Accelerometry-based home monitoring for detection of nocturnal hypermotor seizures based on novelty detection

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***Abstract*—Nocturnal home monitoring of epileptic children is often not feasible due to the cumbersome manner of seizure monitoring with the standard method of video/EEG-monitoring. We propose a method for hypermotor seizure detection based on accelerometers attached to the extremities. From the acceleration signals, multiple temporal, frequency and wavelet based features are extracted. After determining the features with the highest discriminative power, we classify movement events in epileptic and non-epileptic movement. This classification is only based on a non-parametric estimate of the probability density function of normal movements. Such approach allows to build patient-specific models to classify movement data without the need for seizure data that is rarely available. If, in the test phase, the probability of a data point (event) is lower than a threshold, this event is considered to be an epileptic seizure, otherwise it is considered as a normal nocturnal movement event. The mean performance over seven patients gives a sensitivity of 95.24% and a Positive Predictive Value (PPV) of 60.04%. However, there is a noticeable inter-patient difference.**

***Index Terms*—hypermotor seizures, accelerometers, novelty detection, home monitoring**

I. Introduction

GENERALLY, long term home monitoring of epileptic children is not feasible, due to the inconvenient manner of seizure detection based on the gold standard of video/EEG-monitoring. However, long-term home monitoring would be beneficial because in this way, the neurologist would be provided with an objective measure of the number of seizures the patient has during a night. This permits a better observation of the patient, which can increase the quality of life. Another advantage of a home monitoring system is that the parents can be alarmed when a large seizure occurs that requires care or if the child needs to be comforted, as it is alone during the night.

In our setup, accelerometers are attached to the wrists and ankles to register leg and arm movements. The goal is to tune the algorithm only based on information of the normal nocturnal movement of the patient and still get a high sensitivity and positive predictive value (PPV). This approach is applicable since a large number of normal activities and very few epileptic events are observed.

Some commercially available detection systems are already available on the market. EmFit bed sensors (Emfit Ltd.) are already used for the detection of clonic and tonic-clonic seizures. In the literature, studies can be found that use the sensor for sleep monitoring [17] [9] and as a sensor for cardiac measurements [8], but to our knowledge there are no papers about the performance of seizure detection with the EmFit system.

SmartWatch by Smart Monitor Corporation and EpiLert from Biolert are wrist watches used to detect generalized tonic-clonic seizures. In a study of Lockman *et al.* [10], the SmartWatch was succesfully tested on a group of 40 patients (6 with tonic-clonic seizures). Seven of eight tonic-clonic seizures, and 204 non-seizures events were detected, with only one false detection during sleep.

Nijsen *et al.* [14] already investigated the detection of seizures by means of accelerometers, used on myoclonic seizures. They tested various methods, resulting in a maximal sensitivity of 80%, but all with a low PPV. The best PPV reached was 16%. Jallon [6] also investigated epileptic seizure detection based on accelerometers. His algorithm is based on a Bayesian approach using hidden Markov models, resulting in a sensitivity of 88% and 89% in two patients. The corresponding PPV was 75% and 55%, respectively. Conradsen et al. [2] used a multimodal approach for seizure detection, mainly on tonic seizures. They obtained a sensitivity between 91% and 100% with a specificity of 100%.

The advantage over video detection, which is proposed in Cuppens *et al.* [4] and Karayiannis *et al.* [7], is that accelerometers can measure body movement more easily under blankets and can better separate the movements of the individual limbs, but the sensors have to be attached to the body.

Our approach in this study is based on novelty detection. We model normal movement, and try to detect abnormal (novel, not yet or rarely seen) events, i.e. epileptic events. Novelty

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detection is typically used in settings where the abnormalities occur relatively seldom, and when insufficient data is available to model the abnormal activity. This can also be seen as one-class classification, in contrast to the traditional two class (or multi-class) classifiers, where data of all the classes are used for generating the classification model.

For modeling the normal movement, we estimate the probability density function (PDF) using non-parametric Parzen windows [1]. A non-parametric estimator was chosen since such approach does not make any assumption on the form of the data distribution and therefore is more flexible. Parzen density estimation is commonly used in the context of classification and novelty detection [11]. Rathi *et al.* [16] and Rangayyan and Wu [15] modeled the distributions of two classes based on the Parzen window approach and classify instances based on the highest probability. Tarassenko *et al.* [18, 19] and Yeung and Chow [23] use the one-class classification which is the novelty or outlier detection. A PDF for normal behaviour is estimated and new instances with a probability, computed using this PDF, below a certain threshold level are considered abnormal.

