Performance-Power Consumption Trade-Off in Wearable Epilepsy Monitoring Systems
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Abstract—Automated seizure detection methods can be used to reduce time and costs associated with analyzing large volumes of ambulatory EEG recordings. These methods however have to rely on very complex, power hungry algorithms, implemented on the system backend, in order to achieve acceptable levels of accuracy. In size, and therefore power, constrained EEG systems an alternative approach to the problem of data reduction is online data selection, in which simpler algorithms select potential epileptiform activity for discontinuous recording but accurate analysis is still left to a medical practitioner. Such a diagnostic decision support system would still provide doctors with information relevant for diagnosis whilst reducing the time taken to analyze the EEG. For wearable systems with limited power budgets, data selection algorithm must be of sufficiently low complexity in order to reduce the amount of data transmitted and the overall power consumption. In this paper, we present a low power hardware implementation of an online epileptic seizure data selection algorithm with encryption and data transmission and demonstrate the trade-offs between its accuracy and the overall system power consumption. We demonstrate overall power savings by data selection can be achieved by transmitting less than 40% of the data. We also show a 29% power reduction when selecting and transmitting 94% of all seizure events and only 10% of background EEG.

Index Terms—EEG, seizure, data reduction, epilepsy, encryption, wearable, low power, monitoring

I. INTRODUCTION

EPILEPSY is a serious neurological condition that affects 50 million people worldwide [1]. It is characterized by spontaneous debilitating seizures that could cause harm to the individual, deteriorate their quality of life and may even lead to sudden death [2]. Despite its high incidence and serious consequences, 25% of patients have been reported to be misdiagnosed [3]. For definitive diagnosis of epilepsy, an electroencephalography (EEG) recording of the brain activity during an epileptic seizure is often required [4]. However seizures may occur within a space of few hours, weeks or even months and thus long term EEG monitoring is often required to be able to record the patient’s brain activity during a seizure.

There are two main limitations of this long-term monitoring approach. Firstly, the patients undergoing monitoring for long periods of time need to carry around a portable EEG monitoring system which is both uncomfortable and unaesthetic. Because of this most patients prefer to stay at home or in-clinic during these recording sessions. Present portable and ambulatory EEG systems that are suitable for clinical use weigh about 500 g; can monitor up to 72 hours; and have large battery packs connected by long cables (making it difficult to ensure good electrode connection for the entire recording duration) [5]. Thus patients undergoing long-term monitoring for several days are required to attend a clinic regularly to check electrode connections, recharge batteries and save EEG data obtained from recording. The second limitation is that long-term monitoring generates enormous amount of diagnostic data that takes medical practitioners a proportionally long time to analyze (approximately 2 hours per 24 hours of recording [6]).

There has been significant research on methods to improve ambulatory EEG systems in order to make them comfortable, easy to use and last for a longer time. Power consumption of such systems is an important issue since it needs to be reduced to make them wearable [5]. A reduction in the amount of data to be processed can save significant amount of power. Different methods of reducing data for long-term epilepsy monitoring include using lower sampling frequency, compression of data and discontinuous recording [7]. Daou and Labeau [8] presented a method combining compression of EEG and detection of seizures at the same time. Tolbert et al. [9] reduced data by applying wavelet compression when there was no significant activity and transmitted raw data when they detected spikes and related activity. Other methods of reducing data at the sensor node include the use of optimal compression of data and discontinuous recording [7]. Daou and Labeau [8] presented a method combining compression of EEG and detection of seizures at the same time. Tolbert et al. [9] reduced data by applying wavelet compression when there was no significant activity and transmitted raw data when they detected spikes and related activity. Other methods of reducing data at the sensor node include the use of optimal features [10], [11] to save useful information, reducing the number of channels [12] and dynamically selecting relevant EEG channels [13]. All these techniques can lead to reduction in data rate and consequently power consumption.

Several research groups have also worked on methods to reduce the time taken to analyze large volume of recorded EEG data from long-term monitoring. This involves developing algorithms aimed at analyzing the recording for the presence of epileptic seizures automatically. These algorithms could be used to detect either the start or onset of a seizure event, its termination or any part of its occurrence. Furthermore, the algorithms may be developed for offline use or online, real-time application.

Qu and Gotman [14] extracted features including wave amplitude, duration, power and dominant frequency and used template matching for patient-specific seizure onset detection. Osorio et al. [15] proposed a method for real-time detection of seizures and onset prediction using bandpass and median filtering of intracranial recordings. Saab and Gotman [16]...
proposed a method using three features extracted from wavelet coefficients, relative average amplitude, relative scale energy and coefficient of variation of amplitude to estimate the probability of seizure onset. Kuhlmann et al. [10] used the same method to analyze six additional features and compared their performance to determine the best performing features for seizure detection.

