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Accelerometers used for the detection of nocturnal frontal lobe seizures in pediatric patients

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Abstract

Long term home monitoring (multiple weeks) of patients with epilepsy is yet non existing. Frontal lobe seizures, the seizures we want to monitor, often cause bicycle pedaling movements or uncontrolled movements with the arms. A detection system with accelerometers, attached to the limbs, is investigated for the purpose of long term home monitoring. Datasets from four patients suffering from nocturnal frontal lobe seizures are used in this paper for the development of an automatic detection algorithm. After a data reduction step, movement epochs are detected by comparing the calculated standard deviation of a sliding window to a threshold. Afterwards a moving average filter is applied and thresholds are set to the signals of the four accelerometers in order to classify an event into an epileptic seizure or into normal movement. This resulted for three patients in a sensitivity and a positive predictive value (PPV) of 100%, for the other patient the sensitivity was 100% and the PPV was 30,18%. This research shows that epileptic seizure detection by means of accelerometers is possible for this type of seizure.

Keywords: *seizure detection, epilepsy, accelerometers.*

1 Introduction

Epilepsy is a neurological condition which is characterized by recurrent unprovoked seizures [1]. These epileptic seizures can cause uncontrolled movements, changes in emotions and abnormal sensations. Some patients may also show repetitive convulsions, muscle spasms and loss of consciousness. Epilepsy is the most common serious brain disorder during childhood [2].

The golden standard for detecting epileptic seizures is a combination of EEG and video monitoring. An expert analyzes the EEG and video data (the EEG shows the electrical brain activity, the video the (abnormal) movements of the patient) and labels them by determining the time a seizure occurred. Video/EEG monitoring gives a high specificity and sensitivity for identifying seizures.

Although this detection method can robustly determine epileptic seizures, it is not feasible for a long term (multiple weeks or months) home monitoring as the EEG electrodes have to be attached to the patient's scalp which is labor intensive for the technical staff. Furthermore the electrodes are uncomfortable to wear for the patient.

Long term home monitoring can give the neurologist more insight, since it can provide an objective measure of the frequency of nocturnal seizures by logging them. This measure allows a better follow-up and leads to a more correct adjustment of medication for an adequate treatment of the disease, which results in a better quality of life for the patient.

In addition an automatic epilepsy detection system could alarm parents when their child has a seizure. Parents fear missing a seizure at night, so the child often sleeps in their bed. This is a demanding procedure and an automatic detection system could bring solace.

An automatic epileptic seizures detection system can be based on video data, as Cuppens K. et al. [3] have shown. The disadvantage of this method is that it is difficult to detect movements under a blanket. Another option is a system which uses accelerometers.

Nijsen T. et al. already studied the use of accelerometers for the detection of epileptic seizures [4]. Stereotypical patterns for seizures with a motor component were found in the accelerometer data. It was possible to detect myoclonic (a sudden, brief, shock-like contraction) and tonic (a sudden, sustained contraction of multiple muscle groups, fixing the limbs in some strained position) seizures [5] by means of accelerometers, and in some cases the human labeler even detected seizures which were not clearly visible in the EEG signal. Also Becq G. et al. [6] and Conradsen I. et al. [7] use accelerometers, combined with magnetometers and magnetometers-gyroscopes respectively to detect seizures with a motor component. Cuppens K. et al. [8] already conducted a first study, on a limited amount of patients, on the use of accelerometers to detect frontal lobe seizures.

The goal of this paper is to fine tune the automatic detection algorithm for pediatric children and youth based on 3D accelerometers to detect nocturnal frontal lobe seizures and to apply it on a larger amount of patients.

2 Method

2.1 Acquisition of datasets

The datasets of the epileptic patients were acquired at Pulderbos Rehabilitation Centre for Children and Youth (Belgium). Four three-axis accelerometers were attached to the wrists and the ankles to monitor movements (Figure 1). This led to datasets with synchronized video, EEG (electroencephalogram), ECG (electro-cardiogram), EOG (electrooculogram) and accelerometer (ACM) data. The ACM signals are sampled at 250Hz and are ranged between $\pm 3g$. From now we use g as defined here:

$$g = 9{,}81 m/s^2 = 1000 mg \qquad (1)$$

The datasets were acquired during the period the patient is asleep and are therefore not much disturbed by voluntary movement.



