Online Detection of Tonic-Clonic Seizures in Pediatric Patients using ECG and Low-Complexity Incremental Novelty Detection*

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***Abstract*— Home monitoring of refractory epilepsy patients has become of more interest the last couple of decades. A biomedical signal that can be used for online seizure detection at home is the electrocardiogram. Previous studies have shown that tonic-clonic seizures are most often accompanied with a strong heart rate increase. The main issue however is the strong patient-specific behavior of the ictal heart rate features, which makes it hard to make a patient-independent seizure detection algorithm. A patient-specific algorithm might be a solution, but existing methods require the availability of data of several seizures, which would make them inefficient in case the first seizure only occurs after a couple of days.**

Therefore an online method is described here that automatically converts from a patient-independent towards a patient-specific algorithm as more patient-specific data become available. This is done by using online feedback from the users to previously given alarms. By using a simplified one-class classifier, no seizure training data needs to be available for a good performance. The method is already able to adapt to the patient-specific characteristics after a couple of hours, and is able to detect 23 of 24 seizures longer than 10s, with an average of 0.38 false alarms per hour. Due to its low-complexity, it can be easily used for wearable seizure detection at home.

I. INTRODUCTION

Epilepsy is a neurological disorder that affects around 1% of the people worldwide. Refractory patients can not be cured by the known treatments like anti-epileptic drugs or surgery. These patients and their family live with a lot of stress for the rest of their lives due to the unpredictability of these seizures. An online system that automatically detects these seizures is a solution that can improve their quality of life. In such an automated system, relatives can be alerted if a seizure is occurring, who can then come to help the patient.

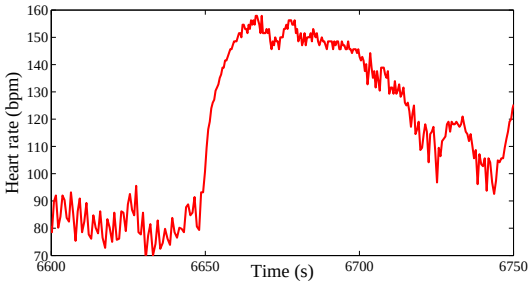


Fig. 1. Example of the ictal heart rate (HR) pattern. It consists of a phase of linear HR increase, a phase of HR stability around a peak HR and a phase of (exponential) HR decrease. The seizure onset is located at 6648s.

Typically seizures are detected by analyzing the electroencephalogram (EEG), but obtaining it outside the hospital is too difficult for long-term monitoring. The electrocardiogram (ECG) is however easily obtainable in a home environment. Earlier studies showed that most tonic-clonic (TC) seizures are accompanied by a specific heart rate (HR) pattern (see Fig. 1) [1,2]. The big challenge here is that the pattern feature values not only strongly depend on the specific patient, but also change in time [3].

Previously discussed seizure detection algorithms using ECG were typically patient-specific algorithms that required several seizure samples to manually set the patient-specific parameters [2,4,5]. It can however sometimes take several days for a seizure to occur, which would make these algorithms unusable during this long waiting period. Therefore a method is proposed that starts with a patient-independent system, which can automatically adapt to the patient-specific feature values. This is done by using a simplified online incremental one-class classifier. It improves itself quickly by using feedback (given by doctors, patients or their relatives) on previously given alarms. Due to its low complexity, it can be easily implemented on wearable devices for online usage.

II. DATA ACQUISITION

EEG, ECG, video, accelerometry (ACM), electromyogram (EMG) and audio were simultaneously recorded in the Rehabilitation Center for Children and Youth in Pulderbos, Belgium. The study was performed in accordance

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TABLE I

OVERVIEW OF THE USED DATASET.

Patient	Age	# TC seizures	# nights	Record duration
1	8	5	2	22:23:50
2	4	1	5	64:25:02
3	17	1/9*	2	23:35:42
4	18	10	1	10:00:13
5	6	3/4*	7	92:11:09
6	12	1	2	26:30:13
7	3	3	1	13:15:43
total	[3-18]	24/33*	20	252:21:52

*Number of TC seizures longer than 10s over the total number of TC seizures. For the other patients, all seizures are longer than 10 s.

