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# Two-stage Hardware-Friendly Epileptic Seizure Detection Method with a Dynamic Feature Selection*

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*Abstract*— **A novel low-complexity method of detecting epileptic seizures from intracranial encephalography (iEEG) signals is presented. In the proposed algorithm, coastline, energy and nonlinear energy features of iEEG signals are extracted in a patient-specific two-stage seizure detection system. The detection stage of the proposed system, which extracts two times more features than the monitoring stage, is only powered on when the monitoring stage detects a seizure occurrence. A new metric is defined to demonstrate the significance of the two-stage architecture and show the time duration over which the detection stage is activated. The new parameter is called detection stage activation ratio (DAR) and it is equal to 0.272 in this work. In addition, the proposed seizure detector outperforms other algorithms which utilize a single feature or multiple features continuously in terms of sensitivity, specificity and DAR. Therefore, it is highly suitable for seizure detector implants in which reducing the power consumption is a critical factor to increase the lifetime of the implanted battery. The algorithm is implemented on a Cyclone V FPGA and has a low dynamic power of 1 µW when tested on human iEEG signals of six patients from the Bern Inselspital dataset. It reaches a perfect sensitivity of 100% tested on 120 hours of iEEG data containing 24 seizure periods of six patients.**

## I. Introduction

Epilepsy is a chronic neurological disorder which affects more than 65 million people globally and approximately 1 out of 26 people will develop epilepsy at some point during their lifetime [1]. Epilepsy is characterized by recurrent temporary electrical disturbances in the brain known as seizures [2]. Approximately 30% of patients remain medicament refractory in spite of available therapies [3]. Using implantable and wearable seizure control devices are considered as a promising and effective alternative. The imperative part of an implantable or wearable device for epilepsy control is an efficient onset seizure detection system from EEG signals.

On one hand, a powerful seizure detection algorithm is required to discriminate between seizure and normal episodes of EEG signals which are called ictal and inter-ictal signals respectively. On the other hand, a sophisticated algorithm is rather power hungry, which must be avoided in an implantable module due the expensive and risk-prone battery replacement issue. Furthermore, it is mandatory to maintain the power consumption of the implant within a minimum range to prevent an undesirable temperature elevation of the neural tissues which can cause detrimental tissue damages [3].

## II. Background

An extensive body of research has been devoted to design automated seizure detection algorithms while most of the algorithms lack a hardware-friendly implementation and cannot be utilized in implantable and wearable devices especially in regards of power consumption. EEG analyses can be categorized into time domain, frequency domain, time-frequency domain and nonlinear methods [4-7].

Authors in [4,8] have used frequency domain features such as power spectral density to detect seizures. A random forest classifier is also used in [8] as a classifier. A major drawback of using spectral power density is having high false positive detections due to increasing power spectral density even in inter-ictal states.

Statistical features in time-domain are extracted in [9]. Although multiple features are extracted in [9], it lacks a feature ranking and selection strategy. [6] used discrete-wavelet transform to extract time domain features which is considered as a computationally expensive method.

Furthermore, a neural network in conjunction with deep learning is applied on spectral power features of EEG signals in [10]. The high complexity of this approach prevents the on-chip application.

In this article, a power-efficient two-stage seizure detection algorithm is presented and implemented on Cyclone V FPGA. A hardware-friendly strategy is employed using coastline, energy and nonlinear energy features which are known as powerful time-domain features in onset seizure detection. Feature ranking and selection strategies are applied to determine the optimal feature for each stage. The proposed architecture enables avoiding redundant computations by turning off two feature extractors when the monitoring stage doesn't detect any seizure. In addition, a voting-based post-processing block is utilized to provide a further enhancement to the specificity of the system. Finally, we compare our novel approach with two conventional methods in which the coastline, energy and nonlinear energy features are extracted without using two-stage approach.

The remainder of this paper is organized as follows. Section III describes the system overview of the proposed method. Section IV introduces the dataset and parameters which are used to assess the performance of the system as well as hardware implementation results. Finally, the main conclusions of this work are summarized in Section V.

