ONLINE SEIZURE DETECTION IN ADULTS WITH TEMPORAL LOBE EPILEPSY USING SINGLE-LEAD ECG

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ABSTRACT

In this paper, a patient-independent algorithm for online epileptic seizure detection using only single-lead ECG is proposed. It is tested on 300h of data from adults with temporal lobe epilepsy. The features are extracted from a period of linear increase of the heart rate, which typically occurs in this kind of patients. These features are classified by two different classifiers: linear support vector machine (LSVM) and linear discriminant analysis (LDA). The best performance is found for LDA with a sensitivity of 80.0%, a PPV of 40.5% and an average detection delay of 31.5s, which are satisfactory results for online usage in monitoring or warning systems.

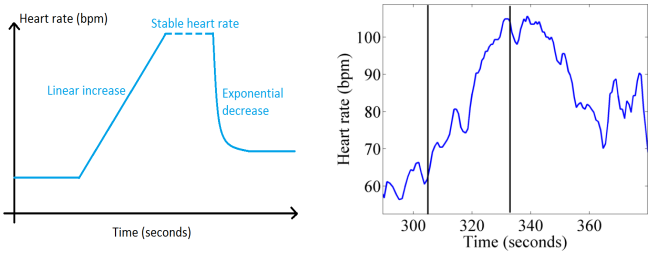
Index Terms— Temporal lobe epilepsy, online seizure detection, ECG, LSVM, LDA

1. INTRODUCTION

Epilepsy is a neurological disorder that affects around 1% of people worldwide. Automatic seizure detection has been ongoing research for decades, primary by using EEG signals. Obtaining EEG is however hard outside the hospital and is rather unpleasant for the patient. Therefore a lot of research is already done to investigate the possibility of seizure detection algorithms using easier obtainable biomedical signals.

An example of this is ECG. Literature shows that the occurrence of a seizure can lead to an increase of the heart rate around seizure onset [1, 2]. For temporal lobe epilepsy (TLE) patients, the occurrence of this heart rate increase is very high and the increase is more clearly visible, following a pattern as shown in Figure 1(a). It consists of 3 phases: a linear increase of the heart rate, an optional phase of heart rate stability and an exponential decrease of the heart rate [3]. The seizure onset is typically around the start of the linear phase.

The number of extensively tested algorithms for online ECG seizure detection in adults is rather limited. A typical approach is to see whether the heart rate is increased sufficiently over a short period of time. The method of two moving windows was proposed in [4, 5]. Another approach is to perform



(a) (b)

Fig. 1. (a) Theoretical heart rate pattern around seizure onset. (b) Heart rate pattern in practice: interference of respiration.

template matching on the entire heart rate pattern [3, 4, 6]. In [3], short fits on the heart rate signal are used in order to find the linear and exponential phase. Only the slope, correlation and length of these fits are used for seizure detection. Other algorithms use information from the ECG morphology, but aren't evaluated on databases with sufficient inter-ictal periods [7, 8]. All these methods — except for [3] — however require (manual) patient-specific training and no optimization for a patient-independent approach is discussed thoroughly. Training periods require the occurrence of at least a couple of seizures, but this can take multiple days for some patients, making the algorithm hardly usable for some applications. Therefore, an online patient-independent seizure detection algorithm for TLE patients will be proposed in this paper. It is trained on the data from other patients and therefore does not need an extra training period per patient. This algorithm can be used as part of a warning system in a home environment for refractory TLE patients (30-40% of patients [9]) or as part of a (home-)monitoring unit.

2. DATA ACQUISITION

Two different datasets are used in this paper, including in total 300 hours of ECG data and 40 seizures. Dataset A contains long-term single-channel ECG data from 4 TLE patients (see Table 1). Database B contains shorter-term ECG data

Patient	A1	A2	A3	A4	B1	B2	B3	B4
Age	29	31	43	23	48	51	55	48
Gender	m	v	m	m	m	v	m	m
Length (h)	72	48	42	81	9	9	27	12
# seizures	7	3	4	6	3	3	9	5
# candidates	79	95	62	118	22	4	16	15

Table 1. Overview of the used dataset.

from another 4 TLE patients, from which segments of 3 hours of data were chosen in which at least one seizure occurred. Both datasets were acquired at UZ Ghent. Both datasets were recorded during video-EEG monitoring and seizures were annotated by experienced specialists using scalp and/or intracranial EEG. Because different sampling frequencies were used in the datasets, all ECG signals were resampled to 250Hz sampling frequency. This was the most frequently occurring sampling frequency in the original ECG signals and was chosen to minimize resampling artifacts in the ECG signals.

