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Seizure Detection Methods Using A Cascade Architecture For Real-Time Implantable Devices

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Abstract

Implantable high-accuracy, and low-power seizure detection is a challenge. In this paper, we propose a cascade architecture to combine different seizure detection algorithms to optimize power and accuracy of the overall seizure detection system. The proposed architecture consists of a cascade of two seizure detection stages. In the first-stage detector, a lightweight (low-power) algorithm is used to detect seizure candidates with the understanding that there will be a high number of false positives. In the second-stage detector—and only for the seizure candidates detected in the first detector—a high-accuracy algorithm is used to eliminate the false positives. We show that the proposed cascade architecture can reduce power consumption of seizure detection by 80% *with high accuracy, offering a suitable option for real-time implantable seizure detectors.*

1. INTRODUCTION

Seizure detection on implantable medical devices is a key step to provide long-term seizure monitoring and treatment solutions for many patients with epilepsy. Yet achieving implantable solutions with robust detection capabilities is still a challenge [1].

Although, a wide variety of algorithms ranging from simple algorithms such as Line-length [2] to sophisticated algorithms based on machine learning [3] or spectral power [4] have been developed for seizure detection, not all of these algorithms are practical for real-time implantable medical devices due to their power, computational and/or space complexity requirements. Most notably, recent studies [5–8] using single/multiple level count-based methods, inter-event based methods and several time-domain features like line-length, energy, and variance, show promising performance using low power on real-time implantable devices. However, these low power, computationally-efficient (i.e., *lightweight*) seizure detection algorithms use only time-domain features including indirect frequency features such as count-based, and inter-event due to the computational complexity of frequency-domain feature computation. Therefore, these lightweight algorithms cause more false positives than algorithms that use both time and frequency-domain features (i.e., high-accuracy algorithms). Thus, it is hard to identify a single algorithm that is both low power, and provides high accuracy (i.e., low false positive rate).

In this paper, we propose a cascade architecture for seizure detection which utilizes the best properties of these two sets of algorithms, namely the *lightweight* and *high-accuracy* seizure detection algorithms.

For the first stage, the proposed method uses a simple seizure detection algorithm to distinguish non-seizure signals from seizure-candidate signals, which includes both actual seizures and artifacts. The second stage operates only when the first-detector detects seizure-candidates. The proposed cascade seizure detection method makes it possible to implant sophisticated seizure detection algorithm with only 20% of its original power consumption. Therefore, the proposed method is optimized for implantable medical devices.

It should be noted that many seizure detection architectures have a pre-filtering stage such as a discrete wavelet transform or band-pass filtering to attenuate artifacts before the signal is applied to the seizure detection algorithms to reduce the false positive rate [9]. Besides the high power consumption of these pre-filtering architectures, the proposed cascade architecture differs from the pre-filtering approaches by having a seizure detector in the first stage (i.e., first detector), which eliminates a significant portion of the data to be processed by the second detector.

In the next section, we introduce the proposed seizure detection methods using the cascade architecture. In Section 3, simulation results and the algorithm complexity based on clock cycles for real-time processing are analyzed. Section 4 presents conclusions and future works.

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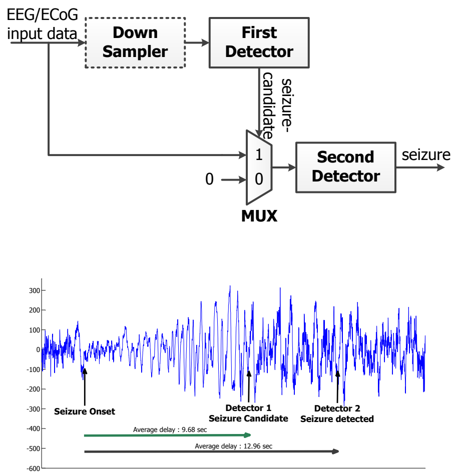

Figure 1: (a) Block diagram for the proposed cascade architecture for seizure detection. (b) Illustration of the seizure detection method using cascade architecture.

2. Cascade Seizure Detection Methods

The block diagram of the proposed cascade architecture for seizure detection is shown in Fig. 1(a). The first detector—a lightweight seizure detector— *continuously* monitors the Electroencephalography(EEG) signal to filter out a large portion of the data, and identifies seizure candidates for further evaluation. The input signal to the first detector can also be down-sampled depending on the algorithm used (Section 2.1). The second detector—a high-accuracy seizure detector— is not activated until the first detector detects a seizure candidate. Once the first detector detects seizure candidates, the second detector starts to operate to evaluate whether the seizure candidate is an actual seizure or not. The second detector only inspects the data starting from the time the seizure candidate is detected (Fig. 1 (b)). If the candidate seizure is classified as a seizure, then this is reported, otherwise the candidate is discarded. In either case, as soon as the second detector completes its evaluation, the second detector is turned off. The seizure detection latency increases slightly due to the cascade seizure detection architecture as given in Section 3.