Figure 1: Four three-axis accelerometers are attached to the wrists and ankles to monitor movements.

The four patients have an age between five and ten. All of the patients suffer from frontal lobe seizures which result in marked motor manifestations, like bicycle pedaling movements or uncontrolled arm movements. Table 1 gives an overview of the used training datasets. It accounts for 55 hours 4 minutes and 10 seconds of data, in which a total of 807 movement events are detected, including 28 epileptic seizures. For patient A, an extra dataset is used in the testing phase. This dataset consists of four hours of data, in which 72 movement events occur, including two frontal lobe seizures. Notice that the movement events are not labeled by an expert but detected by the movement detection step, discussed in the next section.

An expert labels the data, i.e. the starting point and the duration of the seizures are marked together with the type of seizure, with the information from the video/EEG data. This information is considered as the ground truth.

Table 1: Overview of patient training data.

Patient	# hours (hh:mm:ss)	Movement events	Frontal lobe seizures
A	15:46:09	224	8
B	15:00:12	278	2
C	12:20:00	184	16
D	11:57:39	121	2
Total	**55:04:10**	**807**	**28**

2.2 Preprocessing

The preprocessing step performed on the raw data (twelve channels, three per ACM) has two goals: reducing the amount of data and dividing the data into non-movement and movement events. In the top part of Figure 2 the different steps of the preprocessing phase are shown. Figure 3 shows the signals after different steps. In the top image channels one to three of a part of the original ACM data can be seen.

The first preprocessing step consists of filtering the ACM data with a low-pass 36^{th} order type 2 Chebyshev filter with a cut-off frequency of 47 Hz. To avoid the phase distortion introduced by the filter, we processed the input data in both the forward and reverse directions, which results in a zero-phase filtering. The cut-off frequency is chosen such that the filter cancels out the aliasing effect when the data is downsampled. Moreover, a possible influence of the net frequency (50 Hz, and the first harmonic at 100 Hz) is also eliminated. A downsampling by a factor of two to 125 Hz is performed since we noticed that the frequency content of the ACM signals was always smaller than 40 Hz. In a next step the influence of the static earth gravity field (represented by a DC component) is eliminated by a high-pass filter with a cut-off frequency of 0,2 Hz. Here, a fourth order type 2 Chebyshev filter is used. As with the previous filtering, here also a zero-phase filtering is used. The middle figure in Figure 3 are the three channels after these three filtering steps.

Next, the resultant of each ACM signal, which represents the size of the dynamic acceleration of the sensor, is calculated by adding the signals of the three axes of one ACM to result in one signal. The bottom image in Figure 3 (rough line with values on the left) shows the resultant of these three channels. This calculation reduces the data from twelve to four channels. The total data reduction in these first steps is a factor of six (from 12*250 samples per second to 4*125 samples per second).

