Computation Complexity Reduction Technique for Accurate Seizure Detection Implants

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***Abstract*—An automatic seizure detection method from high-resolution intracranial-EEG (iEEG) signals is presented to minimize the computational complexity and realize real-time accurate seizure detection for biomedical implants. Complex signal processing on a large amount of iEEG signals captured via several electrodes is a crucial impediment in seizure detection when it comes to power consumption and real-time processing. Therefore, a subject-customized channel selection method correlated to a feature ranking unit is proposed to improve the computation efficiency and seizure detection accuracy by reducing the dimension of extracted features as well as the electrode channels. Nine popular time-domain features are extracted and ranked to constitute a customized feature subset. Subsequently, electrode channels are ranked with respect to the top four rank features obtained from the feature ranking unit. Then, the number of channels is optimized to reach the highest detection accuracy. The selected channels are compressed into a single channel to minimize the signal processing computation load. The suggested method is tested on seven patients with 37 seizure events from the SWEC-ETHZ dataset of the Bern University Hospital. The perfect sensitivity of 100%, the specificity of 92.98%, and the mean detection delay of 3.6 sec are achieved which outperform the state-of-the-art. In addition, the computation complexity is remarkably reduced which makes the presented method suitable for low-power real-time biomedical implants.**

***Index Terms*—Biomedical digital signal processing, Feature extraction, Channel selection, Seizure detector implants.**

I. Introduction

Automatic seizure detection using brain electroencephalogram (EEG) has become an attractive research topic to replace the continuous monitoring of patients' EEG signals by neurologists over a long period. The seizure detection unit which consists of feature extraction and classification is the heart of a closed-loop epilepsy control device [1]. Several feature extraction algorithms have already been reported in the literature to precisely detect/predict seizure occurrences. However, the computational complexity originating from the high dimensionality of the input signal is a critical hindrance to implement most of those algorithms for low-power real-time implantable applications.

Intracranial-EEG (iEEG) signals captured via multiple electrode channels to enable high spatial resolution signals [2]. On one hand, a huge amount of input signal is fed to a digital signal processor which significantly increases the computational complexity of the feature extraction. On the other hand, EEG signals have non-stationary inherent content that vary from patient to patient. Thus, a patient-specific feature extraction employing various types of features is required to achieve acceptable performance for a large group of patients.

Therefore, the computation complexity of a seizure detector chiefly depends on the number of recording channels as well as the dimension of extracted features. [3] and [4] apply both feature and channel dimension reduction so as to achieve computation complexity reduction. [4] lacks a systematic correlation between feature extraction and channel selection units. [1] reduces the feature dimension by using a two-stage architecture feature extractor. In this case, the effective number of features processed by the detector is remarkably reduced.

[5] and [6] only use channel selection dimension reduction. [5] performs time and frequency domain feature extraction with random forest classification. The channels are selected using supervised classifiers. However, the number of features is still high. [6] determines the best channels according to the average energy of the wide-band signal and selects a certain channel number for all studied subjects which lacks patient-specific channel optimization. [7] conducts only feature dimension reduction for computation reduction in which a single feature is selected from a feature pool that contains multiple features. It still lacks channel selection and may not be practical for implantable application especially when signal is recorded via tens of electrodes.

This work presents a computation complexity reduction method in order to achieve precise patient-specific seizure detection for biomedical implants which require very limited power consumption and resources (less than 2 mW). A novel channel selection approach that is correlated to a customized feature ranking unit is proposed. The feature ranking unit filters out more than half of the features available in the feature pool in a patient-specific way. Subsequently, the novel channel selection algorithm ranks each channel according to the feature ranking unit outputs. As a result, the selected features are only extracted from a single channel which is the average of the selected channels. The proposed seizure detection algorithm

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yields a significant computational complexity reduction by both feature and channel selection that is optimized to achieve a high detection accuracy.

The rest of this paper is organized as follows. Section II explains the methodology of the presented algorithm. Section III describes the feature extraction and feature ranking techniques. The novel channel selection method is introduced in Section IV. The results of testing the algorithm on human iEEG signals are demonstrated in Section V. Finally, Section VI summarizes the main achievements of the paper.

II. Seizure detector architecture

An automatic epileptic seizure detector typically comprises two main blocks: 1) Feature extraction and 2) Classification units. The principal target of this work is to reduce the computational complexity of the detector which is regarded as the main impediment in realizing low-power real-time seizure detector implants. The computation complexity reduction is carried out by channel and feature selection techniques which operate coordinately.