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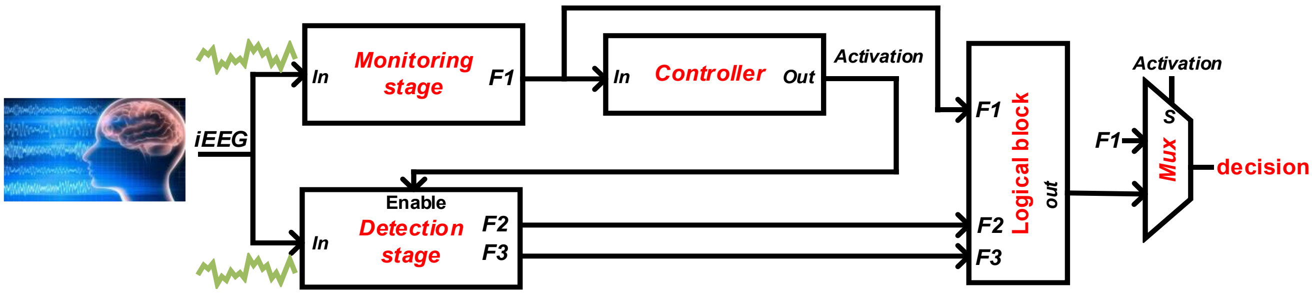


Figure 1. Block diagram of the proposed system

## III. NOVEL TWO-STAGE ARCHITECTURE

The highest priority of a two-stage seizure detection system relates to minimizing the power consumption while keeping the efficacy not affected. In this work, a patient-specific multi-criteria algorithm is proposed to guarantee the efficient operation of the two-stage seizure detector. Three time-domain features used in this work are the coastline, energy and nonlinear energy features. These features have been widely used in the literature of epileptic seizure detection [3,7,9]. An 8-bit feature extractor engine calculates these three features in a two-stage architecture.

The coastline feature measures the difference between adjacent samples at any rising edge of the clock using an 8-bit subtractor and accumulate them over a fixed window of one-second which contains N=512 samples. The accumulated value is compared with the coastline threshold and generates an early detection decision. The early detection decision is used in a post-processing block for further analyses. The mathematical expression of the coastline feature is given in (1) [7].

$$CL = \frac{1}{N}\sum_{i=1}^{N} abs(x[i] - x[i-1]) \tag{1}$$

The mathematical expression associated with the energy feature extraction over a window of length N is given as (2) [7]. The square value of each sample is generated by an 8-bit multiplier which is followed by an accumulator in the hardware design.

$$E = \frac{1}{N}\sum_{i=1}^{N} x[i]^2 \tag{2}$$

The nonlinear energy nonuniformly weights the components at different frequencies using square-law weighting. The mathematical expression is given as (3) [7].

$$NE = \frac{1}{N}\sum_{i=1}^{N} x[i]^2 - x[i-1]x[i+1] \tag{3}$$

### *A. Two-stage patient-specific seizure detection*

The block diagram of the proposed two-stage seizure detection system is depicted in Fig. 1. Although three time-domain features (F1, F2, F3) are extracted in this work, only a single feature (F1) is continuously extracted in the first stage that is called the monitoring stage. Two other features (F2, F3) are extracted in the second stage which is called the detection stage, only when it is enabled by the controller. The controller will activate the detection stage for a limited period of time upon arising a seizure detection flag from the monitoring stage. The logical block and multiplexer are in charge of making the final seizure detection decision in the system.

This architecture presents a practical solution for implantable systems in which lowering the power consumption is of paramount importance. During long inter-ictal states, only one feature is extracted in the monitoring stage and the detection stage is inactivated to avoid unnecessary computations. Different components of the system are described in the following.

*1) Monitoring stage*

The monitoring stage operates continuously during both inter-ictal and ictal states. To avoid redundant computations, only one feature is extracted in this stage and it is determined by a feature ranking approach in the training phase. The most important property of the feature in this stage is having a high sensitivity to minimize activation of the detection stage. The detection flag of this stage arises based on threshold crossing and it followed by a voting-based post-processing block.

*2) Detection stage*

The detection stage is the second stage in the presented system. It is of higher energy consumption compared to the monitoring stage due to extracting two features. The appropriate features for this stage are determined by a patient-specific feature ranking in the training phase.

This stage is temporarily powered on by the controller if a detection flag arises from the monitoring stage. The main role of this stage is reducing false positive detections of the system.

*3) Post-processing*

The hardware implementation of the post-processing block is shown in Fig. 2. It is utilized to improve the system specificity. To this aim, a voting-based strategy with three-second window length is employed. The output signal (post detection) will be '1' when two threshold crossing occur in each three-consecutive windows.