3. METHODOLOGY

Figure 2 gives an overview of the algorithm proposed in this paper. Like stated above, some of the literature methods need the entire heart rate pattern for seizure detection. Waiting for the entire pattern to occur, would introduce a too large detection delay for online usage. Therefore, the focus in this paper will go only to the first phase of the pattern. Features of this linear phase will be extracted and classified in order to make distinction between linear phases occurred due to a seizure or due to other reasons like physical exercise. All these different steps will be discussed in this section.

3.1. ECG preprocessing

At first, an online QRS detection algorithm is needed to construct the heart rate signal. An online version of Yeh & Wang [10] is used in this paper, which is enhanced with adaptive thresholding and a postprocessing step [11]. The instantaneous heart rate — computed as the inverse of the RR interval — is used for the heart rate signal and expressed in beats per minute (bpm).

3.2. Linear phase extraction

Next, an online algorithm is required to extract the linear phases from the heart rate signal. In practice, this linear phase isn't that nicely linear. There are two main factors that are responsible for this. The first one is the effect of the respiratory signal on the heart rate, called respiratory sinus arrhythmia (RSA). When a person breaths in/out, the heart rate will increase/decrease compared to the expected heart rate. Figure 1(b) gives an example of this, but stronger RSA interference is possible. The vertical lines indicate the theoretical

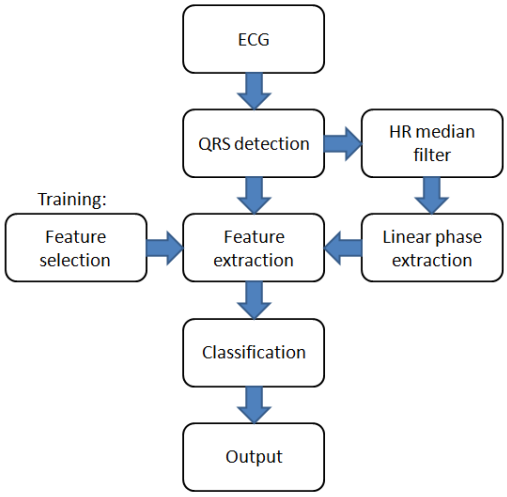


Fig. 2. Overview of the proposed algorithm.

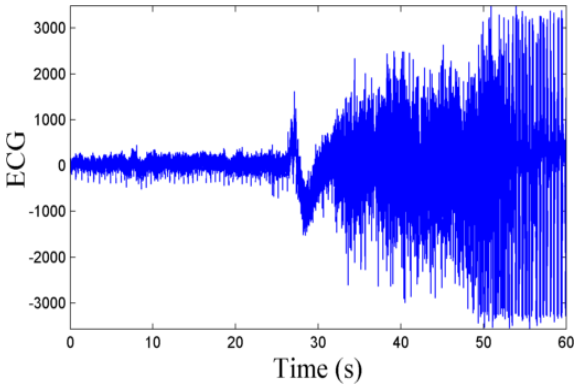


Fig. 3. Example of heavy ictal ECG noise. Scalp EEG onset is located at t=0s.

start and end of the linear phase. The linear phase now seems to be split up in two linear phases due to RSA. The second important factor is the occurrence of ictal ECG noise, which can make the ECG almost unreadable near the end of the linear phase as illustrated in Figure 3. This will lead to QRS complex detections errors, influencing further heart rate processing. Both kinds of artifacts clearly have an impact on the ease of detecting the linear phase. The heart rate signal is therefore filtered by using a median filter with a length of 15 heart beats. The effect of RSA and ECG noise can in most cases be removed by this long median filter, resulting in a signal that will not decrease during the linear phase.