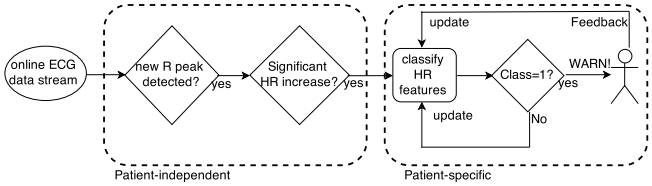


Fig. 2. Overview of the procedure used in this paper.

with the 1964 Declaration of Helsinki and approved by the Medical Ethical Commission of the Antwerp University Hospital, Belgium. Seven of the monitored children got 33 TC seizures during 20 nocturnal recordings (see Table I). Seizures were annotated by a trained EEG specialist using the gold video/EEG standard. The sampling frequency of the ECG is 250Hz. In this paper, the focus lies on the detection of seizures that are at least 10s long.

III. METHODOLOGY

A. Preprocessing

At first, the heart rate is detected by using the online R peak detector mentioned in [6]. Next, a first online selection of data points is done. Significant HR increases are detected by the method discussed in [6] as follows. If a large instantaneous HR gradient ($> 1bpm/s$) is detected in the online constructed tachogram, a potentially significant HR increase is occurring. The beginning and end of this HR increase are found by analyzing when this gradient starts and ends to be positive. The real significant HR increases are then extracted by a rule-based method which imposes patient-independent minimal values for some HR features:

- At least a HR increase of 20bpm should be found.
- The peak HR must be higher than 90bpm.
- The average HR gradient should be at least 0.4bpm/s.

The procedure works with a similar performance as other patient-independent HR-based seizure detection algorithms [6]. These detected HR increases form the data points that are classified in the next step (see Fig. 2).

B. Incremental low-complexity novelty detection

The feature values from the discussed HR pattern however depend strongly on the patient, and patient-independent algorithms might lead to mediocre results. Therefore a low-complexity classifier is proposed here that can incrementally

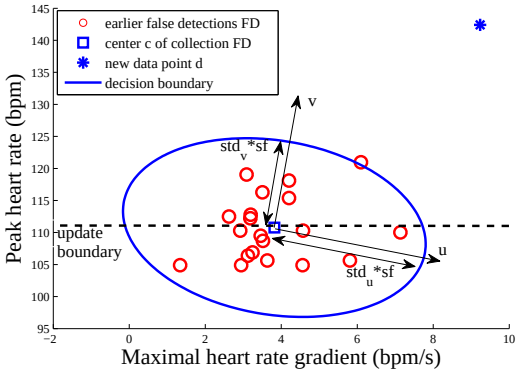


Fig. 3. Illustration of the used incremental learning algorithm. The decision boundary is formed by the ellipse: data points outside the ellipse cause a warning by the system, except if they are under the update boundary (dashed line). In this example, a new seizure data point needs to be classified.

transform the overall algorithm from a patient-independent to a patient-specific algorithm as more patient data become available. It automatically updates itself online by using feedback from the user on previously given alarms. In order to tackle the low amount of seizure samples and the time it can take for a first seizure to occur, the classifier resembles a one-class classifier, which tries to detect outliers compared to the typical non-seizure behavior. Previous studies showed that the peak HR and the maximal HR gradient are strong patient-specific parameters that can improve the patient-specific seizure detection (see Fig. 3) and are the two features that are used for classification [2,5,6].

1) Initial characterization of false detections: The incremental classifier makes use of a collection (called FD) of earlier false detections. This collection is used in order to make an estimate of typical non-seizure HR increases. HR increases caused by seizure activity should be detected as outliers of a patient's normal behavior. The algorithm starts to work after 5 false detections have been found by the preprocessing step. During this initialization phase, all samples from the preprocessing cause an alarm. Once these 5 false detections are found, the initial classifier can be constructed. First, the center c of all data points in FD is computed. Next, the principal components from the twodimensional data points in FD are constructed by using principal component analysis

$$CA = \lambda A \tag{1}$$

with C the covariance matrix of FD, A the matrix containing the principal components and λ the detected eigenvalues. Let us call the directions of the principal components the u and v axes now, and denote data points $d(d_u, d_v)$ from now on based on this coordinate system with a center at c (see Fig. 3). Finally, construct an ellipse with equation

$$\left(\frac{u}{std_u * sf}\right)^2 + \left(\frac{v}{std_v * sf}\right)^2 = 1 \tag{2}$$

with scaling factor sf initialized at 2.5 and std_u and std_v the standard deviations of FD along both axes. All samples

inside the ellipse are now assumed to represent normal non-epileptic behavior for this patient. The form of the ellipse was chosen as the false detections showed a similar shape, but with its main directions not in the used feature directions.