*4) Controller and logical block*

The controller and logical blocks are displayed in Fig. 1. F1, F2 and F3 are the outputs of feature extraction in the monitoring and detection stages, respectively. The controller block is in charge of activating the detection stage for a limited period of $t_{act}$ when F1 is high. The value of $t_{act}$ must be set with respect to the post-processing window length.

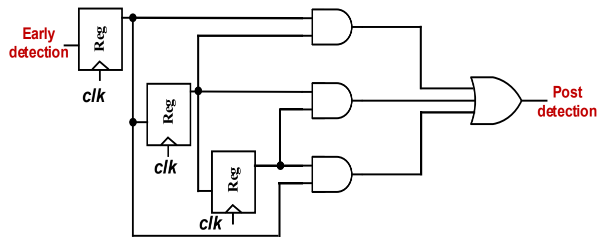


Figure 2. Hardware implementation of the post-processing block

Thus, $t_{act}$ in this work is selected 9 seconds as a compromise between the detection stage activation ratio (DAR), sensitivity and specificity parameters. Besides, the select signal of the multiplexer (s) which selects between the output of the logical block and F1, is determined by the controller output.

On one hand, applying a logical AND to F1, F2 and F3 contributes to reducing the number of false positive detections at the cost of lowering the number of true positive detections. On the other hand, applying a logical OR to them results in increasing false positives. Hence a combination of a logical AND in conjunction with a logical OR is chosen to provide a balanced trade-off between false detections. The logical operation of the logical block is expressed as (4).

$$Logical\ output = F1\ AND\ (F2\ OR\ F3) \qquad (4)$$

### *A. Training phase and feature ranking*

The training data is randomly selected for each patient and it doesn't include more than 50% of seizure events. In the training phase, the thresholds of the features are determined so as to obtain the highest seizure detection performance. It is worth noting that there is a compromise between sensitivity and specificity of the detection when it comes to threshold selecting. Initially, the thresholds of all three features are chosen using the marked dataset to obtain the highest sensitivity. Then, the features are ranked with respect to their sensitivity. The feature with the highest rank is selected for the monitoring stage.

The role of the detection stage is improving the specificity of the system. As a result, the thresholds of the features used in this stage are adjusted in order to obtaining the highest possible specificity.

The proposed two-stage architecture successfully addresses the trade-off between sensitivity and specificity of the system which are reversely proportional to false negative and false positive detections. In conventional threshold-based seizure detectors, reducing the number of false positive detections increases the number of false negative detections. However, this approach minimizes false negative detections of the monitoring stage and false positive detections of the detection stage. Consequently, it enables the design to keep an optimized performance.

## IV. DATASET AND FPGA IMPLEMENTATION RESULTS

This section describes the dataset, performance parameter metrics and FPGA implementation results. The parameters associated with the implementation of the seizure detector on a Cyclone V FPGA is summarized in Table I.

Table I. FPGA implementation parameters

| Operating frequency | Register [#] | Memory bits | Dynamic power | Static power |
|---|---|---|---|---|
| 4 kHz | 955 | 175104 | 1 µW | 135 mW |

### *A. Dataset and performance metrics*

The functionality of the proposed seizure detection system has been assessed by iEEG datasets of six patients from the epilepsy program of the Bern Inselspital [5]. The seizure detector has been tested on 120 hours data which includes 24 seizures.

To evaluate the performance of the algorithm, four parameters including the sensitivity, specificity, detection delay and detection stage activation ratio (DAR) are considered. DAR is a new metric defined in this work to demonstrate the performance of a two-stage seizure detector. DAR is defined as the time duration over which the detection stage is activated when the hardware is tested on a dataset which contains a seizure event per hour.

It is noteworthy that the DAR is reversely proportional to the energy consumption of the system and varies between 0 to 1. DAR=0 means that only one feature of the monitoring stage is extracted for seizure detection, while DAR=1 implies that the system needs to extract all three features continuously when there is a seizure event per hour.

### *B. Hardware implementation results*

Fig. 3 demonstrates an iEEG signal with a seizure event along with seizure detection results using the coastline feature, three features (coastline, energy and nonlinear energy) in a single stage and the proposed algorithm. The iEEG signal of the patient ID1 of the dataset is shown in Fig 3(a). A seizure occurrence begins at t =100 sec and lasts until t = 130 sec. Fig. 3(b), 3(c) and 3(d) demonstrate the superiority of the proposed system over two other methods as it has the lowest fluctuations between zero and one before and during the seizure event.