To extract a candidate linear phase from this filtered heart rate signal, a period in this signal that doesn't contain a decrease in heart rate is sought. A decrease in heart rate is assumed if the slope of the linear line fit over 10 heart rate samples is smaller than 0. Linear line fitting is used here in order to further remove interference of RSA and QRS detection errors. If such a period is found, some simple thresholds are put on the heart rate signal in this period so that only significant candidate linear phases are evaluated in further steps:

- Maximal slope of the filtered heart rate signal during the linear phase $>$ 1 bpm/s.
- Peak heart rate $>$ 90 bpm.
- Heart rate increase during linear phase $>$ 20 bpm.
- Length of linear phase $>$ 15 heart beats.

On the entire dataset, this resulted in 411 candidate linear phases (see Table 1). Only one seizure in patient B3 wasn't accompanied with a candidate linear phase due to the absence of a significant heart rate increase.

3.3. Feature extraction

Features are extracted after a linear phase is found by the method discussed above. The used features can be divided into 3 groups. The first group contains main information about the linear phase: peak heart rate, heart rate at the beginning of the linear phase, heart rate at rest, maximal slope of the filtered and original heart rate signal (which will be called maximal filtered slope and maximal unfiltered slope from now on) and corresponding R^2-values, heart rate increase compared to the heart rate in rest, percentual heart rate increase (heart rate increase divided by the heart at the start of the linear phase), length of the linear phase and the mean and standard deviation of the derivative of the heart rate signal during the linear phase. An estimation of the heart rate at rest is made when the linear line fit using least squares minimization of the heart rate signal over a long period has a slope near zero with limited error.

In a second group of features, frequency information of the linear phase is evaluated. The heart rate signal is therefore linearly interpolated to a sampling frequency of 8Hz. The frequency spectrum is divided into 2 frequency bands: low frequency band (0.04Hz-0.15Hz) and high frequency band (0.15Hz-0.4Hz). For each frequency band, the mean power, maximal power and the power percentage compared to the total power are stored. Also the spectral entropy is extracted.

Finally, also some features from the minute before the start of the linear phase are selected. These are the mean heart rate, the spectral entropy and the Hjorth parameters activity, mobility and complexity [12].

3.4. Feature selection

It is unsure whether all features listed above have a positive impact on classification or not. Therefore a sequential forward feature selection algorithm is used during the training of the classifier. The feature that causes the greatest increase in accuracy — defined as the average of sensitivity and specificity — on the training set is added to the feature pool. This process is repeated until no features with a positive impact on the performance of the training data can be added, starting with an empty feature pool. The first two features are however pairwise selected. This is done for two reasons. The first reason is to avoid the selection of the peak heart rate as first feature. This may be the most interesting stand-alone feature, but further addition of features will hardly improve the performance as this feature is strongly patient-specific. The second reason is the fact that a lot of combinations of 2 features contain very good classification potential as will be shown in Section 4. Feature selection was done using cross-validation on the training set, using the leave-one-patient-out procedure. To avoid overfitting the training set, the maximum number of selected features is set to 5. This number is chosen because performance increases start to become marginal at this point, indicating a possible overfitting of the classifier.

3.5. Classification

To classify the selected features, two different classifiers are evaluated: linear support vector machine (LSVM) and linear discriminant analysis (LDA). In LSVM, two different loss functions are used for both types of error in the primal formulation of the Langragian

$$L_p = \frac{||\mathbf{w}||^2}{2} + C^+ \sum_{\{i|y_i=+1\}}^{p} \xi_\mathbf{i} + C^- \sum_{\{i|y_i=-1\}}^{p} \xi_\mathbf{i} - \sum_{i=1}^{p} \alpha_i [y_i(\mathbf{w} \cdot \mathbf{x_i} + b) - 1 + \xi_i] - \sum_{i=1}^{p} \mu_\mathbf{i} \xi_\mathbf{i} \quad (1)$$

in order to deal with the imbalanced dataset [13]. Both classifiers are trained using cross-validation using the leave-one-patient-out procedure.