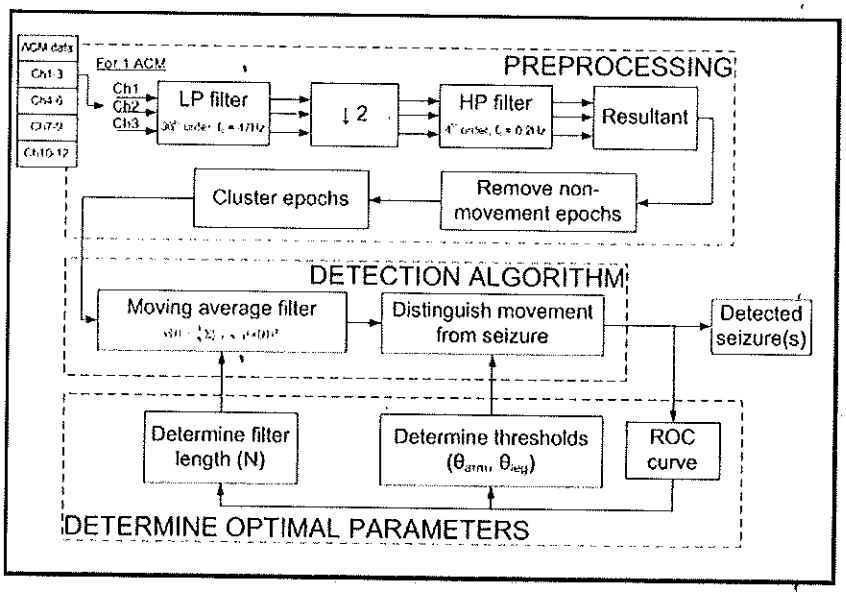


Figure 2: Block diagram of the algorithm, consisting of a preprocessing step, the detection algorithm and the determination of the optimal parameters.

After this data reduction step, the data is divided into movement and non-movement epochs. In order to do so, the standard deviation of a sliding window of two seconds is calculated. If the standard deviation of the ACM signal crosses the threshold for the arms or legs, the epoch is considered to be a movement epoch, otherwise it is discarded. These thresholds are determined by a simulation where a simulator lies in bed during five minutes, after which he makes small finger and toe movements which should be detected by the algorithm. This resulted in a threshold of 10 mg for the arms and a threshold of 5 mg for the legs. In a last preprocessing step the movement epochs are clustered. Epochs within 30 seconds are clustered together and are regarded as one single movement event.
Ten to twenty percent of the data are considered as movement events. Considering all the data reduction steps (counting for a factor of six) this means that only about 1,5% to 3% of the raw data has to be processed by the detection algorithm, which is a considerable reduction.

