Detection of Tonic Epileptic Seizures Based on Surface Electromyography

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***Abstract*— The purpose of this project was to design an algorithm for detection of tonic seizures based on surface electromyography signals from the deltoids. A successful algorithm has a future prospect of being implemented in a wearable device as part of an alarm system. This has already been done for generalized tonic-clonic seizures, and the hypothesis was that some of the same characteristics could be found for tonic seizures. The signals were pre-processed by a high-pass filter to remove low frequency noise such as movement artifacts. Several different features were investigated, including kurtosis, median frequency, zero crossing rate and approximate entropy. These features were used as input in the random forest classifier to decide if a data segment was from a seizure or not. The goal was to develop a generic algorithm for all tonic seizures, but better results were achieved when certain parameters were adapted specifically for each patient. With patient specific parameters the algorithm obtained a sensitivity of 100% for four of six patients with false detection rates between 0.08 and 7.90 per hour.**

I. INTRODUCTION

About 1% of the population is affected by epilepsy, which is a chronic, neurologic disease defined by recurrent, spontaneous epileptic seizures [1]. An epileptic seizure is an unprovoked and uncontrollable, abnormally excessive or synchronous activation of neurons in the brain [1]. About a third of these patients cannot control their seizures by use of antiepileptic drug therapy [2], and untreated epilepsy can have severe consequences both physically and mentally.

An automatic seizure alarm system can increase the quality of life for such patients. The system will send an alarm to inform relatives or caretakers, when a seizure is occurring such that proper action can be taken. This will increase the safety and independence of the patient and reassure relatives that the patient is secure. Furthermore, such a system can assist in keeping track of the exact number of seizures a patient is experiencing, which is important for diagnosis and treatment. Electroencephalography (EEG) combined with video surveillance is the gold standard for analysis of epileptic seizures, but continuous measurements of EEG and video are not suitable for an alarm system for everyday use. Many types of seizures have motor manifestations, which has led to the analysis of muscle activity and movements for seizure detection.

An alarm system based on surface electromyography (sEMG) is already on the market [3]. The system is capable of detecting seizures of a specific type: the generalized tonic-clonic seizures (GTCS). A big proportion of patients with untreatable seizures has this type, but other types are still undetectable including the ones called tonic seizures. Several other groups have also developed seizure detection algorithms (e.g. [4], [5]), but none of them work specifically with sEMG from tonic seizures.

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II. METHODOLOGY

A. Patients

Six patients from Danish Epilepsy Centre in Dianalund, Denmark with tonic seizures were included. The age, gender, number of tonic seizures, and recording length for each patient are listed in Table I.

B. Recordings

The signals were recorded prior to this study and include both EEG, electrocardiography (ECG), and sEMG at several different locations. However, only sEMG signals from the deltoids were used in this project, as these gave the highest detection rates for GTCS in a previous study by Conradsen et. al [6]. Recordings from both deltoids were included as two separate measurements to increase the amount of data. The sEMG was filtered with an anti-aliasing filter of 512 Hz and sampled at 1024 Hz. Seizure onset and offset times were determined by a trained neurologist and clinical neurophysiologist with experience in the evaluation of long-term video-EEG recordings. Some of the recordings also included other types of seizures, seizures with no activity in the deltoids, or periods where it is not certain whether it is a seizure or not. Data from all these periods were excluded from both training and testing of the algorithm. The onset and offset times determined from EEG and video

TABLE I: Age, gender, number of tonic seizures, and recording length for different patients. Besides these seizures, some patients may also have other types of seizures.

Patient	Age	Gender	Total file length [h]	# of tonic seizures
1	58	Male	9.0	3
2	6	Female	0.1	1
3	14	Male	27.5	5
4	30	Male	12.1	10
5	48	Male	4.0	1
6	9	Female	12.1	6

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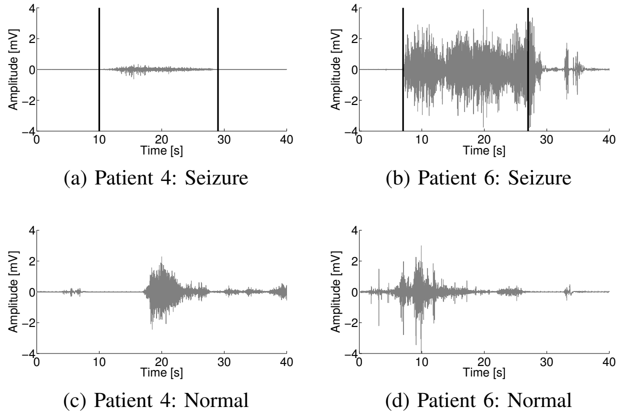


