Seizure 59 (2018) 48–53

Contents lists available at ScienceDirect

Seizure

journal homepage: www.elsevier.com/locate/yseiz

Adaptive nocturnal seizure detection using heart rate and low-complexity novelty detection

Thomas De Cooman[a,b,*], Carolina Varon[a,b], Anouk Van de Vel[c], Katrien Jansen[d], Berten Ceulemans[c,e], Lieven Lagae[d,e], Sabine Van Huffel[a,b]

[a] Department of Electrical Engineering (ESAT), STADIUS, KU Leuven, Leuven, Belgium
[b] imec, Leuven, Belgium
[c] Department of Paediatric Neurology, Antwerp University Hospital, University of Antwerp, Belgium
[d] Department of Child Neurology, University Hospital, KU Leuven, Leuven, Belgium
[e] Rehabilitation Center for Children and Youth Pulderbos, Pulderbos, Belgium

ARTICLE INFO

Article history:
Received 2 March 2018
Received in revised form 23 April 2018
Accepted 24 April 2018
Available online xxx

Keywords:
Seizure detection
ECG
Heart rate
Personalization

ABSTRACT

Purpose: Automated seizure detection at home is mostly done using either patient-independent algorithms or manually personalized algorithms. Patient-independent algorithms, however, lead to too many false alarms, whereas the manually personalized algorithms typically require manual input from an experienced clinician for each patient, which is a costly and unscalable procedure and it can only be applied when the patient had a sufficient amount of seizures. We therefore propose a nocturnal heart rate based seizure detection algorithm that automatically adapts to the patient without requiring seizure labels.
Methods: The proposed method initially starts with a patient-independent algorithm. After a very short initialization period, the algorithm already adapts to the patients' characteristics by using a low-complex novelty detection classifier. The algorithm is evaluated on 28 pediatric patients with 107 convulsive and clinical subtle seizures during 695 h of nocturnal multicenter data in a retrospective study that mimics a real-time analysis.
Results: By using the adaptive seizure detection algorithm, the overall performance was 77.6% sensitivity with on average 2.56 false alarms per night. This is 57% less false alarms than a patient-independent algorithm with a similar sensitivity. Patients with tonic–clonic seizures showed a 96% sensitivity with on average 1.84 false alarms per night.
Conclusion: The proposed method shows a strongly improved detection performance over patient-independent performance, without requiring manual adaptation by a clinician. Due to the low-complexity of the algorithm, it can be easily implemented on wearables as part of a (multimodal) seizure alarm system.

1. Introduction

An important question in epilepsy is how the quality of life of refractory patients can be improved. One of the most proposed solutions is the use of real-time warning systems, which automatically detect ongoing seizures and warns the patients' caregivers when such an event occurs [1]. Such a system is of great demand for pediatric patients and their parents, certainly for nocturnal monitoring. It allows the caregivers to give proper treatment to the patient whenever a seizure alarm is generated, leading to an improved quality of life at home. In order to be used properly in practice, the system should detect most seizures sufficiently fast without generating too many false alarms.

Most proposed modalities for automated seizure detection at home are accelerometers (ACM), electromyogram (EMG), heart rate and electrodermal activity (EDA) [2–5]. The major benefit of the heart rate over the other modalities is that it allows to detect not only convulsive seizures, but also non-motoric focal seizures (seizures with relative limited clinical manifestations such as chewing, etc.) [1,4,6]. Another benefit is that heart rate often allows for a faster seizure detection compared to ACM and EDA due to a faster activation of the autonomic nervous system, which is preferred in real-time usage [7].

The majority of seizures show ictal heart rate changes which can most often be seen as strong heart rate increases leading to tachycardia, but rarely also ictal bradycardia can be found [7–9]. These changes are caused by changes in the autonomic nervous

* Corresponding author at: Department of Electrical Engineering (ESAT), Kasteelpark Arenberg 10, box 2446, B-3001 Leuven, Belgium.
E-mail address: thomas.decooman@esat.kuleuven.be (S. Van Huffel).

https://doi.org/10.1016/j.seizure.2018.04.020
1059-1311/

system and can be triggered by activation of the insula and amygdala [6,8,10]. Previous studies discussed that ictal heart rate changes could thus be used for epileptic seizure detection [4,11].

Most heart rate based detection algorithms work with a patient-independent approach [4,6,12–14]. They do not use any patient-specific data, making them directly usable in practice as a one-fits-all approach. They however result in a too low performance due to the high patient-dependency of the heart rate features [4]. Patient-specific algorithms include prior data/information from the specific tested patient to construct an algorithm specifically for this patient. State-of-the-art patient-specific algorithms require the availability of annotated patient-specific data, which is not always available, certainly if also patient-specific seizure data is required for adaptation [15,16].

Therefore, we propose a fully automated adaptive seizure detection algorithm. Initially, only a patient-independent classifier is used. After a short initialization phase, the algorithm is already adapted to the patient's heart rate characteristics. It continues to adapt further to the patient while being worn. By using a low-complexity novelty detection approach, the newly gathered data does not have to be annotated by either a clinician or the patients themselves, improving the usability of this algorithm. The approach characterizes normal behavior by assuming that the majority of data corresponds to non-epileptic behavior, so that abnormal behavior is then associated with epileptic activity.