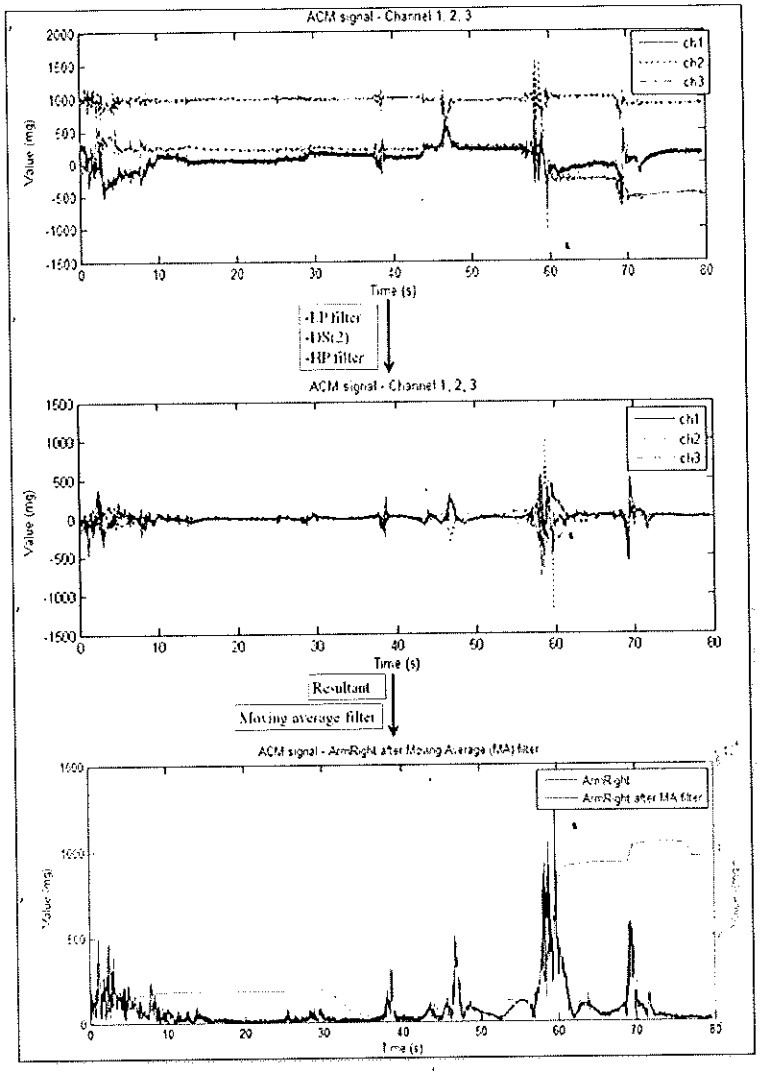


Figure 3: ACM signals of a part of the 12 original channels: the original channels 1, 2 and 3 (*top*) and after LP (low-pass) filtering, DS (downsampling) with a factor 2 and HP (high-pass) filtering (*middle*). The resultant of these channels (*bottom, rough line with values on the left*) and after applying the MA (moving average) filter (*bottom, fluent line with values on the right*).

2.3 Detection algorithm

There are differences in intensity and duration between movements caused by nocturnal epileptic seizures and normal nocturnal movements: movements like

turning in bed only take several seconds, whereas frontal lobe seizures last for ten seconds or more and have a high intensity. To emphasize the strong long movements and suppress short, but nevertheless sometimes strong, movements as turning in bed, a moving average filter applied to the square of the dynamic acceleration signal is used. The mean energy of a sliding window is calculated by the following expression:

$$y[i] = \frac{1}{N}\sum_{j=i-N-1}^{i}(x[j])^2 \qquad (2)$$

where $x[j]$ is the ACM input signal of one limb, $y[i]$ is the output of the filter (in $(mg)^2$) and N is the size of the sliding window expressed in the number of samples, the filter length. The bottom figure in Figure 3 (fluent line with values on the right) are the resultant of the first three channels after the filtering steps, previously mentioned after applying the moving average filter.
The size of the window should be more or less in the order of the length of the seizures to make a good distinction. To distinguish seizures from normal movements a threshold is set to the reduced data, after applying the moving average filter. Because the intensity of the movement of the arms and legs can differ substantially, different thresholds are used for the arms (θ_{arm}) and legs (θ_{leg}). The movement event is regarded as a seizure, if two out of four signals cross the threshold. This is to prevent possible errors, when for example the arms of the patient lie underneath the pillow, and thus the intensity of the arm movement is significantly lower. How to set the ideal values of the thresholds, is discussed in the next section.

2.4 Determine optimal parameters

As we noticed that movements linked to a seizure have inter-patient variations, we chose to determine parameters per patient.
To determine the optimal parameters, we used ROC curves. The parameters which had to be found are the length of the moving average filter (N), the threshold for the arms (θ_{arm}) and the threshold for the legs (θ_{leg}). The aim is to find a combination with which all the epileptic seizures can be detected.
An ROC curve gives an indication of the performance as the parameters change, usually by plotting the sensitivity versus the specificity. The positive predictive value (PPV) is used instead of the specificity, since it is more sensitive to false positives (FP) and because the datasets contain far more true negatives (TN) than true positive events. Under these circumstances a single false positive has a larger influence on the PPV than on the specificity.

$$PPV = \frac{TP}{TP+FP}, \quad sensitivity = \frac{TP}{TP+FN}, \quad specificity = \frac{TN}{TN+FP} \qquad (3)$$

The sensitivity is defined as the number of true detected seizures (TP) divided by the total number of seizures labeled by the expert ($TP + FN$), and the PPV is defined as the number of true detected seizures divided by the total number of seizures regarded by the algorithm ($TP + FP$), as seen in Equation 3.
In this application it is important that all the labeled seizures are detected by the algorithm, thus that there are no false negatives (FN). The amount of wrongly detected seizures (FP) should be as low as possible. Therefore the aim is to find a combination of parameters such that the sensitivity is 1 (or 100%) and the PPV is as high as possible.

3 Results

3.1 Training phase

When we apply the ROC curve to the datasets of the different patients, we get the results shown in Table 2. Over 10 000 combinations of the three parameters were tested with a value for the window length (N) between 0,5 and 20 seconds, a value between 10 000 and 810 000 $(mg)^2$ for the threshold for the arms (θ_{arm}) and a value between 20 000 and 2 000 000 $(mg)^2$ for the threshold for the legs (θ_{leg}). Since we do not want to miss a seizure, we look for a point with a sensitivity of 100%.