(a) Patient 4: Seizure
(b) Patient 6: Seizure
(c) Patient 4: Normal
(d) Patient 6: Normal

Fig. 1: Tonic seizures and normal activity from two patients. The black lines indicate seizure onset and offset marked by trained neurologist and clinical neurophysiologist. Note how the muscle activity for patient 6 does not completely align with the offset mark.

may deviate from the onset and offset of muscle activity. The author has therefore manually excluded uncertain periods in the beginning and end of seizures from training.

The amplitude of sEMG recordings can be quite different between patients. Furthermore, the amplitude during seizures compared to normal movements can also vary between patients. Some patients had greater activity during seizures, while other patients had more subtle seizures with lower activity than during normal movements. Seizures and normal movements from two patients are shown in Fig. 1, which illustrates the great difference in amplitude in the current data.

C. Feature extraction

The signals were pre-processed with a fourth order high-pass Butterworth filter with a cutoff frequency of 30 Hz. This removes low-frequency artifacts from movements and attenuates most of the ECG artifacts as described in [7]. Powerline interference was removed with a comb filter with notches at 50 Hz and higher harmonics. Features were extracted from windows of 1 s with 50% overlap.

Eleven features in total were included in the study. The following features were extracted from the entire frequency band (after pre-processing): approximate entropy, median frequency, AR coefficients, and reflection coefficients (with a model order of 3). The kurtosis was computed for the fourth level of detail coefficients after a discrete wavelet transform[1]. Furthermore was the zero crossing rate (ZCR) computed after a 150 Hz high-pass filtration as it is done in the detection algorithm for GTCS [6]. Several of these features characterize the frequency content of the signal. They were chosen as it was observed in a study by Conradsen et. al [8] that tonic seizures contained relatively more power in the higher frequencies compared to simulated seizures.

[1] 20th Daubechies as mother wavelet

The AR coefficients and reflection coefficients are computed for a model order of 3. A low model order captures the general trend of the signal and keeps the total number of features down. The computation of approximate entropy requires a choice of a parameter r. A feature that uses the same r for all windows and a feature where r is chosen separately for each window were investigated. In the computation of ZCR, a hysteresis was used to avoid counting zero crossings from small random fluctuations. The hysteresis level was determined in the beginning of each recording from a 5 second window that was assumed only to contain noise by setting it to three times the standard deviation of the noise.

There will always be some degree of amplitude increase during a seizure compared to the background. This inspired to a simple binary activity feature that only states if there is activity or not. Then only windows with activity will enter the classification algorithm, while all other windows will be considered not to be seizures. The feature was based on the RMS of the current window relative to the minimum RMS in the previous 20 s. The activity feature is 1 if the relative RMS exceeds a threshold of 2 and 0 otherwise.

D. Classification

The features computed for each data window are classified into seizure or nonseizure by use of the machine learning algorithm random forest (RF).

The basis of RF is decision trees trained with the CART algorithm. Decision trees are rather simple models that split the feature space into cuboid regions belonging to different classes [10]. A new input feature vector $\mathbf{x}$ is classified by passing it sequentially through a binary tree structure, where each node corresponds to a threshold on one of the features. The input starts at the root node in the top and end at one of the leaf nodes in the bottom that corresponds to a certain region in feature space. This region in turn corresponds to a specific class y. In this classification problem, there are only two classes: positive ($y = 1$) and negative ($y = -1$), corresponding to seizure and nonseizure respectively.

An RF model is constructed by growing a large number (B) of decision trees, where each tree is trained from a subset of the training data. These different trees are denoted $h(\mathbf{x};\theta_b),\ b = 1,\ldots,B$, where $\mathbf{x}$ is an input example and θ_b is the subset. The subset is sampled randomly from the training data with replacement, i.e. a bootstrap sample. It has the same size as the original training set and is different for each tree in the forest. A new input is classified by passing it through all trees and the classification is based on the majority vote. That is, the classification is determined by

$$\bar{h}(\mathbf{x}) = \frac{1}{B}\sum_{b=1}^{B} h(\mathbf{x};\theta_b) \quad ,$$
$$\hat{y} = \begin{cases} 1 & \text{if } \bar{h}(\mathbf{x}) > 0.5 \\ -1 & \text{if } \bar{h}(\mathbf{x}) \le 0.5 \end{cases} \quad . \tag{1}$$

It can be shown that the expected error of an ensemble of models will always be at least as small as for a single model [10].