The proposed approach must be contrasted to binary classification methods which use information from both classes (seizures and normal movements) to estimate a model. Requiring information of both classes for estimation implies a costly annotation process. Seizure segments must be isolated from the normal movements by experts using video/EEG. Our one-class method does not require knowledge about the seizure class. Furthermore, since the seizure class is populated with much less examples than the normal class it can typically be assumed that the very small portion of seizure examples has a negligible effect on the estimation of the PDF. In a practical system, when some patient-group specific tuning parameters are fixed, this means that a patient-specific model can be obtained with much less human interaction compared to two-class models.

The main contributions in this paper are a) that we focus on a different patient group (children up until 18 years old) compared to the methods found in the literature and a different type of seizures (hypermotor), and b) an easy-to-apply patient specific training is proposed that does not require any seizures in the training phase. In Van de Vel *et. al* [22] the proposed system is investigated from a clinical point of view, whereas in this paper, the technical aspects are elaborated.

II. Method

A. Acquisition system

The acceleration data was recorded synchronously with video, EEG-, ECG-, EOG- and EMG-data. The synchronization of the signals was done by BrainRT software from OSG (www.osg.be), and a Schwarzer interface box which converted the analog input from the sensors to a digital signal for the connection with the recording computer.

To acquire the data, we developed a hardware system that consists of four 3 dimensional accelerometers, attached to the extremities with comfortable wrist and ankle bands. The setup is shown in Figure 1. The accelerometers range between -3g and +3g, and the data was sampled at 250Hz.

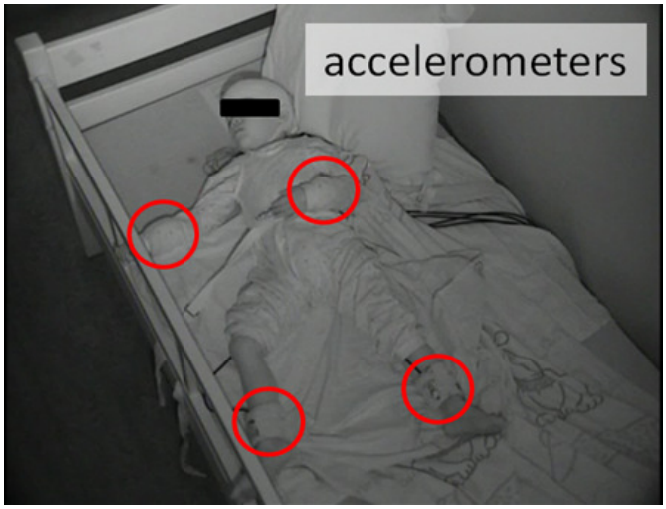

Fig. 1. The acquisition setup, where the placement of the accelerometers is indicated by the circles.

TABLE I
Dataset overview

Patient number	Nights of monitoring	Hypermotor seizures	Normal movements
1	1	2	117
2	2	9	287
3	2	2	439
4	1	2	239
5	5	26	784
6	2	7	381
7	2	3	468
Total	*15*	*51*	*2715*

B. Patients

The group we studied consisted of 7 patients with hypermotor seizures, all between the age of 5 and 16 years. Table I gives an overview of the patients and the number of seizures and normal movements they had during the monitoring. The segmentation in movement events is explained in Section II-C1. The recordings took place during the night, starting typically at 20h00 in the evening and finishing at 8h00 in the morning the next day.

The seizures we focus on, the hypermotor seizures, are marked by a strong and uncontrolled movement of the arms and legs, that can last from a couple of seconds to some minutes. Due to the heavy movement, the patient can injure himself during the seizure. The labeling was performed by an EEG expert based on the video/EEG-data. When it was not clear whether an event was epileptic or not, a group of two EEG experts and two neurologists agreed about the type in a consensus.