Meier et al. [17] used features extracted from scalp EEG, including Continuous Wavelet Transform (CWT) powers, number of zero crossings, mean variance, cross correlation coefficient and spectral powers with a Support Vector Machine (SVM) classifier for online detection of seizures. Zandi et al. [18] also proposed a method using wavelet packet transform to derive a seizure index for real-time seizure detection. Since both of these methods were implemented on a desktop computer for real-time operation, their applicability in a wearable setting, where power budget is extremely limited, is not known. Kelly at al. developed an algorithm, called IdentEvent [19], for offline processing and detection of seizure events. They used pattern-matching regularity statistics, amplitude variation and local maximum frequency with fixed thresholds, and stored the timestamps of detected seizures for later analysis. Shoeb et al. [20] developed an algorithm to detect termination of seizure once its start has been identified using spectral energies and SVM classifier.

Artificial neural networks have often been used to classify seizures with a large number of features used as inputs. Wilson et al. [21] described an algorithm, called Reveal, based on Matching Pursuit and small neural network rules. Ghos-Dastidar et al. [22] used wavelet decomposition and chaos analysis to extract three features in different EEG sub-bands which were used with neural network classifiers. Srinivasan et al. [23] used approximate entropy (ApEn) as feature input to two different types of neural networks and evaluated their performance for seizure detection in ambulatory EEG recordings. Tzallas et al. [24] also used neural networks with power spectral density and features extracted from time-frequency analysis while Yuan et al. [25] used fractal intercept and relative fluctuation index as feature inputs to a neural network for seizure detection. In another method, Alam and Bhuiyan [26] used higher order statistical features with an artificial neural network to classify EEG signals in to healthy, interictal or seizure groups.

More recently, Niknazar et al. [27] applied wavelet decomposition and recurrence quantification analysis to classify scalp EEG recordings as either ictal, interictal or healthy. Hopfengärtner et al. [28] used adaptive thresholding of integrated and average power in 3-12 Hz band to detect seizures in long-term EEG recordings.

The seizure detection algorithms based on neural networks and other complex signal processing methods are suitable for offline analysis of data, or even real-time analysis when power consumption is not a limiting factor. In wearable systems, power requirements, amount of data and system size are all important factors. Therefore any detection method used needs to be of such low complexity that it could run on a very small processor, sourcing power from a small battery and run for a long period of time.

The approach of discontinuous recording [7] for wearable epilepsy monitoring systems, described in [5], allows data reduction in real-time, by selecting interesting data and discarding others. A low complexity algorithm could be incorporated in the portable EEG system to select epilepsy-related brain activity that could be analyzed later by a neurologist. This principle of data selection, shown in Fig. 1, would reduce the duration of data provided to the neurologists and thus reduce the time taken for them to analyze the discontinuous recording whilst keeping their decisive role in diagnosing the patient [5]. Such sampled reviews of discontinuous EEG recording has been shown to not substantially alter the final electroclinical diagnosis of the patient [29], [30]. [5] also suggests combining the data selection algorithm with wireless transmission in order to increase the monitoring duration, reduce the power consumption and subsequently the weight and volume of the portable EEG system. Wireless transmission will also overcome issues of electrode disconnection caused by tugging on long connecting cables.

This paper demonstrates the practical implementation of the discontinuous recording approach for epileptic seizure analysis and detection. It describes the design of a data selection algorithm for epileptic seizures, its implementation on a low-power microcontroller with encryption and data transmission. It demonstrates how the low-power implementation of the data selection algorithm could be utilized to reduce the power consumption of a portable EEG system. Section II describes the theoretical approach proposed in [5], the dataset used in this work and the design and implementation of the data selection algorithm, data encryption and wireless transmission. The performance has been detailed in Section II as a trade-off between the seizure detection accuracy of the algorithm and the power consumption of the overall system. Finally, the design trade-offs of the algorithm and wireless transmission are described in Section III and its implications on the development of a smaller, light-weight EEG system and medical diagnosis of epilepsy will be discussed in Section IV.