The performance of RF is dependent on the strength of the individual tree and the correlation between them [9]. To reduce the correlation, the algorithm for growing a tree in RF is modified. At each node the best split is determined only between a random subset (of size F) of features. The size of the subset is recommended to be the square root of the total number of features. Here, F was chosen to be 3. The number of trees B was chosen to be 500. A third parameter that can be varied, is the cutoff threshold for the number of votes it takes to be classified as positive or negative. The majority decides as default, as in (1), but the cutoff for the positive class can be lowered to increase sensitivity or raised to decrease the false detection rate (FDR). For instance, if the cutoff is set to 0.3, a test example is classified as seizure if at least 30% of the trees give a positive vote.

The dataset contained a substantially larger amount of nonseizure data compared to seizure data. To avoid favouring the negative class, the bootstrap samples were balanced to contain an equal amount of examples from each class.

E. Post-processing

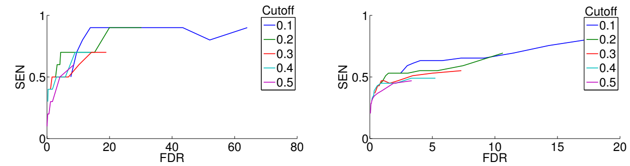
The classification algorithm from the previous section does not consider the sequential nature of the data. Each window will be classified as positive or negative regardless of the preceding or following windows. The sequential information was taken into account by only detecting a seizure if a predefined number of successive windows were classified as positive. The number of positive, successive windows needed to detect a seizure was varied between 6 and 26 to find different trade-offs between sensitivity and false detection rate. The number of positive windows needed will be denoted the time threshold.

In an alarm application, action will be made to help the patient, and he will already be taken care of if a new seizure happens within short time of the first. Therefore some refractory period after each alarm can be allowed, where no new seizures will be detected regardless of the classifier output. This can greatly reduce the number of false alarms, but if the period is too long and the FDR is already high, there is a risk of not detecting real seizures. Here, the refractory period was chosen to be 30 seconds. If the algorithm is used for monitoring, the refractory should be much shorter, since seizures shortly after each other need to be detected as separate seizures.

The algorithm was implemented in MATLAB Release 2013b (The MathWorks, Inc., Natick, Massachusetts, United States).

III. RESULTS

The algorithm was evaluated in a leave-one-out cross-validation. The cutoff and time threshold can both be optimized to find a proper trade-off between high sensitivity and low FDR. Therefore, a grid search was performed, where the time threshold was varied between 6 and 26 windows with an interval of 2, and the cutoff was varied between 0.1 and 0.5 with an interval of 0.1. The FDR and sensitivity was plotted against each other to visually determine the best set of parameters. An example of the FDR plotted against SEN for patient 3 is shown in Fig. 2a, and Table II lists the chosen parameters for each patient. For a generic algorithm, the parameters need to be the same for all patients. Fig. 2b shows the grid search for all patients combined. The choice of generic parameters could either be a cutoff of 0.2 and a time threshold of 18 resulting in SEN = 0.53 and FDR = 1.49, or a cutoff of 0.1 and a time threshold of 20 resulting in SEN = 0.63 and FDR = 4.03, depending on which trade-off is considered best. The results for the individual patients with cutoff and time threshold set to 0.2 and 18 are shown in Table III.



(a) Patient 3

(b) All patients

Fig. 2: Grid search for patient 3 alone and for all patients combined. Each line represents a fixed cutoff where the time threshold is varied.

TABLE II: Patient specific parameters and the resulting performance on the test set.

Test patient	Cutoff	Time threshold	SEN	FDR [h^{-1}]
1	0.3	18	1.00	0.64
2	0.5	22	1.00	0.00
3	0.2	20	0.50	4.12
4	0.1	6	0.75	6.62
5	0.2	6	1.00	7.90
6	0.4	26	1.00	0.08

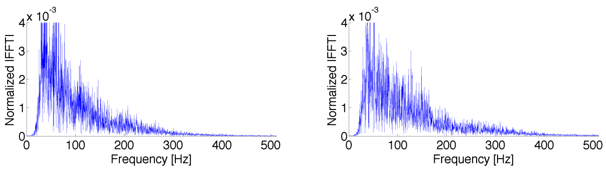
A few false alarms were selected to investigate the difference in frequency content between seizure and normal movement. Fig. 3 shows normalized magnitude spectra for a seizure and a false alarm. Visually, it is difficult to see the difference. The same is the case for other false alarms from other patients.

