sen - Epoch sensitivity; Ep Spe - Epoch specificity.
* denotes recordings with no seizure events; N/A - Not applicable.

supply and its average power consumption is 23 $\mu$W while operating at a clock frequency of 125 kHz. This clock frequency is used to make the SPI module compatible with most microcontrollers. Internally, the seizure algorithm functions at a much lower frequency obtained by dividing the SPI clock by 4,8,16 or 32. This is user selectable and depends on the sampling frequency of the input signal as well as the number of input channels used.

The performance summary of the chip is listed in Table II and a die photograph is shown in Fig. 9 along with its dimensions. The power consumption of the nRF52832 MCU was measured during the different transmit and sleep modes of operation. Assuming a 60-second seizure event happening every 15 minutes, and taking the algorithm performance at 97% sensitivity / 90% specificity point on the ROC curve, only 10% of background data and 50% of seizure epochs are transmitted resulting in BLE transceiver power consumption of 720 $\mu$W. Hence, the the average power consumption of the complete system with the data reduction chip was estimated to be 743 $\mu$W.

Thus, considering a state-of-the-art analog front end for EEG signals [39], and using a 310 mAh hearing aid battery [40], the system can then operate autonomously for about 15 days. Using the same battery with four input channels, the system can operate for just under 10 days.

TABLE II
PERFORMANCE SUMMARY OF THE ALGORITHM ON CHIP

| | |
|---|---|
| Technology | AMS 0.18 $\mu$m CMOS (C18A6) |
| Power Supply | 1.8 V |
| Die Area | 0.26 mm$^2$ |
| Clock Frequency | 125 kHz |
| **Total Power Consumption** | 743 $\mu$W |
| Seizure Chip | 23 $\mu$W |
| BLE Transceiver | 720 $\mu$W |

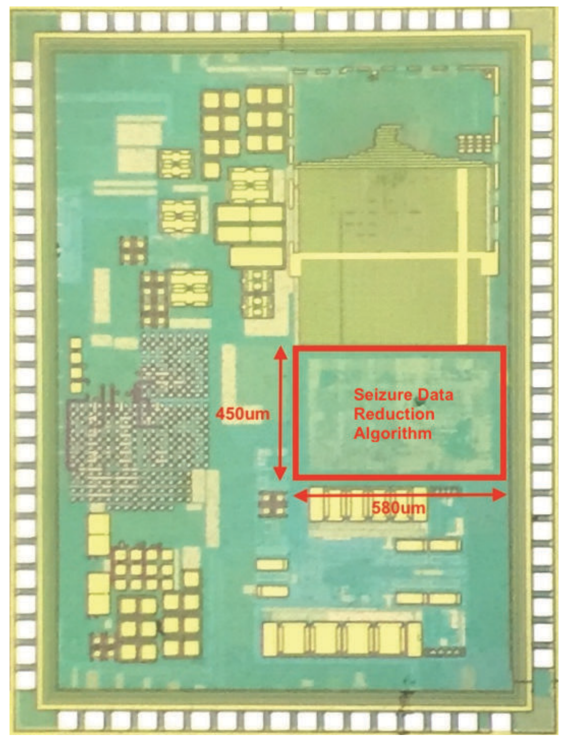


Fig. 9. Picture of the fabricated chip with the seizure algorithm in the rectangle.

### *D. System Demonstration*

To demonstrate the working of the complete system including both the EEG processing and data transmission, the seizure algorithm chip is connected to the nRF52832 MCU and data received on a mobile phone in real-time. Fig. 10 shows three different sections of EEG data that is processed on the chip. These are a representative demonstration of the system, using data that was known to contain seizure sections. The figure shows outputs from the intermediate stages of data processing that were obtained by selecting the input to the epoch buffer. The figure also shows the valid signal which goes from low to high whenever an epoch is classified as seizure.