II. MATERIAL AND METHODS

A block diagram of the wearable EEG system proposed in [5] is shown in Fig. 2. It illustrates the head mounted processing system connected to electrodes placed on the scalp of an individual and a separate base station for recording the
transmitted data. The head mounted processing system consists of: a low power detection unit that contains the front-end circuitry (such as an amplifier, analogue-to-digital converter and anti-aliasing filter) in addition to intelligent signal processing to achieve data reduction; and a data transmission unit consisting of a wireless transmitter with possible encryption. The head mounted system is wirelessly linked to a base station that receives the transmitted data and saves it for real-time or offline analysis by a neurologist or EEG technician.

In this model of the wearable EEG system, the power consumption of the head mounted system, $P_S$, is given by:

$$ P_S = P_F + P_A + CP_T $$

where $P_F$ is the power consumption of the front-end circuitry, $P_A$ is the power consumption of the signal processing algorithm to achieve data reduction, $P_T$ is power consumption of the wireless transmission unit and $C$ is the compression ratio obtained by dividing the compressed bit rate with uncompressed bit rate (lower values of $C$ denote higher compression). In (1), assuming the power consumption of the front-end circuitry to be fixed at 25 $\mu$W per EEG channel [31], there are two interesting cases:

- when there is no data reduction: $P_A=0$ and thus $C=1$.
  The power consumption of the head mounted system is $P_S = P_F + P_T$.
- when data reduction $C$ is achieved and the power consumption of the system is given by (1).

In the latter case, data reduction is only beneficial in terms of power if the implementation of signal processing techniques consume less power than the savings achieved due to reduced wireless transmission i.e. $P_A < (1 - C)P_T$. Nevertheless, the advantage of less analysis time for reduced data would still hold even when power saving is not achieved.

A. Database

The database used for performance assessment in this work was obtained from multiple recordings at the Epilepsy Society (UK), Katholieke Universiteit Leuven (Belgium) [32, 33] and Freiburg University Hospital (Germany). It consists of scalp EEG signals with a total duration of over 168 hours obtained from 21 adults. The data contained 16 EEG channels common to all records: C3, C4, CZ, F3, F4, FZ, F7, F8, FP1, FP2, O1, O2, T3, T4, T5 and T6. A total of 181 recordings were analyzed, 34 of which contained sections of seizure occurrence marked by medical practitioners (total seizure duration of 4158 s). All of the data had been sampled at a frequency of at least 200 Hz during routine, long term and ambulatory monitoring sessions.

B. Data selection algorithm

The proposed multi-channel seizure data selection algorithm is illustrated in Fig. 3. The algorithm contains two parts: channel-specific processing and collating information across channels. The channel-specific processing is identical across all channels and the result from each is then collated for the final decision making. Line length [34] is used as the main discriminatory feature in the algorithm to distinguish between seizure and non-seizure events. This feature is selected because of its high discriminatory ability and low computational complexity, as established in our previous study comparing 65 different features [11].

The multi-channel input EEG signal is represented as:

$$ x = (x_1, x_2, ..., x_N) $$

where $N$ is the number of channels.

All EEG channels are processed separately in parallel, using the input signal $x_n[k]$ where $k$ is a sample in time and $n$ is the channel number. The results from each channel-specific processing is combined to determine whether or not an EEG section contains an epileptic seizure.

In Fig. 3, a single channel EEG signal is initially filtered by a first-order high pass filter with a cut-off frequency of 0.16 Hz to remove any d.c. offset (as recommended by [35]). The output of this is then passed through a third-order Bessel low pass filter (LPF) with a cut off frequency of 10 Hz. The resulting time domain signal is then down-sampled to 20 Hz and split into 2 s non-overlapping epochs. The cut off frequency is selected to achieve maximum down-sampling without affecting seizure detection performance. Next, the line length is calculated within each epoch as:

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

where $F(e)$ is the line length for an epoch $e$ being analyzed, $w$ is the down-sampled signal, $k$ is the sample number and $S$ is the total number of samples within the epoch.

The calculated feature $F(e)$ is normalized to correct for broad level amplitude changes between EEG channels and patients [36] so that a fixed threshold may then be applied to the normalized feature to discriminate between the high amplitude seizure sections and the low amplitude normal EEG sections. Normalization is carried out by estimating the background activity $z(e)$ using median decaying memory and is calculated as:

$$ z(e) = (1 - \lambda) \times \text{median}\{F(e - 1) \cdots F(e - B)\} + \lambda \times z(e - 1) $$

where $B$ is the number of epochs preceding the current epoch that is used to estimate background activity, $\lambda$ is a decay
constant and $z(e-1)$ is the background estimate calculated for the previous epoch. The maximum transient or ramp-up time of the background estimate has been selected as 2 minutes to ensure that $z(e)$ has reached steady-state when analyzing seizures in the test database (the earliest time of seizure commencement from the start of recording was found to be 2 minutes). During the transient phase the median is calculated within all available epochs using $\lambda=0.92$ to ensure that the normalization estimate $z(e)$ reaches the same range of values as the feature $F(e)$. In the steady-state $\lambda=0.99$ such that the effect of any newer median $\{F(e-1) \cdots F(e-B)\}$ decays to 1% in about 15 minutes, which is a reasonable lifetime considering the majority of records in the test database have a duration of more than 1 hour. Since the background estimate is calculated over a period of 2 minutes (120 seconds), $B$ should be 60 for 2 s epochs.