C. Epileptic Seizure Detection

In three steps, the raw data is processed to a classification result. In the first step, which is a preprocessing step, movement events are detected. In the second step, features are extracted from the events. The third and final step, consists of the seizure detection algorithm. A model is built based

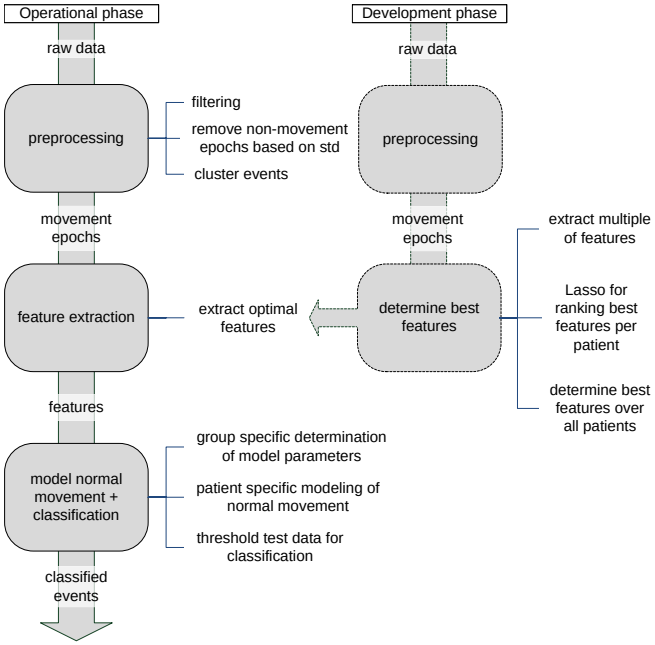

Fig. 2. Schematic overview of algorithm. The determination of the optimal features is only done during the development phase of the algorithm. In the operational phase, only the flow in the left part of the scheme is followed.

on normal movements and tested afterwards to measure its performance. An overview of the approach is given in Figure 2.

In the development phase of the algorithm, the features with the highest discriminative power are selected. Only the optimal features that are found during the development phase are further used in the operational algorithm. During the operational phase this step does not have to be executed anymore.

1) Preprocessing: Thanks to the preprocessing step, the events that do not contain movement information are discarded, which results in a reduction of the data to process. Furthermore it divides the data into separate movement events. This preprocessing is already described in our previous work [3] and is shortly described below.

The preprocessing step first filters the raw data with a low pass filter with a cut-off frequency of 47Hz. In order to avoid phase distortion, the data is processed in a forward and reverse direction to get a zero-phase filtering. The cut-off frequency is chosen to avoid aliasing when downsampling to 100 Hz and to eliminate the noise from the net frequency (50 Hz). We can easily downsample the data because the frequency content above 40 Hz is negligible. The influence of the static earth gravitation is then eliminated by a high pass zero-phase filter with a cut-off frequency of 0.2 Hz.

After filtering, the norm (the 3D vector amplitude) of each accelerometer is calculated, which gives one signal per sensor (hence 4 signals). To detect body movement, the standard deviation of each signal is calculated from a sliding window of two seconds. If the standard deviation crosses the threshold for the arms or legs, the event within the window is considered as movement. 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 are the smallest motions to 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. This difference can be explained by the fact that toe movements have a lower influence on the accelerometer signal than the finger movements. Eventually, movement events lying less than 30 seconds apart are clustered, because the duration of the epileptic activity we want to monitor is typically long (tens of seconds) and sometimes, during one hypermotor seizure the patient stops moving (order of seconds). Note that after this clustering step, the movement events have a variable duration. In the remainder of this paper, these events with variable length are used.

Typically, 80% to 90% of the data is discarded as it contains no movement. Considering all the reduction steps (including the dimension reduction and downsampling) only 1.5% to 3.0% of the raw data is preserved.

2) Feature extraction and selection: From the events we got from the preprocessing, we derive several features in the time, frequency and wavelet domain. After this step we evaluated the Lasso technique [21] for each patient individually to find the features with the highest discriminative power. The results are then combined to determine the best features over all patients.

Table II shows an overview of the features that are selected from the events, which are features that are found in the literature. These are commonly used features as described in [5] and [20], but also features specifically used for the detection of seizures using accelerometers such as the ones derived from the signal of the posture (orientation) as described in Nijsen *et al.* [13]. The wavelets were based on a model to describe arm movements in patients with myoclonic seizures [12]. Furthermore, Conradsen *et al.* [2] also make use of wavelet features for the detection of seizures based on accelerometers. The features in [5] are derived from accelerometer signals, in multiple cases, including human movement. Temko *et al.* [20] derive features from EEG-signals for epileptic seizure detection.