## VI. DISCUSSION

This paper discusses the implementation of a wearable epilepsy monitoring system for capturing seizure events in real-time. It uses a low-complexity algorithm to pre-select data segments that are likely to contain seizure events and transmits only those segments. This algorithm has been implemented on

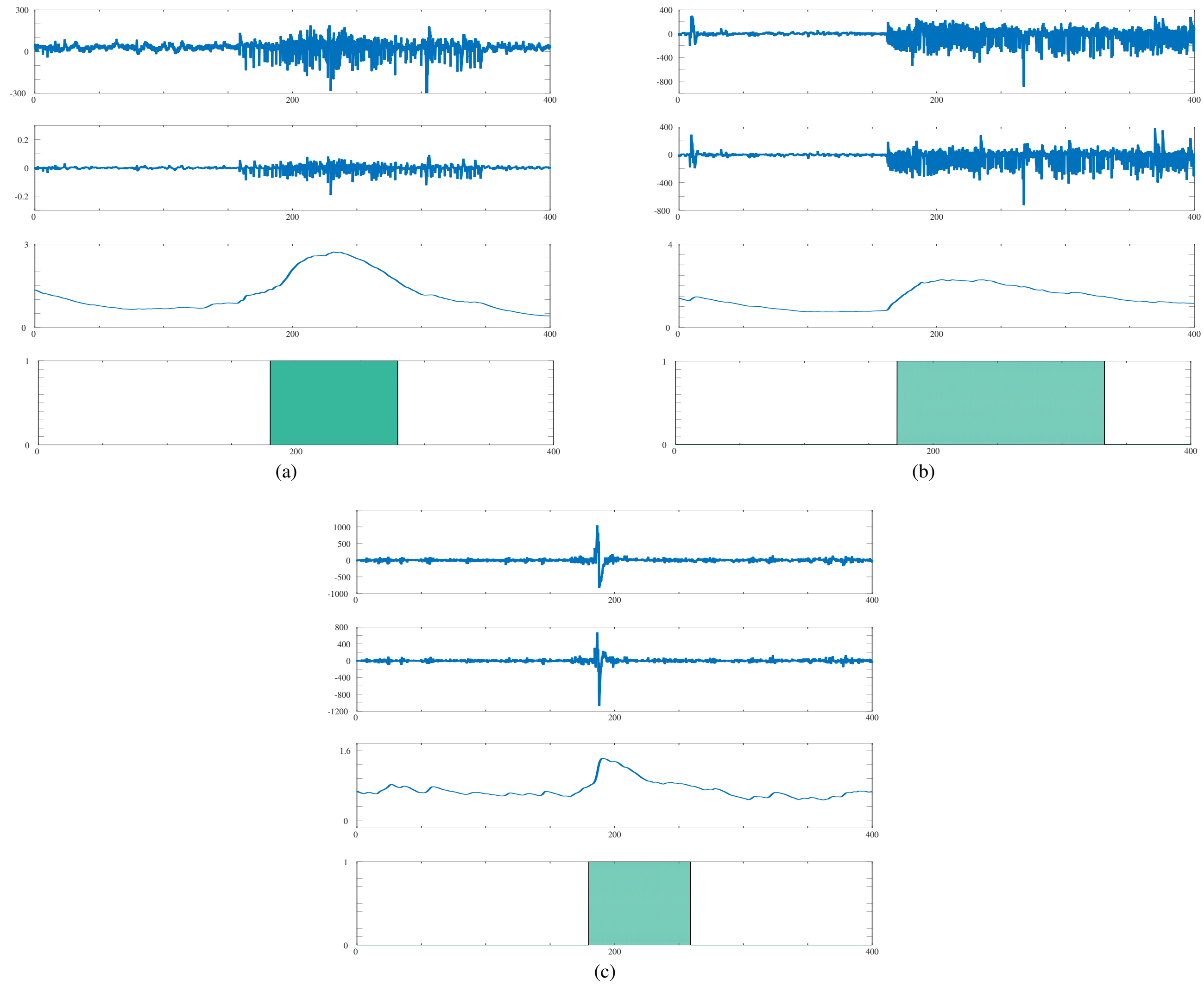

Fig. 10. Three different examples of 400-second EEG data being processed and seizure epochs identified by the system. In each of the examples, the first plot shows the raw EEG signal, second plot shows the filtered EEG signal after passing through HPF and LPF stage, third plot shows the normalized line length and the fourth plot shows the detection stage with seizures being identified at the shaded area.

chip to classify EEG data segments in epochs of 2 seconds, and stays in an idle mode when there is no data to process. It has been designed to save as much power as possible by gating each module in the system, sharing arithmetic resources, and using fixed-point computations. The output from the chip is then connected to a BLE transceiver to enable data transmission on to smartphones and tablets, and can also be read out instead by using its SPI interface.