The feature $F(e)$ is divided by the normalization estimate $z(e)$ to restrict the range of values prior to applying a fixed detection threshold.

$$A(e) = F(e)/z(e)$$

The normalized feature $A(e)$ is then compared against a fixed threshold $\beta$. If $A(e)$ exceeds $\beta$, a detection flag for the channel $n$ being analyzed, $DF_n(e)$, is set to one. If not, the flag is set to zero. The detection threshold $\beta$ is a tunable parameter that can be set to vary the algorithm sensitivity.

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

The channel-specific processing has now ended and information in the epoch across all $N$ channels can be analyzed. The flags across all the channels are summed and compared to $\gamma$ (the minimum number of channels required for a detection which is set to 4) to see how many channels have detected the presence of abnormal activity within the same epoch. If the sum of flags $C(e)$ exceeds $\gamma$ then it is considered a seizure and 2 s data from all $N$ channels are selected for transmission. Otherwise the epoch is rejected as a non-seizure event.

$$C(e) = \sum_{n=1}^{N} DF_n(e)$$

$$S(e) = \begin{cases} \text{Seizure}, & \text{if } C(e) \geq 4 \\ \text{Non-seizure}, & \text{otherwise} \end{cases}$$

**C. Hardware Implementation**

The algorithm is implemented on Texas Instruments MSP430F5438A microcontroller [37] and uses Nordic Semiconductor nRF24L01+ transceiver [38] for wireless transmission of data. Both components were selected for their ultra low power consumption. The hardware connection diagram in Fig. 4 shows the microcontroller connected to the wireless transceiver using serial peripheral interface (SPI). In the figure, two pins in the SPI bus are used for full duplex communication. The third pin provides clock signal from the microcontroller (master) to the transceiver (slave) for synchronous data transfer. The two control pins, CE and CSN are used to enable the nRF2401+ chip and activate the SPI communication respectively. The IRQ pin is an interrupt request input that notifies the microcontroller whenever data transmission is complete and when new data is received. The master clock frequency of the microcontroller is selected such that epochs from all the channels can be processed completely before the start of next epoch.

Each channel-specific processing stage starts with a high pass filter (Fig. 3). This filtering operation is performed on the microcontroller with the following transfer function:

$$y[k] = 0.9975x[k] - 0.9975x[k-1] + 0.9950y[k-1]$$

where $y[k]$ is the filtered output and $x[k]$ is the raw input. The filter coefficients are represented as 16-bit signed fixed point numbers (Q15 format), thus using simple integer arithmetic operations. Multiplication is performed on the MSP430.
using the dedicated MPY32 hardware multiplier in fractional mode with two 16-bit operands as inputs.

The next stage is a third-order Bessel low pass filter that has been realized as a cascade of a first order filter followed by a second order section with the following transfer functions:

\[
\begin{align*}
u[k] &= 0.1000y[k] + 0.1000y[k-1] + 0.7423u[k - 0\text{B}]
y[k] &= 0.1000u[k] + 0.1999y[k-1] + 0.0999u[k-2] \\
&+ 1.5452v[k-1] - 0.6283v[k-2] 
\end{align*}
\] (11)

The output of the filter, \(v[k]\), is multiplied by a constant gain of 0.2679. The low-pass filter coefficients and gain are represented in Q4.28 format (32 bits with 4 integer bits and 28 fractional bits) for increased accuracy. The filtered signal that goes downstream for further calculation is also kept in this format. It was empirically determined that 4 integer bits were sufficient to represent the maximum number produced in the algorithm in most cases. In a rare case where an unusually large number would appear after computation, the number of integer bits would increase while sacrificing some fractional bits.

The filtered signal \(v[k]\) is down-sampled to 20 Hz (factor of 10). This step reduces the arithmetic computations performed downstream when calculating the line length thereby saving processing cycles and consequently power. The next step is the computation of line length. This is the sum of absolute differences between the samples in an epoch and hence it is a simple operation to implement in the microcontroller. A variable to store line length is initialized to zero at the start of a new epoch. Each time a new filtered sample arrives, the difference between the new sample and the previous sample is calculated. The absolute value of this difference is then added to the line length variable which gets updated. The value at the end of epoch is then the required feature.