The system architecture of the presented seizure detector is depicted in Fig. 1 containing all blocks used in the training and test phases. In the training phase, nine widely used time-domain features are extracted in a feature pool ($F_1 - F_9$) and the optimized detection thresholds are also computed. The extracted features are ranked in the feature ranking block ($FR_1 - FR_9$) and non-beneficial features are subsequently filtered out in the feature reduction block. Then, the electrode channels are ranked according to the top rank features ($Ch_1 - Ch_n$). Lastly, irrelevant channels are eliminated by the channel reduction unit as displayed in Fig. 1a.

The block diagram of the system in the test phase is demonstrated in Fig. 1b. The top rank channels are chosen and compressed into a single channel by the channel selection and channel compression blocks respectively to highly condense the dimension of the input iEEG signals. The feature extractor extracts the top rank features and the detection function proceeds to the initial detection decision. The detection flag is generated by the post-processing block. The properties of each block are described in the following sections.

III. Feature extraction and ranking

A. Feature pool

Nine widely used time-domain features are available in the proposed feature pool: 1) Coastline (CL), 2) Energy (EN), 3) Nonlinear energy (NE), 4) Variance (VAR), 5) Minimum (MIN), 6) Maximum (MAX), 7) Range (RNG), 8) Average (AVG) and 9) Correlation (COR). Two critical issues of extracting all features from patients are as follows. Firstly, extracting nine features per channel contributes to remarkable computation complexity which must be avoided in low-power real-time seizure detector implants. Secondly, extracting a fixed feature set for all patients generally results in including redundant features which deteriorate the detection performance. Thus, the functionality of the features must be assessed in a training phase to find out the optimal feature set in a customized way.

TABLE I: Feature ranking applied on human iEEG

Patient No.	Rank 1	Rank 2	Rank 3	Rank 4
1	NE	EN	VAR	AVG
2	NE	VAR	EN	CL
3	NE	VAR	EN	CL
4	AVG	MIN	RNG	MAX
5	NE	CL	COR	MIN
6	CL	NE	COR	MIN
7	COR	MIN	RNG	MAX

B. Feature ranking and dimension reduction

The feature ranking unit ranks the features in order to reveal to what extent the features are discriminating during seizure events. The features are ranked based on a feature score which shows the variation of a feature upon seizure occurrences. The features used are categorized into amplitude-based features (CL, MIM, MAX, RNG, AVG and COR) and amplitude square-based features (EN, NE and VAR). The scores of amplitude-based and amplitude square-based features are calculated as (1) and (2), respectively.

$$Feature\,score(i) = \frac{\frac{\sum_{t_{sz}} F_i}{t_{sz}}}{\frac{\sum_{t_n} F_i}{t_n}} \tag{1}$$

$$Feature\,score(j) = \sqrt{\frac{\frac{\sum_{t_{sz}} F_j}{t_{sz}}}{\frac{\sum_{t_n} F_j}{t_n}}} \tag{2}$$

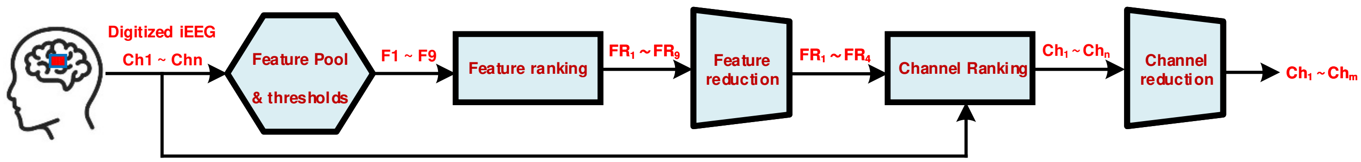
Where F_i and F_j are the i^{th} amplitude-based and the j^{th} amplitude square-based features, respectively. t_{sz} and t_n are the time duration of seizure and normal states, respectively. It is noteworthy that a feature with a higher feature score is considered the more discriminating feature on the grounds that it demonstrates more variation when a seizure occurs.

More than 50% of the features are filtered out in the feature reduction block with respect to their corresponding feature scores, and only the top four rank features play role in the detection function. The feature ranking outcomes of the proposed algorithm tested on the SWEC-ETHZ dataset [8] are given in Table I.