The main objective of this work is to demonstrate the advantages of discontinuous data transmission for reduction power consumption in the context of long-term epilepsy monitoring. The algorithm used in this paper is one of many that can be used to identify seizure-related events. It is implemented on chip to show its low power consumption that translates directly into long-term continuous monitoring. Several other algorithms and their circuit-level implementation have also been published for seizure detection using different approaches.

A comparison of the proposed system with other related state-of-the-art seizure detection systems is shown in Table III. It shows the design and implementation aspects of different seizure monitoring/detection systems as well as their classification targets and detection accuracies. The comparison between different systems is not straightforward though since the constraints and objectives when designing for seizure data reduction and automated seizure detection systems are different. For example, some of the systems in this comparison have been designed for applications such as implantable seizure detectors, hence the trade-offs and requirements in them are bound to be different. The algorithmic detection results are all over 90% however, the data used in different systems and their duration is different thus the statistical significance is not the same. An additional factor to note in comparison of these systems is the number of channels they use. Most of these systems have been designed to use a higher number of data channels to detect and store seizure events that are subsequently retrieved using read-out circuitry. Using a larger number of channels is necessary in cases to identify seizures from different areas of the brain. However, the focus of this work is primarily to realise a wearable monitoring system for long-term usage. To aid the development of user-friendly system, the number of input EEG channels is limited to a maximum of four while any seizure data detected is wirelessly transmitted.

The approach of discontinuous transmission is beneficial only if the total power consumption of classifying and transmitting EEG data segments is lower than transmitting raw EEG data continuously. Assuming a seizure event occuring every 15 minutes, the power consumption of the proposed system is 743 $\mu$W. For the same scenario, continuous transmission of data using the same BLE transceiver requires 4.5 mW of power. This translates to a 6 times increase in operating time, using the proposed system, powered with a hearing aid battery. It should also be noted that an integrated circuit implementation here results in a power consumption that is an order of magnitude lower than what is achievable using an off-the-shelf microcontroller, as previously demonstrated [14]. This can be improved further by implementing more efficient filters on chip, either in digital or analog domain (prior to digitization), as well as using RAM macros instead of the register banks to buffer data prior to transmission. Apart from the huge savings in power, and thus increased battery life, the system presented in this paper has several other advantages. It transmits data wirelessly which allows easy access to data for real-time monitoring, and does not require special data read-out procedures. Specifically, it uses a BLE transceiver which enables maximum compatibility with existing smartphones and tablets. Using the system with familiar mobile device improves its usability since the user can control the system using a mobile application. For example, an application can be used to turn the system on or off, change its operating modes, query its battery status, and even raise an alert if a cluster of events are detected in a short period of time. Another advantage of this system is the use of a data selection selection algorithm which results in 50% data reduction while identifying 80% of seizure events [14]. This performance may be improved further by using more discriminatory features together with more complex classifiers. However, this may come at the cost of additional power consumption thus affecting the battery life. Further, it also saves time for neurologists by reducing the amount of time needed to analyse this data.

The system presented in this paper is intended to be used with data from one EEG channel for processing and classifying seizure events. While this improves the usability of the system being handled by a patient, it may not be sufficient in cases where more information is required and also affect the reliability of the data being obtained due to poor electrode contact. Hence, although demonstrated using one EEG channel, the system has been designed to accommodate a maximum of four EEG input channels. Additionally, the approach of discontinuous data transmission has an inherent limitation since any data not transmitted, due to misclassification, is completely lost. In contrast, if a lossless compression scheme is used, all data can be reliably recovered at the receiver end. However, these limitations are greatly outweighed by the advantages discussed earlier. The use of just one channel vastly improves the usability of the system that patient needs to wear for few months as opposed to eight or sixteen channels that are not only difficult to attach but also uncomfortable for long-term use.