A high correlation is expected between the amplitude-based features and the seizures due to the often violent manifestation of this type of seizures. In the frequency and wavelet space we would expect a relative higher contribution of energy in the higher frequency bands from the seizures compared to normal movements. This because we presume that the uncontrolled shock-like movements contain information in a wider frequency spectrum compared to a smoother normal movement.

Features that are derived from individual channels are not likely to be descriptive over time or patient, as if the patient rotates a limb, the same discriminating feature can be found in another channel. Indeed, the channel which is discriminative can change depending on the orientation of the patient. Therefore we chose to only take into account features that contained more general information including information of all the channels of one limb or from all the accelerometers combined. Therefore, to get more general features, for the kurtosis, RMS, skewness, orientation and frequency features, only the mean and the minimal and maximal values over the calculated values over the 12 channels were considered. The other features are used as illustrated in Table II.

TABLE II
OVERVIEW OF FEATURES IN THE TIME, FREQUENCY AND WAVELET DOMAIN. THESE FEATURES ARE INVESTIGATED ON THEIR ABILITY TO DISCRIMINATE BETWEEN NORMAL AND SEIZURE EVENTS.

Group	Features
Time domain	• mean and standard deviation over 12 mean amplitudes in time of each channel • mean and standard deviation over the 12 standard deviations (std) in time of amplitude of each channel • maximal amplitude of resultant in time per limb • correlation between the resultants of limbs • kurtosis of individual channels • root mean square (RMS) of amplitude of individual channels • skewness of individual channels • mean jerk over time on orientation signal • variance of magnitude in segment on orientation signal • range of block signal on orientation signal
Frequency domain	• peak frequency of spectrum of individual channels • energy in signal of individual channels • spectral edge frequency (80%, 90%, 95%) of individual channels • power in sub-bands (1-3Hz, 4-8Hz, 9-13Hz, 14-20Hz) of individual channels
Wavelet domain	• ratio between the power in scale 2-9 and the total power for each limb and over all channels • ratio between the power in scale 25-48 and the total power for each limb and over all channels • ratio between the power in scale 2-9 and the power in scale 25-48 for each limb and over all channels

For the feature selection, we used an embedded approach. We use the Lasso technique [21] for determining the optimal feature set in a multivariate way. Using this approach, we first determined the best patient specific features by using a 10-fold cross-validation. From every patient we obtain the feature set according to the lowest mean squared error in the 10-fold cross-validation of the regression models compared to the input data. The different regression models are constructed by varying the regularization parameter λ. Note that the weighting of the seizure data is 20 times higher compared to the normal data to compensate for the imbalance in the data. The features are voted, the ones that appear most over all patients (in at least three patients) are included in the final feature subset. Because the features are combined after they are selected patient specifically, all patients get the same weighting, regardless of whether one patient has more seizures than the other.

The feature subset using this approach is listed below:

- the max of resultant over both arms (Equation 1)
- the mean std over all channels (Equation 2)
- the mean of the means over all channels (Equation 3)
- the max of resultant over both legs (Equation 4)
- the length of the event, n
- the mean over all limbs of the norm of the ranges of the channels (Equation 5)

In a more formal way, these features can be expressed using the following equations:

$$max_{arms} = \max_t \left(\|x_{1-3}(t)\|, \|x_{4-6}(t)\| \right), \tag{1}$$

$$mean_{std} = \frac{1}{12} \sum_{i=1}^{12} \sqrt{\frac{1}{n-1} \sum_{t=1}^{n} (x_i(t) - \bar{x_i})^2}, \tag{2}$$

$$mean_{means} = \frac{1}{12} \sum_{i=1}^{12} \frac{1}{n} \sum_{t=1}^{n} x_i(t), \tag{3}$$

$$max_{legs} = \max_t \left(\|x_{7-9}(t)\|, \|x_{10-12}(t)\| \right), \tag{4}$$

$$mean_{ranges} = \frac{1}{4} \sum_{i=1}^{4} Range_i, \tag{5}$$

where $x_{a-b}(t)$ represents the channels with index a until b as a function of time. n is the number of samples (thus the length) of a certain movement event. $Range$ is defined by the following equation:

$$Range = \sqrt{\sum_{k=1}^{3} (\max(x_{slw_k}) - \min(x_{slw_k}))^2}, \tag{6}$$

where x_{slw} denotes the block-like signal that contains the information of the orientation of the accelerometers. This signal is the result of a median filtering with a window length of one second. The features that do not hold information on the orientation, are calculated based on the dynamic acceleration where the orientation information is subtracted from the raw signals.