2) Classification: For each new data point $d(d_u, d_v)$ that is detected (in coordinate system (u,v)), check if

$$\left(\frac{d_u}{std_u * sf}\right)^2 + \left(\frac{d_v}{std_v * sf}\right)^2 > 1. \quad (3)$$

Only if this condition holds and the peak HR of d is not lower than that of c (see Fig. 3), an alarm is given. This extra condition is required in order to avoid alarms for HR increases smaller-than-average, which is illogical in this case.

3) Online incremental updates of the classifier: After feedback has been given to the system by one of the users, the classifier immediately updates itself by using this scored data sample d. For now the assumption is made that all given feedback is correct. Four possible actions can occur:

- A false positive (FP) or true negative (TN) occurred: FD and the corresponding classifier are updated by adding d to FD. If d is however detected as a false outlier of the system (if $d_u > 2 * std_u * sf$ and $d_v > 2 * std_v * sf$), the update procedure does not occur. This typically occurs if false detections are caused by R peak detection errors.
- A seizure is successfully detected (TP): If $d_u > 1.1 * std_u * sf$ and $d_v > 1.1 * std_v * sf$, rescale sf to $1.1 * sf$. In this case, there is a clear difference between seizure and non-seizure HR increases and a wider ellipse is allowed for improved performance.
- If a seizure is missed (FN): A missed seizure might indicate that the ellipse is too large. Feedback can be given to indicate that a seizure has been missed. In this case sf is rescaled with a factor 0.9 if the peak HR of d is higher than that of c (see Fig. 3).
- Other non-TC seizure activity was detected: As this activity is neither a real FP nor a real TP, the system does not update itself when annotated like this. This action is advised in every case of doubt from the user.

In order to keep the computation time limited, the maximum size of FD is fixed to a length of 20 samples. The initial and maximal size of FD and the initial value of sf have been optimized heuristically. Smaller maximal sizes of FD could be used, but this would also require an update of sf as the standard deviation values might become less trustworthy. FD is updated by using the First In, First Out procedure. In this way, it is also possible to take into account the time variability of the HR features.

IV. Results and Discussion

The main focus lies on the detection of TC seizures that are at least 10s long. All these seizures (24/24) were successfully detected by the patient-independent preprocessing step, but also resulted in 924 FPs in over 252 hours. By using the discussed incremental classifier on these data points, 23/24 seizures longer than 10s are detected (see Table II). None of the seizures shorter than 10s are however detected by this procedure, while 6/9 of these seizures were detected during preprocessing. Longer seizures result in a longer sympathetic activation of the HR, which is responsible for the low-frequency HR increase shown in Fig. 1. If however this activation does not last long enough, there might not be a significant difference between epileptic and non-epileptic HR increases such as arousals. Therefore they can not be detected as an outlier to the typical non-seizure HR increases. Seizures were detected at an average of 24s after the EEG onset.

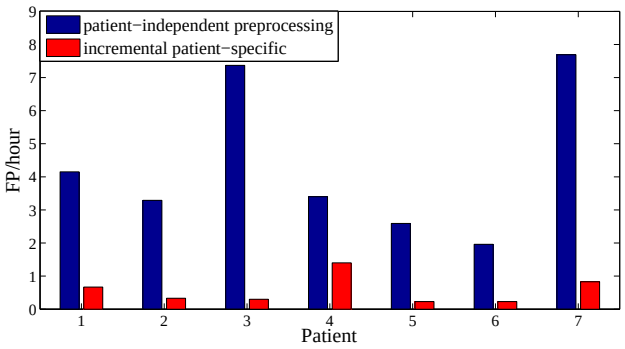


Fig. 4. Comparison of FP/hour for each patient between the patient-independent preprocessing and the incremental patient-specific algorithm.

The number of FPs drastically decreases by using the incremental novelty detection, leading to an average of 0.38 false alarms per hour (see Fig. 4). If the initialization period is taken out of the analysis (at average 3 hours per patient), only 0.26 false alarms per hour were detected. 14 of these false alarms were however caused by other seizure activity such as tonic seizures and clonic seizures (of which 7 in patient 4). Other typical reasons for false alarms were arousals (27%), noisy ECG segments (13%), non-epileptic jerks (12%) and HR increases when the patient was fully awake (11%).

The preprocessing without R peak detection and the classification procedure (both programmed in Matlab) took 708s to process more than 252hours of heart rate data on a desktop pc with 24GB RAM and a 3.6Hz processor. This shows that the procedure could be easily added to widely spread wearable R peak detection implementations (such as smartwatches) without much extra required computation time.