3.6. Evaluation criteria

In order to evaluate the overall algorithm, multiple factors need to be evaluated. The sensitivity (Se), specificity (Sp) and positive predictive value (PPV) of the classifier will be investigated to check its performance. The seizure that is missed during the linear phase extraction will be taken into account in these measurements. The number of false positives per hour (FP/h) and false positives per seizure (FP/seiz.) give an indication of the overall performance. Another important factor for an online seizure detection system is the detection delay. This is the time difference between the alarm of the algorithm and the EEG seizure onset. The alarm can go off after the detection of the linear phase and classification. In order to remain useful, this delay should stay in a reasonable interval.

4. RESULTS AND DISCUSSION

Feature selection always resulted in using the linear phase length and the maximal unfiltered slope. Figure 4 shows a scatter plot of these samples in function of these 2 features in case of perfect QRS detection. An overall trend seems to be visible between both features: shorter linear phases need

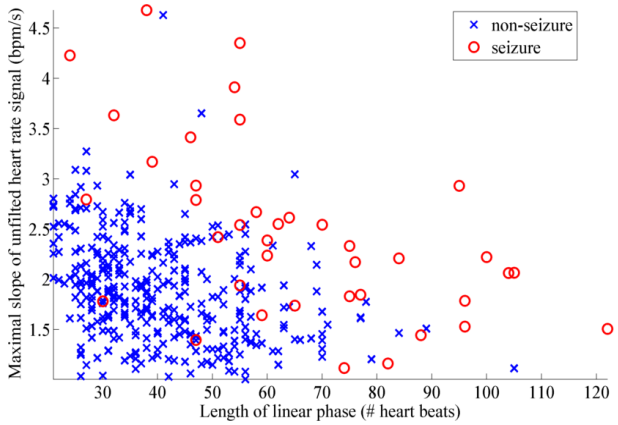


Fig. 4. Scatter plot of seizure and non-seizure samples in function of linear phase length and maximal unfiltered slope.

higher maximal slopes, while longer linear phases can have lower slopes. Three seizures show poor classification results for these 2 features. These include a linear phase that is split up due to extreme RSA interference of the linear phase and 2 minor seizures compared to other seizures of that patient. Another much chosen feature was the spectral entropy of the heart rate signal before the linear phase. Note that these 3 features are easily computable, making them an interesting choice for online seizure detection.

Table 2 shows the results of the complete algorithm for the discussed classifiers for both the feature selection method as when using the 3 features mentioned above. The usage of the 3 best features results in slightly better classification, for which the gain is higher for LDA than for LSVM. The slight improvements in this performances may be due to overfitting of the training data during feature selection. The best performance is found for LDA using this approach, resulting in a sensitivity of 80.00%, a specificity of 87.37% and a PPV of 40.51%. Table 3 gives the results per patient for this classifier. For the patients from Database A, the number of FP/h ranges between 0.10 and 0.21. Patient A2 has the worst performance in this statistic. The patient has a high heart rate variability, which can lead more quickly to sudden high inter-ictal heart rate increases that may be classified as a seizure. A lot of the FP's occur in the post-ictal phase due to the occurrence of low frequency heart rate increases [14] and high noise levels. Therefore the number of FP/h seems a bit higher than expected for the shorter-length datasets. The missed seizures are typically seizures of which the linear phase is split up due to grouped QRS detection errors or strong RSA interference.

An average detection delay of around 40 s is found in all mentioned methods. Small changes between both classifiers depend on which seizures are detected, not on the classifier itself as only the linear phase extraction influences it. Around 5 to 6 seconds of this detection delay are due to the median filter used for the linear phase extraction. When selecting only the 3 mentioned features for feature extraction, an improvement for this detection delay is possible. During linear phase extraction, at the detection of every new heart rate sample, the temporary linear phase can be evaluated to see if it can already be classified as a seizure or not. If the maximal filtered slope doesn't occur at the end of the linear phase (this is typically only the case in short linear phases), only the length of the linear phase will change. Because the boundary between both classes can be seen as a hyperplane in 3D space, an increase in linear phase length can only lead to a seizure output if it would have been a seizure in the original algorithm (see Figure 4), so no extra FP's are introduced by this procedure. Table 2 shows the results of this improvement. A mean delay of 31s is found in both classifiers, a gain of around 8.5s.