Table 2: Overview of the training results per patient. The sensitivity and the PPV are listed, together with the amount of corresponding parameter combinations giving these results.

Patient	Seizures	Sensitivity (%)	PPV (%)	# parameter combinations
A	8	100,00	100,00	243
B	2	100,00	100,00	583
C	16	100,00	30,19	50
D	2	100,00	100,00	157

As shown in Table 2, a sensitivity and a PPV of 100% could be reached for patients A, B and D. They even have multiple optimal points, matching different combinations of parameters, but they do not have optimal parameter combinations in common. The optimal points for patient A are shown in Figure 4.
For patient C a point on the ROC curve with a sensitivity and a PPV of 100% could not be found. The results for patient C are plotted in Figure 5. In this figure the red line corresponds to the optimal ROC curve. There are also different (50) combinations, resulting in a sensitivity of 100% and a PPV of 30,19%: a window

length of 3 or 4 seconds, a threshold of 5 000 $(mg)^2$ for the arms and a threshold for the legs between 200 000 and 2 000 000 $(mg)^2$.

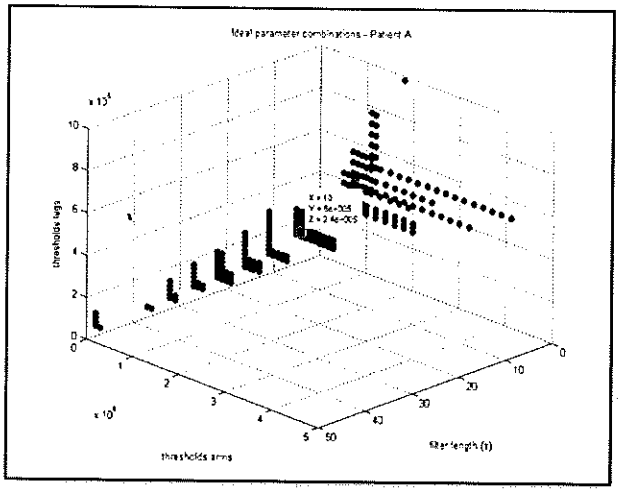


Figure 4: Ideal training parameter combinations of the filter length (N), the threshold for the arms (θ_{arm}) and the threshold for the legs (θ_{leg}) for patient A.

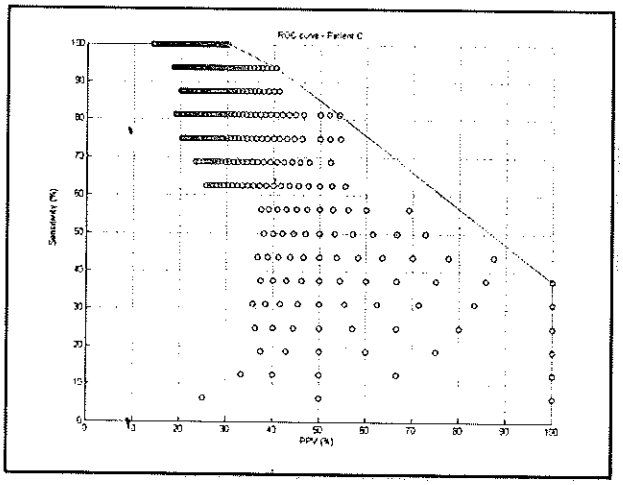


Figure 5: Scatter plot of the performance for different parameter combinations for patient C. The red line corresponds to the optimal ROC curve.

When applying the algorithm on all the training datasets from Table 1, the ROC curve, shown in Figure 6, is attained. There are parameter combinations for which a sensitivity of 100% is reached, but the PPV is only 11,24% or less in these cases.

3.2 Testing phase

The testing phase was only performed on data of patient A, since not enough data was provided for the other three patients. The algorithm was tested on the extra dataset, consisting of four hours of data, in which 72 movement events occur, including two frontal lobe seizures. Since there are multiple (200-250) optimal parameter combinations in the training set, the point in the centre of the scattered combinations is chosen as the combination used (see Figure 4). This point represents a window length of 10 seconds, a threshold for the arms of 600 000 $(mg)^2$ and one for the legs of 240 000 $(mg)^2$. The sensitivity and the PPV of the result with these parameters are both 100%.