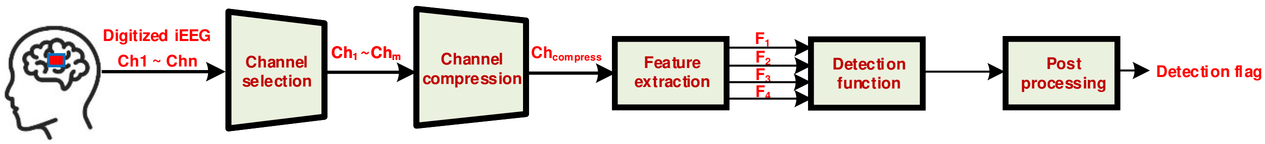
C. Seizure detection function and post-processing

Feature scores and ranks are determined in the training phase, and only the top four rank features (F_1, F_2, F_3, F_4) are extracted in the test phase to enable a low computational complexity system. A majority function is employed for the final seizure detection in which the detection flag appears high when at least three features pass their thresholds [4].

Furthermore, a three-second post-processing technique is utilized to limit the number of false positive detections when signal processing is done with one-sec window length. The post-processing block generates a seizure detection flag based on majority voting in which at least two detections are needed



(a)



(b)

Fig. 1: System architecture of the proposed seizure detector in the (a) training phase and (b) test phase

in every three consecutive windows to have the final seizure detection flag.

IV. Electrode Channel Selection

A. Channel dimension reduction

iEEG signals are recorded via several electrodes to provide sufficient spatial brain coverage. Indeed, electrode channel selection plays an undeniable role not only in the signal processing computational efficiency but also in the performance enhancement of the seizure detector.

Reducing the number of iEEG channels by channel selection can remarkably decrease the computation load of the feature extractor. Furthermore, non-focal redundant electrode channels degrade the accuracy of seizure detection. Thus, it is of paramount importance to decrease the channel dimension prior to feature extraction.

B. Channel selection correlated to feature extraction

The top four rank features are the outputs of the feature reduction block ($FR_1 - FR_4$) as depicted in Fig. 1a. Then, each channel is ranked according to a two-dimensional channel score array which exhibits the seizure detection ability of each channel with respect to the top four rank features. The channel score array is defined as (3).

$$channel\ score(n,k) = \frac{\frac{\sum_{t_{sz}} F_k(n)}{t_{sz}}}{\frac{\sum_{t_n} F_k(n)}{t_n}} \tag{3}$$

Where n and k represent the channel number and the feature type, respectively. $F_k(n)$ is the feature of type-k extracted from the n^{th} electrode channel. A high channel score indicates that a certain feature extracted from a specific electrode channel exhibits a remarkable variation when a seizure event occurs. The channel scores of a sample subject for the top four rank features are displayed in Fig. 2. The final rank of each channel is obtained by averaging its ranks of four selected features.

Subsequently, the optimal number of selected channels is determined in the channel optimization block in a patient-specific manner to realize the maximum detection accuracy during the training phase. The channel optimization