We propose using simple time-domain features like line-length or area for the first seizure detector because the amplitude variation in seizure status is the most common distinguishable feature. For the second detector, we propose using frequency-domain features like spectral entropy or a wavelet transform to eliminate false detections.

In this paper, we use the area feature and multi-window count method for the first detector. For the second detector, we propose to use a multi-window count method and spectral entropy. These algorithms are summarized in the following sections. Further details of these algorithms can be found in [5, 10, 11].

2.1. Area-based Seizure Detection

Area [11] is a time-domain feature for calculating the average absolute amplitude of the signal as shown in Eq. (1).

$$Area(k) = \frac{1}{N}\sum_{i=1}^{N}|x[i+N(k-1)]| \qquad (1)$$

where N is the window size and x is the sampled input data. A large deviation (*i.e.,* above a certain threshold) in the computed value of area in a short-term window with respect to the long-term average is considered as a seizure indicator.

An area-based seizure detection requires only very simple computational primitives such as addition, shift, and comparison, and thus has low computational complexity and power consumption. Furthermore, its accuracy stays virtually the same even for down-sampled data, which further reduces the power needs of this algorithm, making area-based seizure detection suitable for the first detector. In this work, area is calculated after down-sampling input data up to $1/16^{\text{th}}$ of the actual sampling rate.

2.2. Multi-Window Count Seizure Detection

The count-based seizure detection algorithm using single window count (SWC) is proposed as an efficient method for seizure detection in [5]. The SWC method counts the number of samples whose amplitudes fall in between a positive threshold and a negative threshold in a given time window. A small sample count below a certain threshold indicates a seizure.

We slightly modified the count-based method as shown Fig. 2 to reduce number of incremental count operations and false detections by partitioning a single window into small windows. The multi-window count (MWC) method partitions a single window with k small windows and counts only when the samples are above the positive threshold (C_{up}) and below the negative threshold (C_{dn}). This can reduce the number of incremental count operations.

If the C_{up} or C_{dn} has zero value in a small window data set, we reset all the count values to zero, because a zero in the positive value (negative value) shows that the input signal is biased towards negative values (positive values). The long-term sample-counts C_s can be determined by iterating this process k times. Since, we count samples that fall out of thresholds, C_s is compared

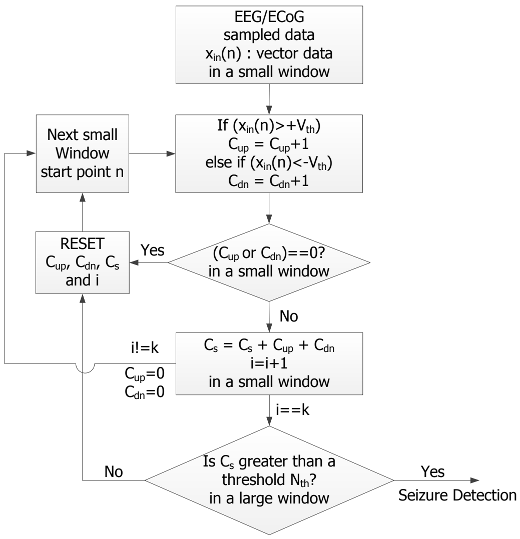

Figure 2: Flow chart for the multiple windows count-based method.

with pre-defined threshold $N_{th} = N - C_{th}$, where N is the number of samples in a single window and C_{th} is the same parameter as in [5]. Therefore, both short-term and long-term sample-counts are considered. MWC is also suitable as the first detector, since it only requires a small number of comparison and addition operations. Yet, MWC shows better FPh (number of false positives per hour) compared to SWC.

