A 1.8 mW 12 channel wireless seizure detector for miniaturized portable EEG systems

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***Abstract*— There is a well established need for the creation of highly miniaturized, long lasting and comfortable EEG systems. Power consumption, particularly of wireless transmission stages, is a major obstacle to the creation of these new EEG systems. This paper presents a 1.8 mW, 12 channel seizure detection algorithm for providing real-time power reduction of the wireless transmitter. An algorithm that can detect 88% of seizures while removing 90% of the background EEG signal is reported and implemented on a low-power micro-controller platform. This algorithm can be used to decrease the power consumption of the wireless transmitter stage by 90% to allow long term monitoring from very physically small batteries.**

I. INTRODUCTION

There is a well established need for the creation of highly miniaturized, long lasting and comfortable EEG (electroencephalography) systems for use in epilepsy diagnosis and treatment [1]–[4]. Power consumption is a major obstacle to the creation of these new EEG systems as the system size is dominated by the volume and weight of the battery, and physically smaller batteries have lower energy storage capacities.

Highly miniature EEG systems can be split into two parts as shown in Fig. 1: the monitoring unit placed on the head of the subject; and the recording unit used to receive and store the transmitted EEG data. Both the monitoring and recording units should be miniaturized and light-weight to allow the subject to carry out routine activities during monitoring, which for certain people could last several weeks [1]. During such long-term recordings the overall power consumption is dominated by the wireless transmitter [1], receiver, and storage in non-volatile memory and is linearly proportional to the amount of EEG data transmitted from the head mounted monitoring unit.

Significant power reduction can therefore be achieved by reducing the amount of EEG data that needs to be transmitted and stored. To provide this reduction, [1] recommended using a data selection algorithm to pre-select interesting data, such as epileptic seizures, prior to wireless transmission, as shown in Fig. 1. This would reduce the amount of data

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The research leading to these results has received funding from the European Research Council under the European Community's 7th Framework Programme (FP7/2007-2013) / ERC grant agreement no. 239749.

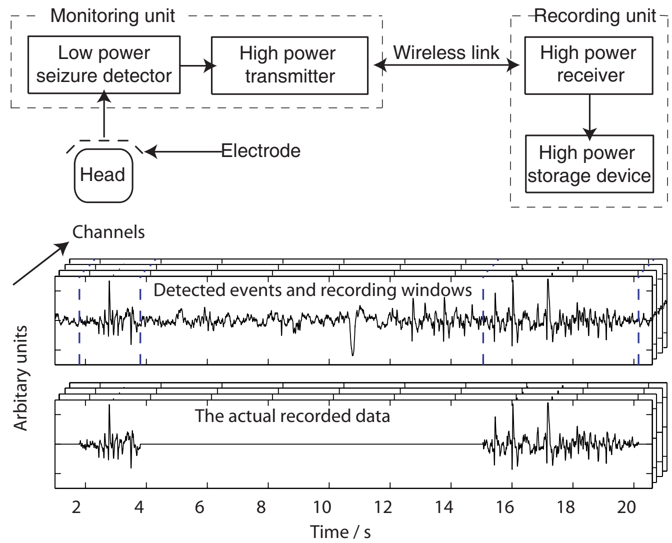

Fig. 1. Low power online data selection can be used to reduce the amount of EEG data to be transmitted and stored. This simultaneously reduces the system power consumption and reduces the burden of interpreting all of the EEG data by a human.

transmitted and received and thus the power consumption of the respective blocks. Of course, an overall power saving at the monitoring device can only be obtained if the power consumption of the data selection algorithm, at the low power detection stage in Fig. 1, is lower than the power saving at the transmitter. At the recording unit, any reduction in the amount of data received would reduce the power consumption of the receiver and writing to non-volatile memory.

In addition, an ideal data selection algorithm should only select to store data that is potentially useful for diagnosis later by a neurologist. It can therefore simultaneously decrease the time taken by the neurologist to review the long duration EEG recording (it takes about 2 hours for a neurologist to review a continuous 24 hour recording [5]). Such a review of discontinuous EEG has been reported to not substantially alter the final electro-clinical diagnosis of the patient [6].