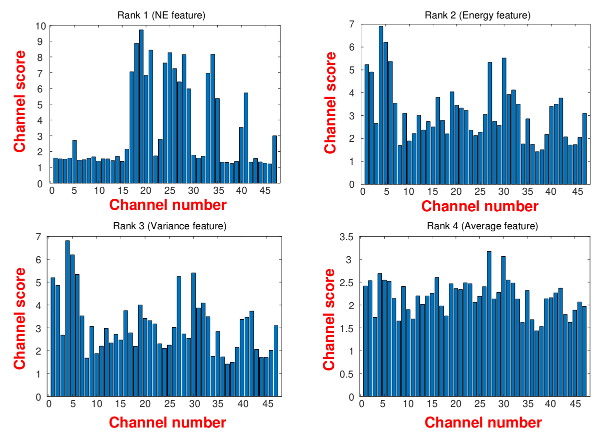


Fig. 2: All channel scores for the selected features of ID1

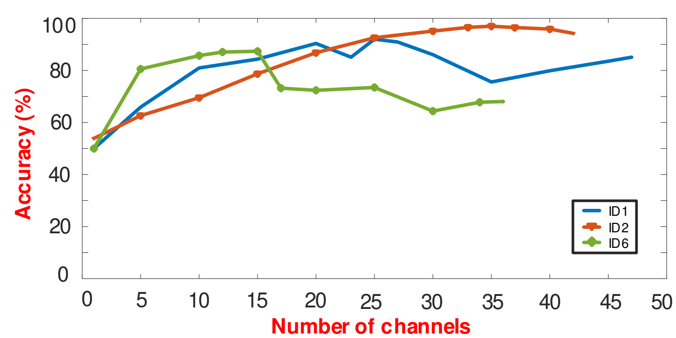


Fig. 3: Patient-specific channel optimization

plots of three subjects are illustrated in Fig. 3. The noteworthy point is that the proposed channel selection algorithm not only decreases the dimension of the input iEEG signals but also ameliorates the detection performance by eliminating the non-informative channels.

During the test phase, the top rank channels are averaged and compressed into a single channel in the channel compression block, and fed to the feature extractor to accelerate computation complexity reduction.

TABLE II: Dataset details

Patient No.	Electrodes[#]	Age	Seiz[#]	Trained Seiz[#]
1	47	46	13	6
2	42	48	4	2
3	98	32	2	1
4	42	19	4	2
5	54	31	10	5
6	64	31	4	2
7	36	36	2	1

V. METRICS AND RESULTS

A. Database info

The evaluation of the proposed seizure detector is done by testing the algorithm on short-term human iEEG signals of seven patients with pharmaco-resistant epilepsy from the SWEC-ETHZ dataset of the Bern Inselspital [8]. The data is passed through a digital band-pass filter to minimize the phase distortion, and it is stored at the rate of 512 Hz. Table II contains the clinical characteristics of the patients under the test.

B. Results and comparison

Three widely-used performance metrics in seizure detection domain are regarded as 1) sensitivity, 2) specificity, and 3) mean detection delay. Sensitivity and specificity demonstrate the performance of the system in terms of true positive and true negative detections, respectively. The mean detection delay is a measure to evaluate the rapidity of the seizure detection.

Besides, the main focus of this paper is on computation complexity reduction. Hence, a new metric called *Computation Dimension* (*C.D*) is introduced as (4) to enable a fair comparison among the computational complexity of different seizure detector systems available in the literature.

$$C.D = Feature\,dimension \times Num\,of\,channels \tag{4}$$

In this work, the feature reduction block takes the top four rank features out of nine available features from the feature pool. In addition, a single compressed channel of iEEG is given to the feature extractor for processing tasks. As a consequence, the *C.D* metric of the proposed detector is 4×1.

Table III compares the performance of the proposed design (the average results of patients) with recently published state-of-the-art that also uses the SWEC-ETHZ dataset. The MATLAB simulation results evidence a sensitivity of 100% as [9] which is better than other works. In terms of specificity and detection delay, the presented method outperforms the state-of-the-art. Also, the computational complexity of our algorithm reflected by the *C.D* parameter is outstandingly lower than the other works. Using the effective number of features for two-stage architecture systems and the average number of electrode channels of all patients cause floating point values of *C.D* for [2], [8] and [9].

TABLE III: Comparison with the state-of-the-art

	Sensitivity	Specificity	Delay (sec)	C.D
[2]'2018	97.08%	89.98%	12.65	65.14
[8]'2020	94.03%	88.84%	13.4	65.14
[9]'2021	100%	92.1%	7.8	87.75
[1]'2021	96.66%	92.37%	8.16	223
This work	100%	92.98%	3.6	4

VI. CONCLUSION

The huge feature dimension caused by sophisticated signal processing on iEEG signals captured from tens of electrode channels is not compatible with low-power real-time operation of seizure detector implants. Moreover, extracting more than one feature is necessary to yield patient-specific accurate seizure detection for a large number of subjects with different epilepsy patterns. This work develops a channel selection algorithm coordinated with a feature ranking unit to enable a highly accurate seizure detection with extremely low computation complexity suitable for implantable applications. Feature dimension reduction is performed by selecting the most discriminating features in the feature ranking unit. Subsequently, the irrelevant iEEG channels are detected and eliminated with respect to the top rank features. The selected informative channels are averaged and compressed into a single channel so as to extremely reduce the computation complexity of the feature extractor. The results of the proposed algorithm evidence low *C.D* of 4 with 100% sensitivity and a 3.6-sec mean detection delay which surpasses the performance of the state-of-the-art.

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