IV. DISCUSSION

The results are not near the performance requirements for a usable alarm system. For comparison, the algorithm in the current alarm for GTCS obtained SEN = 1.00 and FDR = 0.04/h [6]. The best performance in this study is SEN = 0.53 and FDR = 1.49 or SEN = 0.63 and FDR

TABLE III: Results with generic parameters that are the same for all six patients. The cutoff is set to 0.2 and the time threshold is 18.

Test patient	SEN	FDR [h^{-1}]
1	1.00	1.92
2	1.00	0.00
3	0.70	5.24
4	0.10	1.04
5	0.00	1.53
6	1.00	1.42



(a) Seizure (b) False alarm

Fig. 3: Normalized magnitude spectra for a seizure and a false alarm. The spectrum is computed for a 5 second window and normalized to sum to 1.

= 4.03, depending on the choice of parameters. There is, however, a great variability between patients, and for three of the patients the sensitivity is satisfactory. Using patient specific parameters this increases to four patients. The high FDR values pose a greater problem. The maximum tolerable number of false alarms is about 1 per day, but this number exceeds 24 for all patients except patient 2. The FDR for patient 2 is not reliable due to the very small amount of data (see Table I). It should be noted that the cutoff and time threshold is optimized on the test set. Optimally, they should have been applied to a third unseen dataset, but the amount of data did not allow this.

A hypothesis could be that normal movements will be similar to simulated seizures, and that a difference in frequency content could be observed. The difference between the false alarm and the seizure shown in Fig. 3 is, however, very small, unlike the example with a tonic seizure and a simulated seizure in [8]. An explanation could be that the simulated seizures consist of maximal voluntary contractions (MVC). During MVC there will be a synchronization between motor neurons, which results in higher amplitude and more power in the lower frequencies. The false alarms are normal movements and are most often submaximal contractions. Therefore, this synchronization may not occur, and consequently will the false alarms be more similar to seizures with lower power in the lower frequency components.

More work can be put into the feature extraction. AR and reflection coefficients are used as separate features even though they are related in some way. The relationship could be investigated further, either to find a way to exploit it or to reveal redundancies. Furthermore, could the order model be optimized. The hysteresis used for ZCR is determined in the beginning of the recording, but if the noise level changes, it would desirable if the hysteresis could adapt. Generally, the feature set should be reduced if the algorithm should work on a low-power wearable device. RMS and waveform length computed for different wavelet bands as well as the second spectral moment were also included as features initially, but they were not suitable for distinction between seizures and normal movements, because of the amplitude differences seen in Fig. 1. Kurtosis for other wavelet bands than the fourth was also included, but they were also quickly discarded due to a too small discriminative power.

The use of patient specific parameters requires optimization for all new patients if the algorithm is to be used in the field. This is a constraint compared to the use of generic parameters, as sEMG has to be recorded during several seizures, before the alarm can be taken into use. Of course only a subset of patients with epilepsy experiences tonic seizures. However, in combination with the already developed algorithm for GTCS, a successful detection algorithm for tonic seizures can help a lot of seriously disordered patients. Possibly, solutions to other seizure types can be developed as well.

V. CONCLUSION

An algorithm was developed for detection of tonic epileptic seizures based on sEMG. The results showed that the sensitivity for some of the patients was satisfactory, but too low for other patients. The results were better using parameters optimized for each patient separately. The number of false alarms was too high for practical use in both cases. It was shown that the frequency content of some false alarms showed to be visually similar to seizures based on power spectra. Thus features based alone on the frequency spectra may not be as easy to use to discriminate seizures from normal activity as first expected based on the study comparing tonic seizures to simulated tonic activity. This study showed that the tonic seizures may be very different from each other both in the time and frequency domain. A solution could be to calibrate parameters for each patient. When more data is collected it could be an idea to investigate, whether the group *tonic seizures* should actually be split in several subgroups to clarify and describe their characteristics better.

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