This paper presents a suitable EEG data selection method by: using a seizure detection algorithm to only record sections of EEG data that look like candidate seizure activity; and implementing this algorithm on a low power micro-controller platform. The low computational complexity seizure detection algorithm is reported in Section II where its performance is evaluated using 168 hours of scalp EEG data. The low power hardware implementation is then reported in Section III where it is shown that a 90% reduction in the transmission power consumption can be achieved. Finally the implications of our low power system approach are discussed in Section IV.

II. AUTOMATIC EPILEPTIC SEIZURE DETECTION

Our real-time data reduction is based upon using an automatic epileptic seizure detection algorithm to highlight periods of EEG recordings that are characteristic of potential epileptiform activity. The algorithm utilised here is an improved version of that in [7], enhanced for detection accuracy and to require a low number of operations on the chosen micro-controller platform. The new algorithm is illustrated in Fig. 2.

The first processing step is to high pass filter the incoming EEG signal as recommended in [8]. Only low frequency information (less than 10 Hz) is then used for seizure detection, and thus the resulting EEG signal is downsampled to 20 Hz to greatly reduce the number of computations that need to be made per second, and thus reduce the power consumption. Within each 2 s non-overlapping epoch of N EEG samples the *line length* is then calculated as:

$$L(e) = \sum_{k=2}^{N} |x(k-1) - x(k)| \tag{1}$$

where e is an index denoting the epoch being analysed, x is the vector of N EEG samples and k is an index denoting a particular EEG sample.

To correct for broad level changes in EEG amplitude, for example between different subjects, the line length is normalized by a measure of the background EEG amplitude as

$$N(e) = \frac{L(e)}{z(e)} \tag{2}$$

where $z(e)$ is a *median decaying memory* [9]:

$$z(e) = \lambda z(e-1) + (1-\lambda)\text{median}[L(e-1) \cdots L(e-58)]. \tag{3}$$

In this work $\lambda = 0.99$ is used. For the initial 58 epochs, the median is calculated using all available epochs and λ is set to 0.92.

Finally, to raise a channel detection flag $N(e)$ is compared to a pre-determined threshold, β. A final detection of candidate seizure activity is made when $N(e)$ exceeds β in four or more channels. When this occurs the same 2 s of data across all 12 input EEG channels are transmitted. If not, the 2 s data section is rejected as background EEG and is discarded.

The performance of this algorithm has been evaluated on over 168 hours of scalp EEG data obtained from 21 adult patients and containing 34 seizures (4158 s seizure duration). The data has been obtained from multiple epilepsy clinics [10], [11] and has been marked by medical practitioners for seizure start and end.