To calculate the normalization estimate in (4) the median of previous \(B\) data points is required. In the previous section, \(B\) was set to 60 to cover a duration of 2 minutes. However, at the implementation stage, 59 epochs were used to determine the median instead of 60. This is because finding the median from an even number of samples requires averaging the two middle values. Using the closest odd number smaller than 60 allows saving some processing cycles without affecting the algorithm output. The median is implemented on the microcontroller using linked lists based on Phil Ekstrom’s method [39] with a sorting complexity of \(N\). When a new value of feature \(F(e)\) is available, it is inserted at the appropriate position in an already sorted list and the oldest value is removed at the same time. The data in the list do not need to be shifted and only the pointers of the neighboring elements in the list need to be updated when a new element is added or an existing element is removed. Since the list is always sorted, the median is trivially the middle element of the list (average of two middle elements in a list with even number of elements). The transient and steady-state values of \(\lambda\) and \((1 - \lambda)\) in (4) are stored in Q15 format on the microcontroller.

Instead of calculating the normalized feature \(A(e)\) in (5) and then comparing against the threshold, the equivalent operation in (12) is performed to check for seizure detection on the microcontroller. This allows using the hardware multiplier instead of a costly division operation. A detection flag is set for each channel whenever the condition in (12) is true. The detection flags are summed and checked for seizure detection as in (8).

\[F(e) \geq z(e) \times \beta\] (12)

Since 2 s of EEG data are used to compute the feature and subsequently checked against the threshold for seizure event, this data needs to be stored for transmission in case of a positive detection. For this reason, 2 s of unfiltered EEG is stored in the microcontroller RAM. The on-chip memory sets an upper bound on the amount of data that may be buffered and, therefore, the number of channels that may be processed by the microcontroller. For the MSP430F5438A, this works out to be 12 channels sampled at 200 Hz and is also the reason for using 12 channels in this work. When an epoch is deemed to be a non-seizure event, the detection flag is set to zero and all the EEG data buffered for transmission is cleared.

D. Wireless transmission & encryption

To guarantee security of patient data according to the UK Data Protection Act 1998 [40] and NHS Code of Practice [41] EEG data should be transmitted wirelessly in encrypted form. The Advanced Encryption Standard (AES), issued by the National Institute of Standards and Technology (NIST), is one of the most popular and widely used encryption technique that encrypts data in blocks of 128 bits, and cipher key size of 128, 192 or 256 bits. In this work, when a seizure epoch is detected by the data selection algorithm, data from all 12 channels are encrypted using the AES-128 standard (128-bit cipher key) prior to transmission.

The encrypted data is then transmitted using a nRF24LO1+ transceiver, powered at 2 V, with the transmit power set to 0 dBm and over-the-air data rate of 2 Mbps. One seizure epoch of 2 s, sampled at 200 Hz will generate 9600 bytes of data across 12 channels. The transmitter will only need to be switched on when there is encrypted data ready for transmission. The transceiver uses Nordic Shockburst protocol for transmission with a payload size of 32 bytes in each round and an additional five bytes for preamble, address and CRC (Cyclic Redundancy Check).
E. Performance assessment criteria

The performance of the algorithm and its hardware implementation is assessed with the following metrics: sensitivity to identify epileptic seizures; specificity (ability to reject non-seizure data); and power saving of the overall head-mounted system. Each of these metrics will be described in detail below.

1) **Sensitivity** is a measure of the fraction of expertly marked seizure epochs and events that has been correctly identified by the algorithm. Two variants of sensitivity are determined: **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. For example, a 10 s seizure event will have five 2 s seizure epochs. The average **epoch sensitivity** is calculated as:

\[
\text{Epoch Sensitivity} = \frac{1}{N} \sum_{n=1}^{N} \frac{epTP_n}{epTP_n + epFN_n} \times 100\%
\]  

(13)

where \(epTP_n\) is the number of true positives (correctly identified seizure epochs) in record \(n\), \(epFN_n\) is the number of false negatives (incorrectly rejected seizure epochs) in record \(n\) and \(N\) is the number of total seizure containing records present in the test database.

The **epoch sensitivity** does not reflect on the actual fraction of seizure events correctly identified but instead it measures the fraction of total seizure duration. Thus the fraction of expert marked seizure events correctly identified, **event sensitivity**, is sometimes reported in addition to this metric.