The aim of this paper is to evaluate whether a heart rate based seizure detector can be personalized fast in a fully automated way in order to make it more usable in practice. The evaluation is done in retrospective study, in which the data is analysed in an environment that mimics a real-time setting. To the best of our knowledge, it is the first time a heart rate based seizure detection algorithm is developed that automatically personalizes without requiring seizure annotations. A precursor of this work, discussing a nocturnal adaptive algorithm using seizure annotations, is described in [17].

2. Methodology

2.1. Data acquisition

The data used to evaluate the proposed algorithm were recorded in two clinical centers. A first part of the dataset contains nocturnal data from the Pulderbos Revalidation Center for Children and Youth. 14 pediatric patients with 69 seizures were monitored from bed time until the morning (±7–8 a.m.). In the second dataset, data from another 14 pediatric patients with 38 seizures were obtained from the University Hospital of Leuven. Only the night time parts of these recordings (22 h–8 h) were used here. Both datasets contain electrocardiogram (ECG) signals with 250 Hz sampling frequency. In total 694.6 h of data was recorded, and both convulsive and subtle seizures are analyzed, both with focal (temporal and frontal lobe) and generalized onsets. Seizures were annotated by experts using video-EEG as gold standard. Only seizures with a duration of at least 20 s were evaluated here as detection of shorter seizures is very difficult with heart rate based seizure detection [4,18]. 68 additional seizures shorter than 20 s from both databases are not taken into account in this study, of which 40 seizures were shorter than 10 s. The study was performed in accordance with the 1964 Declaration of Helsinki and approved by the Medical Ethical Commission of the Antwerp University Hospital, Belgium and Leuven University Hospital, Belgium. Signed informed consent forms from all parents were obtained prior to inclusion in the study. Schwarzer head box sets were used for data recording in both datasets. The obtained data was analyzed in a retrospective study using Matlab®, in which a real-time setting was mimicked. An overview of the used datasets is added to the Supplementary material.

2.2. Preprocessing

The proposed adaptive seizure detection algorithm uses as input the real-time tachogram. The preprocessing procedure is similar as in [4] according to the following steps. The heart rate is obtained in real-time from the ECG by using an R peak detection algorithm based on dynamic thresholding on the derivative signal. A second preprocessing step extracts strong sympathetic heart rate increases (HRIs). A HRI is detected if the heart rate gradient rises above 1 bpm/s. The start and end of the HRI are found by evaluating when the gradient becomes negative again. This HRI is then said to be a strong HRI if the increase in heart rate (both absolute and percentual) exceeds predefined threshold values and if the HRI lasts longer than 8 s. These preprocessing steps are called *HRI-EXTRACT* from now on.

Different features are extracted from these HRIs or 1 min before these HRIs. In [17], it was shown that the maximal peak heart rate and the maximal heart rate gradient already result in a good patient-specific performance for nocturnal heart rate based seizure detection. In order to keep the complexity of the algorithm sufficiently low for usage with wearable devices, we restrict ourselves here using only these two features.

2.3. Adaptive classification

Based on these two features we wish to decide whether a HRI is caused by a seizure or not. Although it is possible to update machine learning classifiers in real-time [19], it is computationally too expensive to do it in real-time with limited hardware specifications. It also requires the availability of seizure annotations, which are typically not available or possibly inaccurate in a home environment [20].

Therefore, we propose a heuristic adaptive classifier here. Normally, classifiers are characterized by a boundary line, splitting up the data points from the different classes. In our case, this boundary is heuristically constructed by using a very limited set of data points. We try to characterize normal HRI behavior by fitting a two-dimensional ellipse around the majority of patient-specific data.

Whenever a patient-specific data point (coming from a HRI) is detected, it is stored in a pool of noisefree patient data points PD_{pool}. A HRI is assumed to be noisefree if less than 25% of the absolute differences between consecutive heart rate values during this HRI is higher than 10%. When 5 such HRIs are detected, the adaptive classifier can be initialized. HRIs assumed to be caused by noise do not lead to an update of the classifier.

By assuming that the majority of data is caused by non-epileptic behavior, we try to characterize normal behavior into an ellipse. Data points inside the ellipse can then be seen as normal heart rate behavior, and data points outside the ellipse can be seen as potential seizure activity.

This ellipse is defined by 3 variables (see Fig. 1):

- The center of the ellipse $c(c_x, c_y)$: Defined as the mean value of the data points collected in PD_{pool}.
- Main directions of the ellipse (u, v): The main directions of the ellipse are found by the principal components from PD_{pool} (with the center $c(c_x, c_y)$ subtracted) by means of principal component analysis [17].
- The widths of the ellipse w_u and w_v along both main axes u and v with origin $c(c_x, c_y)$: These are defined as

$$w_u = std_u * sf \quad \text{and} \quad w_v = std_v * sf, \tag{1}$$