The system can also be adapted for use in cases where higher number of channels is definitely needed. This is possible since it has the circuitry (registers, multiplexers, etc.) to handle data from four EEG channels on the same chip. Multiple modules of the 4-channel system can be combined together to increase the number of channels while using the on-chip SPI interfaces to transmit data to a single BLE transceiver that acts as the central hub. The increase in number of channels would however lead to a higher volume of data to be transmitted. The maximum number of channels that can be used will be dictated by the data rate that can be achieved by the BLE transceiver. Hence, while the system has been designed to be ideally used with a small number of channels, its modular approach lends it to scale up in order to acquire data from a higher number of channels. It should be noted though that regardless of the number of channels, the algorithm performance is dependant on acquiring EEG signals of sufficient quality. That, in turn, depends on proper placement of electrodes and the physical set up of the equipment [42]. Thus, for long term use, it is important to ensure that this aspect is taken into account to maintain the algorithmic performance.

While there are many other complex algorithms out there for seizure detection, the work presented in this paper complements these since the focus is on intelligently reducing data. From the perspective of wearable EEG systems (in epilepsy), an ideal system would require multiple algorithms to detect different characteristics of seizures and in many cases focus purely on reducing data without actual detection. However, having more than one algorithm running would only make sense if they consume very little power. In a scenario where our proposed system is used with an offline or remote algorithm for seizure detection, it can serve as a gateway to reduce power consumption of the wearable part of the system. The classification of seizures using a more complex algorithm can then happen at a remote computer or in cloud where the power constraints of the wearable system are not applicable. In other words, our system provides benefit by reducing the power consumption, extending the battery life and improving the overall user experience regardless of how the seizure events are classified at the end. Hence, in that sense this work also demonstrates a low-power and light-weight component for a much larger system.

## VII. Conclusion

The integrated circuit presented in this paper has been designed to intelligently reduce EEG data in wearable epilepsy monitoring systems. It uses a small number of datapath components to implement a seizure data reduction algorithm such that only EEG segments with potential seizure events are preserved and transmitted wirelessly while others are discarded. It is then interfaced with a BLE transceiver to maximise compatiblity with existing smartphones and tablet

TABLE III
COMPARISON OF PERFORMANCE WITH OTHER RELATED SYSTEMS.

| | Verma [18] JSSC 2010 | Mirzaei [24] TBCAS 2013 | Lee [41] JSSC 2013 | Chen [25] JSSC 2014 | Altaf [22] TBCAS 2016 | This Work |
|---|---|---|---|---|---|---|
| **Signal** | EEG | iEEG | EEG | iEEG | EEG | EEG |
| **# Channels** | 1 | 8 | 1 | 8 | 8 | 1 |
| **Feature Extraction** | o | x | o | o | o | o |
| **On-chip Classification** | x | o | o | o | o | o |
| **On-chip AFE** | x | o | x | o | o | x |
| **Read-out Circuit** | Serial | x | x | Wireless | Serial | SPI |
| **Supply (V)** | 1.0 | - | 1.2 | 1.8 | 1.8 | 1.8 |
| **Feature(s)** | Spectral energy | x | Band-limited signal components | Entropy and power spectrum | Filter banks coefficients | Line length |
| **Classifier** | x | Thresholding | SVM | LLS | NL-SVM | Thresholding |
| **Patient-sepcific Training Needed** | - | o | o | o | o | x |
| **Avg. Power/channel** | 9 $\mu$J/feature | 1.5 $\mu$W | 273 $\mu$J/class | 162 $\mu$W | 19.6 $\mu$W | 23 $\mu$W |
| **Technology** | 0.18$\mu$m | 0.13$\mu$m | 0.13$\mu$m | 0.18$\mu$m | 0.18$\mu$m | 0.18$\mu$m |
| **Classification Target** | Eye state (alpha) | Seizure | Seizure | Seizure | Seizure | Seizure |
| **Detection Accuracy** | 100% | 100% | - | 92% | 95% | 97% |
| **Test Data Details** | 5 minutes (1 recording) | 34 recordings (2 patients) | - | 72 hours (4 Long-Evans rats) | 906 hours (24 patients) | 168 hours (21 patients) |

device. Both the integrated circuit and transceiver stay in an idle mode at most times, waking up only when processing or transmission are required. This, together with an on-chip implementation, greatly reduces the power and area requirements that are heavily constrained in a wearable device. The overall power consumption of this system is 743 $\mu$W, and with a suitable analog front end, results in an effective battery life of 15 days using a single hearing aid battery. This demonstrates the potential of our work to be used as an effective wearable system for long-term epilepsy monitoring and diagnosis.

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