For **event sensitivity**, the ground truth is the total number of seizure events expertly marked in the test database. The average **event sensitivity** is calculated as:

\[
\text{Event Sensitivity} = \frac{1}{N} \sum_{n=1}^{N} \frac{evTP_n}{evTP_n + evFN_n} \times 100\%
\]  

(14)

where \(evTP_n\) and \(evFN_n\) are the number of true positives (correctly identified seizure event) and false negatives (incorrectly rejected seizure event) in record \(n\) while \(N\) is the total number of records in the database. Here an event is considered to be a true positive if there is an overlap of at least one epoch (2 s) between the detected event and the corresponding seizure event in the ground truth.

2) **Specificity** is the fraction of non-seizure epochs correctly rejected. It is calculated as:

\[
\text{Specificity} = \frac{1}{N} \sum_{n=1}^{N} \frac{epTN_n}{epTN_n + epFP_n} \times 100\%
\]  

(15)

where \(epTN_n\) is the number of true negatives (correctly rejected non-seizure epochs), \(epFP_n\) is the number of false positives (incorrectly detected non-seizure epochs) and \(N\) is the total number of tests. When the algorithm is tested on a patient, the duration of seizure data is mostly insignificant in comparison to the duration of non-seizure (normal EEG data) and thus the specificity of the algorithm in such cases is equal to the achieved data reduction. If seizure duration is considered, the total data reduction would be marginally less than the specificity of the algorithm.

3) **Power saving**: The sensitivity and specificity of the algorithm must be traded-off with the power consumption of the algorithm hardware implementation as high sensitivity and specificity can be achieved if the algorithm used more computationally complex signal processing techniques but the hardware implementation of such methods would generally require higher power consumption. Thus the power consumption, or more importantly, the power saving, achieved by introducing the data selection algorithm in the wearable EEG system should be quantified. The power consumption for continuous wireless transmission can be measured and the data reduction/compression \(C\) at a specific threshold \(\beta\) is known. Thus the power consumption of continuous and discontinuous transmission can be calculated as in (1).

III. RESULTS

In this section the accuracy of the algorithm is first evaluated by determining the number of true seizure events present in the reduced data. The power consumption of the algorithm is then determined in its idle, processing and transmission stages. This is used to evaluate its overall average power consumption. Using these, a power-performance curve is plotted to demonstrate how much power savings can be achieved due to data reduction at different compression ratios and the consequent degradation in algorithm’s detection performance due to reduced data being transmitted.
β threshold about 51% of background data needs to be transmitted. For 80% of seizure epochs to be correctly identified for transmission, 22% of background data. For 80% event sensitivity) when 65% of seizure epochs are selected of data transmitted. All seizure events are detected (100% mission (shown by epoch sensitivity) for the same amount of data transmitted and vice versa. The fraction of seizure duration detected for transmission (shown by epoch sensitivity) for the same amount of data transmitted. All seizure events are detected (100% event sensitivity) when 65% of seizure epochs are selected for transmission amongst 22% of background data. For 80% of seizure epochs to be correctly identified for transmission, about 51% of background data needs to be transmitted. The percentage of data transmitted at each sensitivity / threshold \( \beta \) can be used to determine the power consumption of the algorithm and wireless transmission, which will be discussed next.

A. Data selection accuracy

The accuracy of the algorithm at identifying seizure EEG and rejecting normal brain activity is shown in Fig. 5. In the figure, the sensitivity-data reduction trade-off can be seen where high sensitivity can be achieved if larger amount of data is transmitted and vice versa. The fraction of seizure events detected, as given by event-sensitivity, is consistently better than the fraction of seizure duration detected for transmission (shown by epoch sensitivity) for the same amount of data transmitted. All seizure events are detected (100% event sensitivity) when 65% of seizure epochs are selected for transmission amongst 22% of background data. For 80% of seizure epochs to be correctly identified for transmission, about 51% of background data needs to be transmitted.

The percentage of data transmitted at each sensitivity / threshold \( \beta \) can be used to determine the power consumption of the algorithm and wireless transmission, which will be discussed next.

B. Power consumption

To determine the power consumption of the microcontroller and wireless transmitter system, it is necessary to mention the three distinct modes in which the system operates, and the current drawn by the system during them:

1) Idle: both microcontroller and transceiver are not used and thus are in low power idle mode. The current drawn in idle mode is, \( i_{idle} = 0.03 \text{ mA} \).

2) Processing: the microcontroller is performing certain operations such as filtering, line length computation, encryption, etc. while the transceiver is in idle mode. The current drawn is, \( i_{proc} = 4.20 \text{ mA} \).