The proposed algorithm differs from other existing systems for seizure detection using ECG in two ways. At first, the proposed method is able to update itself automatically and online by using the feedback from the patient or its relatives. No offline (most often manual) annotation of previously recorded data is necessary, which would typically need to be done by professionals. It can quickly adapt to the patient-specific characteristics, already improving the performance greatly after the initialization phase has passed (see Fig. 5). During this initialization phase, the patient-independent preprocessing already provides a nice filter on the amount of alarms so that the performance during initialization is also acceptable. It was already shown in [6] that this preprocessing step performs comparably to other

TABLE II

RESULTS OF THE INCREMENTAL SEIZURE DETECTION PROCEDURE.

Patient	TP	FN	FP	TN	Se (%)	PPV (%)	Sp (%)	FP/h	FP_{ai}/h	mean latency (s)	End initialization period
1	5	0	15	80	100.0	25.0	84.2	0.67	0.56	20.5	04:28:32
2	0	1	21	191	0.0	0.0	90.1	0.33	0.27	20.8	04:38:53
3	1	0	7	169	100.0	12.5	96.0	0.30	0.08	10.5	00:26:04
4	10	0	14	28	100.0	41.7	66.7	1.40	1.07	34.9	01:35:49
5	3	0	21	227	100.0	12.5	91.5	0.23	0.19	1.8	05:45:46
6	1	0	6	42	100.0	14.3	87.5	0.23	0.04	28.7	03:18:30
7	3	0	11	92	100.0	21.4	89.3	0.75	0.42	21.9	01:22:16
total	23	1	95	829	95.83	19.5	89.7	0.38	0.26	24.2	03:05:07

Se (sensitivity): percentage of correct alarms over number of seizures. Sp (specificity): percentage of correct neglected alarms over total non-seizure samples. PPV (positive predictive value): percentage of correct alarms over total number of alarms. FP_{ai}/h: number of FPs per hour in case the initialization phase is not taken into account.

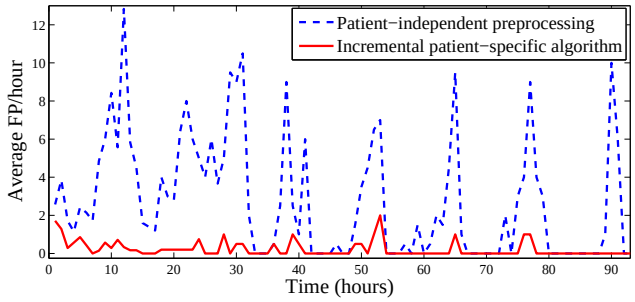


Fig. 5. Average number of false positives per hour for each hour after the start of recording per patient for both the preprocessing part as the complete algorithm. The number of FPs/hour decrease immediately, already during the first hour for some patients. Peaks in number of FP/hour collide with typical awake periods at the end of each night recording.

patient-independent ECG methods from the literature.

Secondly, a one-class classifier solution is provided here. By trying to characterize the patient-specific non-seizure HR increases and detecting seizure HR increases as outliers to this behavior, no seizure date is required for a good classifier performance. It also resolves the problem of the huge unbalance between available samples for both classes [7]. The assumption that seizure HR increases can indeed be detected as outliers to normal HR behavior has proven to be correct in most cases, provided that the seizures last long enough for the HR to increase to its maximal HR. If also the short seizures need to be detected, it is not possible with currently known HR features without drastically increasing the number of FPs. Extra information might then be needed from the ECG signal itself or from other signals such as ACM and/or EMG [7-9].

The classifier relies on the correctness of the given feedback from the users. For now the assumption was made that all feedback was correct, but in practice this will not always be the case. In some cases the patient is not sure about the occurrence of a seizure and thus can not mark the alarm as a seizure with sufficient certitude. In case of uncertainty, no system update should occur. The feedback on the seizures were however not crucial for the system performance. By removing all updates after seizure samples have occurred, only 5 additional FPs and 1 FN were found. The system thus keeps working with a similar performance as long as there are enough scored non-epileptic data samples.

V. CONCLUSION

The discussed incremental classifier showed a good performance for the online detection of nocturnal epileptic seizures using the ECG. It can update itself automatically online from a patient-independent towards a patient-specific algorithm by using feedback from the user to previously given or missed alarms. Its performance can already approach full patient-specific results after a couple of hours. Due to its low complexity, it can be easily integrated into wearable devices for seizure detection at home. In future work the effect of false or missing feedback on this algorithm should be evaluated. Further analysis will also be done to further lower the number of false alarms and the detection delay.

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