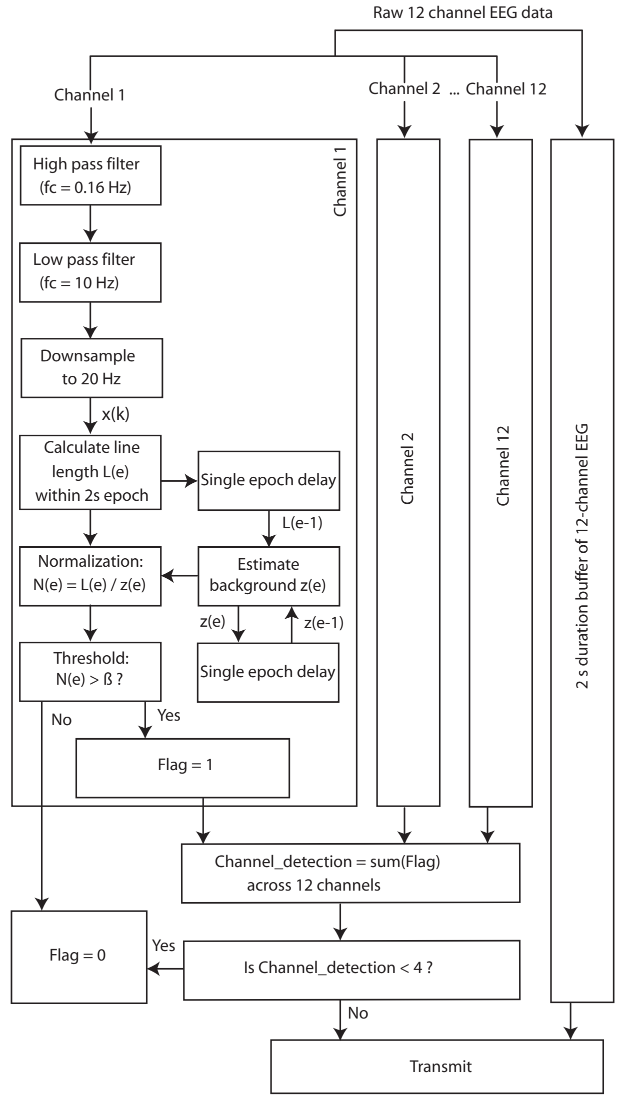

Fig. 2. The low power epileptic seizure detection algorithm used in this work to highlight seizure periods in EEG recordings. By recording only these periods real-time data reduction is provided.

To obtain different trade-offs between sensitivity and specificity values, the detection threshold β has been varied from 0 to 20 and the results are plotted in Fig. 3. Using a fixed β value of 2 the algorithm correctly detects 88.24% of seizures, selecting 53.17% of the total seizure duration and achieving a 90.78% reduction in the amount of background EEG data recorded. This is a high level of data reduction performance and thus the algorithm now needs to be translated into a low power hardware implementation.

III. MICRO-CONTROLLER IMPLEMENTATION

To demonstrate the low power consumption utility of the proposed algorithm, an ultra-low power wireless system has been set up based on using a Texas Instruments MSP430 micro-controller and a Nordic Semiconductor nRF2401+ wireless transmitter, as shown in Fig. 4. The MSP430 is used to implement the low power seizure detection algorithm

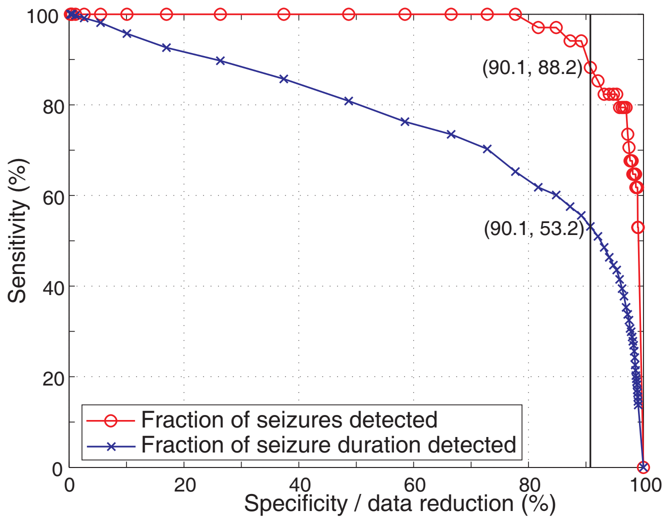

Fig. 3. The seizure detection performance of the algorithm when tested on over 168 hours of EEG data and 34 seizures. The trade-off between sensitivity and specificity can be varied by altering the β detection threshold. Printed values of performance are for $\beta = 2$.

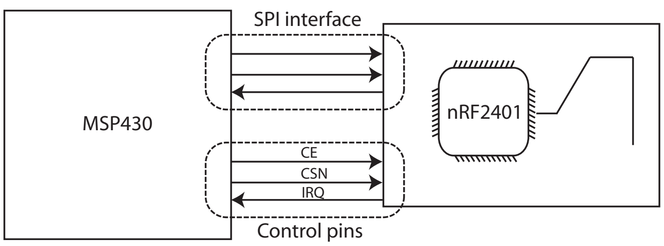

Fig. 4. An overview of the platform, based upon a Texas Instruments MSP430 micro-controller and a Nordic Semiconductor nRF2401+ wireless transmitter, that has been used to implement the low power wireless seizure detector.

and to control the operation of the Nordic transmitter. An MSP430-F5438A was selected for the implementation due to its low supply voltage (1.8–3.6 V), its large 16 kB RAM, and the availability of a 32-bit hardware multiplier. The Nordic Semiconductor nRF2401+ is an ultra low power wireless transceiver, ideal for the EEG monitoring application. Using the Nordic Shockburst protocol it can transmit at a 2 Mbps data rate, with a 32 byte payload on each transmission cycle, and a 0 dBm transmission power. The combined MSP430 and Nordic system operates from a 2 V supply (the minimum for the transceiver) with a 16 MHz clock.