3) Transmission: microcontroller and transceiver are both operating in active mode. The current drawn in this mode is, \( i_{tran} = 10.96 \text{ mA} \).

The current drawn in each mode of operation is shown in Fig. 7 which illustrates the current drawn while the microcontroller processes input EEG data in 2 s epochs; then transmits the analyzed data if it is a candidate seizure event; and finally when both the microcontroller and transmitter are in idle mode until the next 2 s EEG epoch should be analyzed. As shown in Fig. 7, the highest current is drawn during transmission and thus minimizing the time spent in transmission mode and maximizing the time spent in the idle mode will reduce the overall power consumption.

Subsequently the measured current at any instance in time would be the current drawn at one of the three modes of operation. The average current drawn over time, \( I_{avg} \), can be calculated by measuring the fraction of time spent in each mode of operation:

\[
I_{avg} = i_{idle} \times t_{idle} + i_{proc} \times t_{proc} + i_{tran} \times t_{tran}
\]

The time spent in a mode of operation has been determined for the computations of a single epoch of 2 s duration. The average power consumption is then the average current multiplied by the supply voltage (2 V). Using (16), the power consumption of continuous transmission (encryption and transmission of all data) and discontinuous transmission (data selection algorithm, encryption and transmission) have been determined:

- Continuous transmission: For 12 channel 16-bit input EEG sampled at 200 Hz to be transmitted in 2 s sections, the average current was 1.4 mA. The power consumption for encrypting and transmitting all the EEG data was 2.8 mW.

- Discontinuous transmission: The microcontroller implementation of the data selection algorithm analyzing the same 12 channels of EEG data required 1.7 mW. Using this, the power consumption for encryption and transmission can now be calculated at different points of the sensitivity-data transmitted curve in Fig. 6.

C. Performance-power consumption trade-off

Fig. 5 shows the trade-off between sensitivity of detecting epileptic seizures versus the specificity of rejecting non-seizure data sections. For the same set of sensitivity and threshold values, Fig. 6 illustrates the total power consumption for discontinuous transmission. From Fig. 6, it is possible to determine the maximum and minimum power consumption. If no data is selected for transmission, the algorithm will have 0% sensitivity and the total power consumption will be equal to the power consumption of the algorithm (1.7 mW). If all the data is selected for transmission, the algorithm will achieve 100% sensitivity and the total power consumption will be equal to the power consumption of the algorithm plus the power consumption of continuous transmission, which adds up to 4.5 mW.

In Fig. 6, a trade-off limit has been plotted as a dot-dash vertical line at 2.8 mW (the power consumption for continuous transmission). This illustrates the maximum sensitivity-data reduction that can be achieved by the algorithm without the total power consumption of discontinuous transmission.
The data selection approach used here has two main advantages. The first one is reduction in specialist analysis time. Taking the same analysis point as above, a neurologist will be able to view 54.04% of seizure duration of 32 out of 34 seizure events (94.12% event sensitivity) but will only unnecessarily analyze 9.98% of non-seizure data. Since seizure duration is significantly less than non-seizure duration, the time taken by the neurologist to analyze the discontinuous recording would be approximately a tenth of the time taken to analyze a continuous EEG recording, saving time for the neurologist. Alternatively the patient could be monitored for a longer duration without an increase in analysis time for the neurologist. The second advantage of data selection is a reduction in power consumption at the wireless base station since the power consumption of the receiver is also proportional to the amount of data received. Data reduction will allow the receiver to be turned on only when data is available for transmission. Thus for truly portable systems where the wireless base station (such as a mobile phone) is also carried by the patient during monitoring, the power reduction at the head mounted transmitter will be matched at the portable receiver.

A further benefit of this method, as opposed to automated diagnostic systems, is that it maintains the crucial role of the doctor in diagnosing a patient whilst reducing the time taken for the doctor to analyze the recording. Although an obvious disadvantage is that it adds a slight delay in obtaining diagnostic results in contrast to online seizure detection systems where the result is instantaneous (without doctor’s involvement). However, online seizure detectors use sophisticated signal processing and classification methods. This adds computational complexity increasing power consumption and reducing battery lifetime.

Although the reduction in data (and subsequently power) is advantageous since it saves analysis time of medical practitioners, there is a possibility of losing important information using the data selection approach. Ideally there should be no loss of data when it is being reduced however that is practically impossible. Therefore, a trade-off must be found to reduce data and power consumption up to a point where this reduction does not lead to considerable loss of information.