The features used in the monitoring and detection stages are chosen based on the feature selection approach. Information regarding the dataset and the rank of features for six patients are provided in Table II. It also evidences the significance of employing the feature ranking in the two-stage architecture system since the rank of features varies from patient to patient. Thus, the features which are extracted in the monitoring and detection stages are adopted based on their ranks when the feature with highest rank has the highest seizure detection sensitivity and it is used in the monitoring stage.

The seizure detection results of the proposed novel two-stage architecture system are compared with two other methods in Table III. The method-1 uses the coastline feature for seizure detection which is widely used in literature [7, 9]. In method-2, the coastline, energy and nonlinear energy features are used in a conventional single stage way.

Table III evidences that the proposed algorithm outperforms method-1 in terms of specificity. In addition, it

Table II. Dataset information and feature ranking results

| Patient information | | | Feature ranking | | |
|---|---|---|---|---|---|
| *ID* | *Total Seiz [#]* | *Trained Seiz [#]* | *Rank 1* | *Rank 2* | *Rank 3* |
| 1 | 2 | 1 | Coastline | Nonlinear energy | Energy |
| 2 | 2 | 1 | Coastline | Nonlinear Energy | Energy |
| 3 | 4 | 2 | Energy | Coastline | Nonlinear energy |
| 4 | 4 | 2 | Coastline | Nonlinear energy | Energy |
| 5 | 8 | 3 | Coastline | Energy | Nonlinear energy |
| 6 | 4 | 2 | Nonlinear energy | Energy | Coastline |

Table III. Performance comparison table

| Parameter | Method-1 | Method-2 | Novel system |
|---|---|---|---|
| Sensitivity [%] | 100 | 100 | 100 |
| Specificity [%] | 88.5 | 94.01 | 92.1 |
| Delay [sec] | 5.7 | 12.9 | 7.8 |
| DAR | n.a | 1 | 0.272 |

has much faster detection time and lower DAR compared to method-2. Hence, the presented work provides an optimized trade-of between detection speed and false positive detection. The DAR parameter of the proposed system is 0.272 which means that the system needs to extract all three features only in 27.2% of the time and in 72.8% of the time only the single feature used in the monitoring stage, is extracted.

## V. Conclusion

An efficient two-stage methodology for onset seizure detection is developed and implemented on hardware. It exploits coastline, energy and nonlinear energy features of iEEG signals, and the features are ranked based upon their seizure detection sensitivity in the training phase. It determines the optimized features for the monitoring and detection stages. The presented seizure detection algorithm demonstrates a perfect sensitivity of 100% as well as offering an optimized trade-off between the seizure detection speed and false positive detection. It outperforms the coastline algorithm in terms of specificity. Furthermore, it has demonstrated its superiority over using three features in conventional way in terms of detection speed and DAR. The proposed seizure detection system has a dynamic power consumption of 1 µW, thanks to the low DAR value of 0.272.

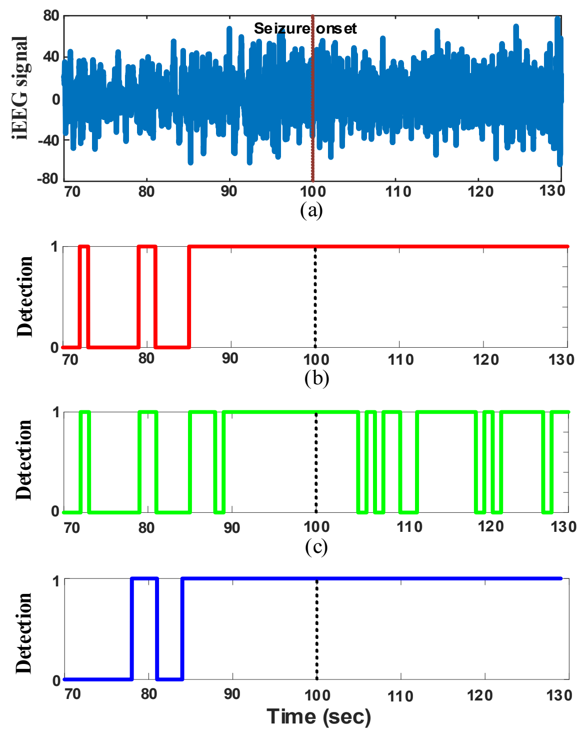


Figure 3. (a) iEEG signal with a seizure event (b) Seizure detection using coastline (c) Three features in a single stage and (d) proposed method

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