2.3. Spectral Entropy-Based Seizure Detection

Spectral Entropy (SPE) [10] provides a frequency domain measure of signal complexity. During a seizure, signals show rhythmic synchronized features causing a decrease in SPE. Thus, a low SPE value can be considered as a seizure indicator. SPE can be calculated from the following 3 steps. First, calculate power spectrum $P(f_i)$ from the Fourier transform $X(f_i)$,

$$P(f_i) = |X(f_i)|^2 \tag{2}$$

where $X(f_i)$ is frequency amplitude at f_i. Then, the power spectrum is normalized as shown in Eq. (3)

$$P_n(f_i) = \frac{P(f_i)}{\sum_{f_i=f_1}^{f_2} P(f_i)} \tag{3}$$

Finally, SPE within the frequency range $[f_1, f_2]$ is computed as follows.

$$S[f_1, f_2] = \sum_{f_i=f_1}^{f_2} P_n(f_i) \log \frac{1}{P_n(f_i)} \tag{4}$$

In this work, SPE is calculated after down-sampling input data up to $1/4^{\text{th}}$ of the actual sampling rate. A 64-point Radix-2 FFT architecture is used for the Fourier transform. Since, calculating the exact *log* value is not needed, we can substitute *log* calculation with additions, comparisons and shift operations.

3. Simulation and Results

The proposed cascade seizure detection architecture was evaluated against recordings from 7 patients in the CHB-MIT scalp EEG database [12]. These recordings last for 272 hours, and include 34 seizures. The data is sampled at 256 Hz.

Table 1 shows the performance and complexity of individual seizure detection algorithms. The clock frequency is determined by calculating the number of cycles required for the processing of 1 second worth of data per channel (acquisition, calculations and serial memory access) on a 16-bit microcontroller (MSP430, Texas Instruments) in real-time. For an exact comparison, we apply the same window size (5 sec), *i.e.,* the algorithm decides whether there is a seizure in or not only once for each window.

Table 1: Performance comparison of individual seizure detection algorithms for real-time processing.

Algorithm	**Sensitivity**	**FPh**	**Latency [sec.]**	**f_{clk} [MHz]**
Area	34/34	11.82	9.87	0.06
SWC [5]	34/34	11.66	10.14	0.80
MWC	32/34	3.77	12.12	0.80
SPE	32/34	2.69	16.11	5.48

The sensitivity of all the seizure detection algorithms in Table 1 is high. However, the hourly false positive rate varies highly, and as expected, the hourly false positive rate of an algorithm decreases as the required clock frequency of the algorithm and thus its power consumption increases. This conclusion confirms that although high sensitivity is common in even the simplest algorithms, for high selectivity the price paid is an increase in power consumption.

Table 2 shows the performance and complexity for the proposed cascade architecture. Here, the sensitivity is still high, yet, the hourly false positive rate drops significantly. Although, the required clock frequency is still higher for a lower hourly false positive rate, compared to the performance of the individual algorithms, both the FPh and the required clock frequency are much lower. More specifically, the proposed cascade architecture has over 94% sensitivity, with 0.9 false positive per hour running on an average clock frequency of 830 kHz. Furthermore, the required clock frequency in the cascade seizure detector is close to the first detector clock frequency as shown Table 1, since the second detector is rarely on.

Table 2: Performance of the proposed cascade architecture for seizure detection for real-time processing.

Algorithm	Sensitivity	FPh	Latency [sec.]	f_{clk} [MHz]
Area+MWC	32/34	2.21	12.96	0.074
Area+SPE	33/34	1.33	17.49	0.150
MWC+SPE	32/34	0.90	18.52	0.830

The average clock frequency of cascade seizure detector can be calculated using Table 1. In Area+MWC case, Area detects about 12 seizure candidates per hour, therefore, the second seizure detector MWC operates only 12 times per hour. Therefore, the average f_{clk} can be calculated as follow.

$$f_{clk} = \frac{3600 \times f_{clk_1} + FPh_1 \times N_2 \times f_{clk_2}}{3600} \tag{5}$$

where f_{clk_1}, f_{clk_2} are the average clock frequency for the first detection algorithm and the second detection algorithm, FPh_1 is false positive per hour of the first detection algorithm and N_2 is window size for the second detection algorithm. Therefore, we can achieve more than 80% reduction in power consumption with almost the same accuracy, better false positive rate, but with approximately 4 sec additional detection latency.

4. Conclusion and Future Works

For the realization of implantable medical devices, we need to optimize from algorithm level to hardware design level. The proposed seizure detection methods using a cascade architecture provide a trade-off between detection latency and performance and low power. The proposed seizure detection method improves the performance by using two different features and also reduces power consumption by using a turn-on/off scheme at the second detector. We show that better performance is obtained when using two different features rather than one single feature. Further, we show that the proposed seizure detection methods using cascade architecture can save up to 80% power consumption with reasonable latency. Therefore, the proposed seizure detection methods are suitable for implantable medical devices. The proposed method is especially suitable for wireless seizure data monitoring which is less sensitive to detection latency. In our future work, we will investigate our cascade architecture with different window sizes, and new features to reduce FPh.

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