The micro-controller and wireless transmitter were initially set up for continuous transmission of 16 bit EEG data sampled at 200 Hz across 12 channels (that is, with no data selection algorithm running). The measured power consumption for processing and transmission was 130 μW per channel.

The algorithm in Fig. 2 was then implemented on the micro-controller. For this, the power consumption of the MSP430 was minimized by using fixed point arithmetic (primarily 16 bit operations) and all filters were split into first and second order sections in sequence. For the median calculation, a fast median filtering with sorting complexity

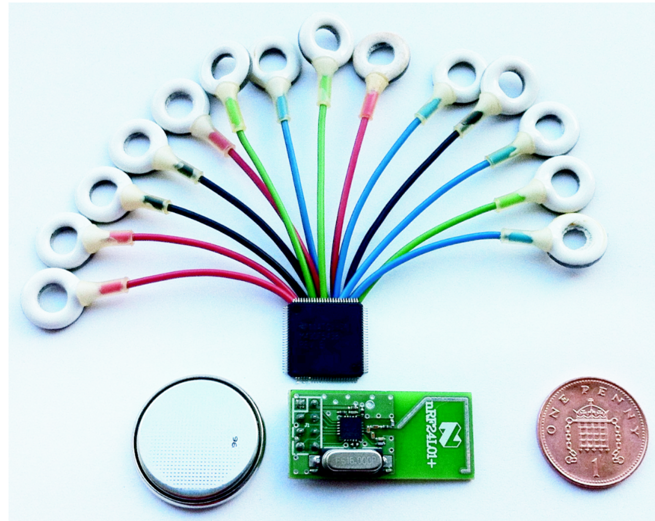

Fig. 5. Illustration of the end-solution: 14 electrodes (12 channels with a reference and ground); the MSP430-F5438A micro-controller; the Renata CR2430 lithium coin cell battery; the nRF2401+ wireless transceiver; and a UK one pence coin for scale.

of N was implemented with linked lists [12]. The transceiver was set up to remain in sleep mode until a detection is made by the data selection algorithm when there is candidate seizure data to transmit.

The net result, of introducing the data selection algorithm before the wireless transmitter, is that the micro-controller can run the algorithm with an average power consumption of 140 μW per channel and reduce the amount of EEG data to be transmitted by 90%. This low power consumption is achieved by keeping the micro-controller in low power mode for 80% of the time, with an average current consumption of 0.03 mA at the 16 MHz operating frequency (peak current of 14 mA).

IV. IMPLICATIONS OF THIS WORK

Using the data selection algorithm, the data transmitted was reduced by 90% and thus the power consumption of the wireless transmitter is reduced by 90% to 13 μW per channel. Overall the power consumption of the monitoring unit (processing and transmission) is 153 μW per channel, corresponding to 1.8 mW across the full 12 channel system. This channel count is limited by the 16 kB of RAM available in the micro-controller.

Overall the power consumption of the 12 channel system corresponds to 19 days of operation from a single lithium coin cell battery (Renata CR2430) with a nominal capacity of 285 mAh at 3 V [13]. The selected battery has dimensions of 24.5 $\times$ 3.0 mm and weighs 4.1 g [13]. To illustrate the potential, the key components of the 12 channel wireless seizure detector are shown in Fig. 5 (12+2 electrodes, MSP430, battery, transmitter and a UK one pence coin).

It should be noted that the battery lifetime here does not take in to account the power consumption of the essential front-end circuitry for a complete EEG system, such as an instrumentation amplifier and analogue-to-digital converter, which would require an additional 25 μW per channel [14]. Including these circuit blocks would reduce the battery lifetime to just over 2 weeks of operation.

Until now, the power consumption of the recording unit in Fig. 1 has not been discussed. The power consumption of the receiver is expected to be equivalent to that presented for the transmitter. Thus the real-time data reduction provided by the seizure detection algorithm would also reduce the power consumption of the receiver by 90%. In addition, this approach would result in power savings in other data reduction linked factors such as encryption prior to transmission and data storage at the recording unit.

Thus the 90% data reduction achieved makes the system much more suitable for the use of physically unobtrusive batteries, and providing longer monitoring times from these small batteries. It is expected that the power consumption of the algorithm could be further reduced through custom analogue, digital or mixed signal integrated circuit design and this is an active area of research.

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