There are other ways of reducing power consumption including the use of flash memory to save sections of data rather than transmitting them. In [42] we showed that saving the data on a NAND flash consumes less power than transmitting using the Nordic transmitter used here. Further, wireless transmission may also lead to packet losses requiring multiple retransmission of data. Nevertheless, wireless transmission is more comfortable to the user, allows the capability of real-time analysis and assistance.

It should be noted that the algorithm utilized in this study is a first prototype developed to demonstrate the performance-power consumption trade-off in wearable epilepsy monitoring system. Thus the data selection accuracy or power consumption of the algorithm may be improved through the use of another algorithm evaluated using the same methods utilized in this study or an alternative hardware implementation (for example, in analog or digital ASIC). Further, the algorithm

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**Fig. 7. Current draw in different operation modes. Only a portion of algorithm period is shown followed by data transmission of 160 bytes (32 bytes during each of the five transmission rounds).**

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exceeding the power consumption of continuous transmission. In other words, sensitivity values that are on left hand side of the trade-off limit will lead to power reduction through discontinuous transmission while the performance on right hand side of the trade-off limit will lead to an overall increase in power consumption. From Fig. 5 and Fig. 6, an overall power saving can be obtained if data transmission is less than or equal to 40%, which in turn corresponds to event-sensitivity up to 100% but epoch-sensitivity only up to 75%.

Ideally a medical practitioner will decide on the threshold (β) such that at least a minimum level of sensitivity is achieved. For the sake of analysis, let us assume that over 90% of seizure events must be detected with at least 50% duration selected for recording. In this case, the closest threshold would be selected to give 94.12% event sensitivity (missing only 2 events) with 54.04% of seizure duration selected for transmission in addition to 9.98% of non-seizure data. This corresponds to a power consumption of 2 mW for the 12-channel algorithm with discontinuous encrypted data transmission, which is a 29% reduction in power consumption in comparison to continuous transmission or raw data.

**IV. DISCUSSION**

The data selection algorithm implemented here showed a discernible reduction in power consumption through discontinuous transmission. This reduction in power consumption translates to an equivalent increase in the lifetime of a battery-powered portable EEG system. Alternatively, a battery with lower energy capacity (and thus lower weight and volume) can be selected to allow the system to operate for the same lifetime. In portable EEG systems, the battery dominates the weight and volume of the entire system and thus selecting a lower energy capacity, lighter, smaller battery would significantly reduce its weight and volume making it more comfortable for the patient to wear.
implemented in this paper was designed specifically to detect seizure events and not to predict their occurrence or termination. To detect other seizure features, different low power algorithms can be developed. The methods of data selection proposed in this paper would still be applicable for any alternative implementation.

Furthermore, these results are obviously linked to the choice of algorithm. This algorithm was designed having the power constraint as a requirement, so it is relatively low complexity, and consequently its implementation was expected to require low power at the cost of accuracy. Different algorithms might lead to different power/accuracy tradeoff points. In the microcontroller implementation of the algorithm discussed above, it is also interesting to note that the current drawn by the microcontroller during processing time is less than half the current drawn during transmission. Thus it may be possible to achieve better data selection accuracy and more power reduction by adding more signal processing staging (and thus increasing the computational complexity of the algorithm) provided it reduces the amount of data transmitted by more than twice the increase in power consumption of the microcontroller.

V. CONCLUSION

This paper presents a new EEG data selection algorithm together with its implementation on a low power microcontroller with AES-128 encryption and wireless transmission. It demonstrates how data reduction can be utilized to reduce the power consumption of wireless transmission and subsequently of the overall EEG system. The data selection algorithm proposed here selected 94.12% of seizure events and 54.04% of total seizure duration for transmission, in addition to only 9.98% of normal brain activity. Utilizing this data selection algorithm to selectively transmit candidate seizure sections would allow 29% reduction in power consumption of the EEG system, thus increasing the battery lifetime proportionally. Additionally, the discontinuous EEG recording would reduce the analysis time for the neurologist to a tenth of the time taken to analyze the continuous recording, whilst not significantly altering the final electroclinical diagnosis of the patient. The paper also discusses the trade-offs between the data selection accuracy of the algorithm and the power consumption of wireless transmission, where higher accuracy can be achieved if higher power consumption is tolerated; and the potential for increased power saving through alternative hardware implementation. This study proves that online data selection algorithms designed for low power consumption can be utilized to reduce the power consumption of wireless battery-powered EEG systems whilst aiding clinical diagnosis through discontinuous recording of candidate epileptiform EEG.

REFERENCES


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