

# Low-complexity data-driven seizure detection algorithm for home monitoring of patients with epilepsy using wearable EEG

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**Abstract**— New wearable electroencephalography (EEG) devices allow home monitoring of epileptic patients. Due to miniaturization, these devices have limited memory and computing power, precluding them from running most state-of-the-art seizure detection algorithms. In this work we present a seizure detection algorithm designed to run on systems with minimal memory and computing power. It uses fully automated data-driven filtering to identify seizures. It was validated on a pilot dataset from 7 patients with absence seizures recorded in a home environment.

## I. INTRODUCTION

Advances in EEG equipment now allow monitoring of patients with epilepsy in their home environment. The large volumes of data that can be collected from long-term home monitoring require novel algorithms to process the recordings on board of the device to identify and log or transmit only relevant data epochs (seizures or interictal events). Existing seizure-detection algorithms are generally designed for post-processing purposes, so that memory and computing power are rarely considered as constraints. They typically extract many complex features from the EEG, which are then fed to a classifier [1]. This is a computationally expensive process that cannot be easily embedded in low-power miniature wearable EEG devices. We propose a novel multi-channel EEG signal processing method for automated seizure detection which is specifically designed to run on a microcontroller with minimal memory and processing power.

## II. METHODS

Data were collected from 7 patients with refractory absence seizures recruited at UZ Leuven hospital (Belgium). The study was approved by the local ethical committee and written informed consent obtained. The patients were equipped with a 20-channel mobile EEG unit (Medatec BrainWalker3) for 24h-home recording. A neurologist annotated seizures and interictal events. The automatic seizure detection is based on a patient-specific data-driven filter that is precomputed offline based on the spatial signature of the seizure and noise statistics. Let  $\mathbf{y}(t) \in \mathbb{R}^N$  denote an  $N$ -dimensional vector containing the sample at time  $t$  collected at  $N$  EEG channels. We combine the  $N$  EEG channels into a single-channel output signal  $o(t)$  using a linear model  $o(t) =$

$\mathbf{w}^T \mathbf{y}(t)$ . The weight vector  $\mathbf{w}$  is optimized in a data-driven fashion to maximize signal-to-noise ratio of  $o(t)$  over a training set, solving  $\max_{\mathbf{w}} \frac{E\{(\mathbf{w}^T \mathbf{s}(t))^2\}}{E\{(\mathbf{w}^T \mathbf{n}(t))^2\}}$  where  $E\{\cdot\}$  is the expectation operator,  $\mathbf{s}(t) \in \mathbb{R}^N$  the observation of  $\mathbf{y}(t)$  during a seizure epoch and  $\mathbf{n}(t) \in \mathbb{R}^N$  during non-seizure epochs. To identify seizures, a threshold is then applied to the average power of the output signal  $o(t)$  over a 3s sliding window. This threshold can be chosen based on the desired sensitivity (fig. 1). The algorithm is validated for each patient using a leave-one-seizure-out cross validation.

## III. RESULTS

Median false detection per hour rate over the whole group is 0.4 for 85% sensitivity. Figure 1 shows the distribution of receiver-operating curves over all patients. The algorithm requires only 1.28 kilobytes memory for storing  $\mathbf{y}, \mathbf{w}$  and 3s of  $o^2$  (2 bytes/sample, sampled at 200Hz); and 20 additions and 20 multiplications per sample.

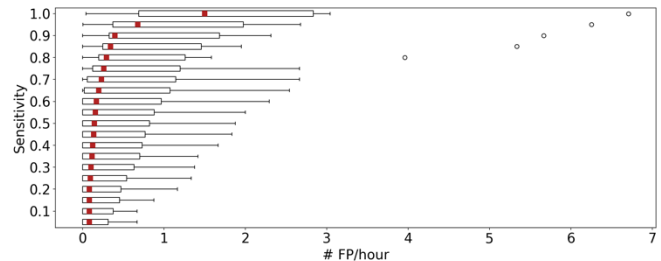


Figure 1. Distribution of receiver-operating curves over all patients. The median of the distribution is represented by a red square.

## IV. DISCUSSION & CONCLUSION

This algorithm provides a practical solution for real-time seizure detection in a home environment, provided one day of initial labeled training data containing at least one seizure is available to determine the patient-specific filter. To our knowledge it is the first seizure detection algorithm that is designed to run on a microcontroller in an ambulatory setting [2]. The performance of the algorithm should be evaluated on different seizure types and confirmed in larger patient populations.

## REFERENCES

- [1] Baumgartner, C, Koren, JP. Seizure detection using scalp EEG. *Epilepsia* 2018;59(S1),14-22.
- [2] Kurada, A, et al. Seizure detection devices for use in antiseizure medication clinical trials: A systematic review. *Seizure* 2019;66,61-69

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