4 Discussion

The optimal values of the three parameters (the length of the moving average filter (N), the threshold for the arms (θ_{arm}) and the threshold for the legs (θ_{leg})) were determined per patient in a training phase.

For patients A, B and D several points on the ROC curves could be found with a sensitivity and a PPV of 100%, as shown in Figure 4 for patient A. In these cases all seizures were detected and no normal movement was seen as an epileptic seizure. For patient C an optimal combination of parameters was not reached. In this case all seizures were correctly detected (sensitivity is 100%), but there were 37 false alarms (FP) corresponding to a PPV of 30,19%. After inspection of the data, we saw that patient C had nocturnal movements similar in duration and length to epileptic seizures. The algorithm also detects these movements, which explains the high amount of false positives.

To have a thorough analysis of the algorithm, the performance on a test dataset with the parameter combination obtained in the training phase, is required. In order to do this, more accelerometer data has to be acquired. For patient A the obtained parameters were tested on an extra dataset, and this resulted in a sensitivity and a PPV of 100%.

Finally, when combining the individual results of the algorithm we can conclude that all 30 seizures were detected (no FN), and there were 37 false alarms (37 FP), all arising with patient C. Furthermore we noticed that no parameter setting could be found so that all four patients had a sensitivity and a PPV of 100%. The highest PPV was 11,24%, while not missing any epileptic seizure (Figure 6). This indicates

that a patient specific training is required (preferably in a specialized institution) before the system is utilized at the patients home.
Comparing these results to related work is difficult since, to our knowledge, we are the first to work on frontal lobe seizures. T. Nijsen et al. focused on myoclonic and tonic seizures, a different type than the kind of seizures in this paper. In their work it was possible to detect myoclonic seizures with a sensitivity of 71-80% and a PPV of 15-16%, while a sensitivity of 83% and a PPV of 35% was reached for tonic seizures on a testing dataset.

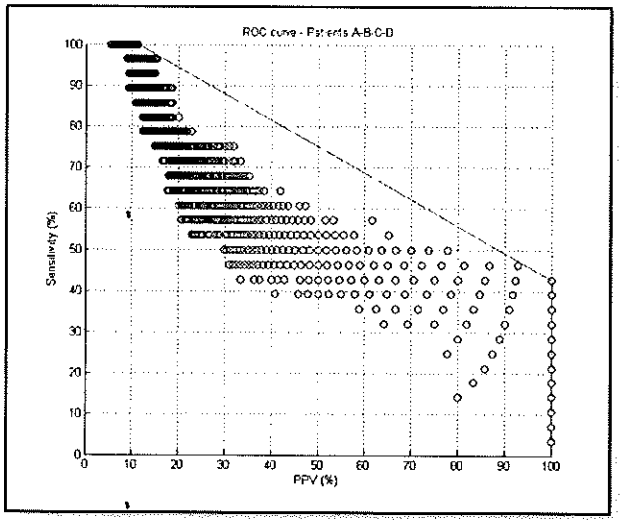


Figure 6: Scatter plot of the performance for different parameter combinations for the testing datasets of all patients. The red line corresponds to the optimal ROC curve.

5 Conclusion

A detection algorithm for nocturnal frontal lobe seizures is developed and tested on a group of patients. A sensitivity and a PPV of 100% is reached in the training phase for three out of four patients, who have seizures with a large motor component. For the fourth patient, patient C, the sensitivity is 100% and the PPV is 30,19%. In the testing phase on an extra dataset of patient A, an optimal parameter combination was chosen for the algorithm. This resulted in a sensitivity and a PPV of 100%.
This research shows that epileptic seizure detection by means of accelerometers is possible for this type of seizure in pediatric patients. Our future work will include the optimization of the algorithm and the development of detection algorithms for other types of seizures with a motor component.

Acknowledgments

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