Table 2 also shows the results for the methods described in Section 1. All the discussed methods originally required manual parameter setting, but intensive automatic parameter testing is used in order to find an approximation of the best parameter values for the used dataset. This means that for the original patient-specific algorithms [4, 5], the parameters are no longer set for each patient separately, but for all patients at once. In order to compare these algorithms with the proposed one, their parameters are set so that they resulted in a similar

Method	Se(%)	Sp(%)	PPV(%)	FP/h	delay(s)
LDA	75.00	90.32	45.45	0.12	39.82
LSVM	77.50	84.68	35.23	0.19	39.65
LDA*	80.00	87.37	40.51	0.16	40.06
LSVM*	77.50	85.22	36.05	0.18	39.65
LDA*-F	80.00	87.37	40.51	0.16	31.50
LSVM*-F	77.50	85.22	36.05	0.18	31.10
method [3]	80.00	-	9.07	1.07	32.36
method [4]	80.00	-	5.28	1.76	25.58
method [5]	75.00	-	8.11	1.13	25.68

Table 2. Comparison between proposed algorithms and patient-independent versions of other literature methods. LDA stands for the original feature selection method using LDA, LDA* for the method using the 3 best features and LDA*-F stands for the fast version of the latter method. Similar notations are used for LSVM.

Pat.	Se(%)	Sp(%)	PPV(%)	FP/h	FP/seiz.
A1	85.71	83.33	33.33	0.17	1.71
A2	100.00	89.13	23.08	0.21	3.33
A3	100.00	93.10	50.00	0.10	1.00
A4	66.67	88.39	23.53	0.16	2.17
B1	100.0	84.21	50.00	0.33	1.00
B2	66.67	100.00	100.00	0.00	0.00
B3	66.67	62.50	66.67	0.11	0.33
B4	80.00	80.00	66.67	0.17	0.40
tot.	80.00	87.37	40.51	0.13	0.90

Table 3. Results using LDA with the 3 best features.

sensitivity as the proposed algorithm and an optimal PPV. In order to remove the impact of the different used QRS detection algorithms, the method discussed in Section 3.1 is also used in the ECG preprocessing step of these algorithms.

The methods using two moving windows [4,5] are able to detect the seizures with an average detection delay of 25.58s and 25.68s, which is faster than the proposed algorithm. The number of FP's per hour are however higher for these algorithms compared to the proposed algorithm on the used dataset. One of the main reasons for this is that these algorithms rely on information of how fast the heart rate will increase over a certain time. This information is very patient-specific, so trying to set patient-independent parameter values introduces a lot of FP's if sufficient sensitivity is required. Method [3] results in less FP's compared to the other methods from the literature, due to more sophisticated analysis of the linear phase. It introduces however a larger detection delay due to the exponential phase analysis.

One of the main issues that remains, is the high number of QRS detection errors near the end of the linear phase due to strong EMG interference. A lot of important information gets lost due to this errors. After manual correction of all the candidate heart rate signals, improved performance can be found with a sensitivity of 90.0% and a PPV of 49.3% for LSVM. Further investigation needs to be done in order to improve the QRS detections in such noisy conditions. A possible solution for this is the addition of other biomedical signals, which can be used for noise removal (EMG) or improved QRS detection.

5. CONCLUSION AND FUTURE WORK

The procedure proposed in this paper can be used as aid during the monitoring of temporal lobe epilepsy patients or as (part of) a warning system. No training period is needed as the algorithm is patient-independent. The used procedures are easily computable, making it possible to use this approach online with limited need for computational power. An important issue that remains however is the need for more reliable QRS detection during the strong ictal EMG noise interference on the ECG signals. Further reduction of the detection delay could also be a possible enhancement, but for this more than only heart rate information might be needed.

Acknowledgments

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