3) Model estimation and hyperparameter tuning: With the features selected in the previous paragraph, we modeled the normal activity (example is given in Figure 3). Movement events are classified in the test phase. When they are outliers of the normal activity distribution, they are classified as seizures.

To model the normal activity, we estimated its PDF with the Parzen window method [1], by placing a kernel function in every training data point and add them. In this work a radially symmetrical Gaussian kernel function is chosen which is smooth and can be completely specified by a bandwidth (variance) parameter only.

This bandwidth is a hyperparameter (β) that should be determined. It has an influence on the smoothness of the estimated distribution as a larger bandwidth results in a smoother density estimation. Another hyperparameter that needs to be determined is the threshold on the PDF (τ) at which we separate normal from epileptic movement. We determine this threshold based on a fixed probability of 95%. This means that the 5% movements with the lowest probability to be normal are classified as epileptic.

To determine the bandwidth β, we used the approach that is shown in Figure 4. Different values of β are evaluated on the

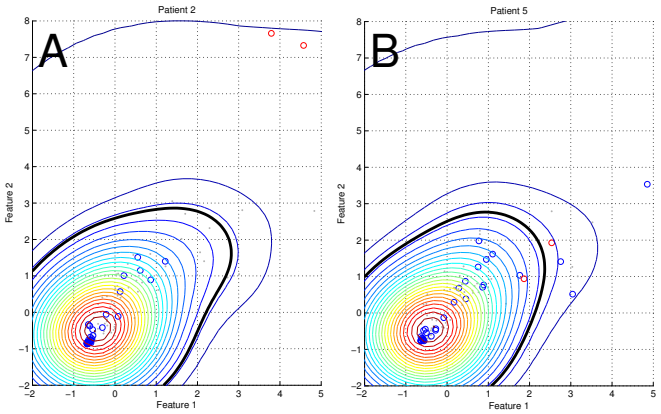

Fig. 3. Probability density functions of patient 2 and patient 5. The red dots are the seizures in the test phase. The normal activity is in blue. The gray dots represent the normal activity that is used for constructing the classification model in the training phase. The normal activity and epileptic seizures are well separable in patient 2 (a) and not separable in patient 5 (b) The decision line in black corresponds with the 95% probability contour.

performance using a cost function. More specific, the evaluated values are 2^n where $n \in \{-2, -1, ..., 4\}$.

For determining the threshold τ, we calculate the probability of each point from our training set based on the PDF. From these probabilities, a histogram and its cumulative distribution function (CDF) is calculated. Using this CDF we can determine the threshold (probability value) that is associated with the 95% border.

To make the approach as general as possible we want the hyperparameters to be group specific (i.e. for all patients with hypermotor seizures) and not patient specific. In this way, they do not have to be adjusted per patient. Therefore, to determine β, we made use of a leave one out approach on a patient basis. Since we have 7 patients, we use 6 of them to estimate β (training phase), and the remaining patient in patient-specific test phase to estimate the PDF and classify movement events.

In this experiment we used two third of the normal movements of all nights as training, and 33 complementary normal movements and 2 seizures for testing the performance of the chosen bandwidth β. These numbers for the test set were chosen because we wanted to have the same number of examples in each patient, and for some patients we only had 2 seizures and not much more than 100 normal movements (so 33 for one third of the data). This training and testing is done in a 10-fold randomization, so for each value of β and for each patient, 10 PDFs are built and tested. We calculated the performance of the model as the average of 10 costs using:

$$cost(\beta) = -(2 \times \text{sensitivity}(\beta) + \text{PPV}(\beta)). \quad (7)$$

Here, the weight of the sensitivity is higher than the weight of the PPV, as missing a seizure is worse than generating a false positive for this type of seizure.

Although the number of data points in every patient is small to train an SVM classifier, we also did an attempt to train an SVM model on the three patients with at least 4 seizures and validated it in a 3-fold cross-validation in 10 randomizations.

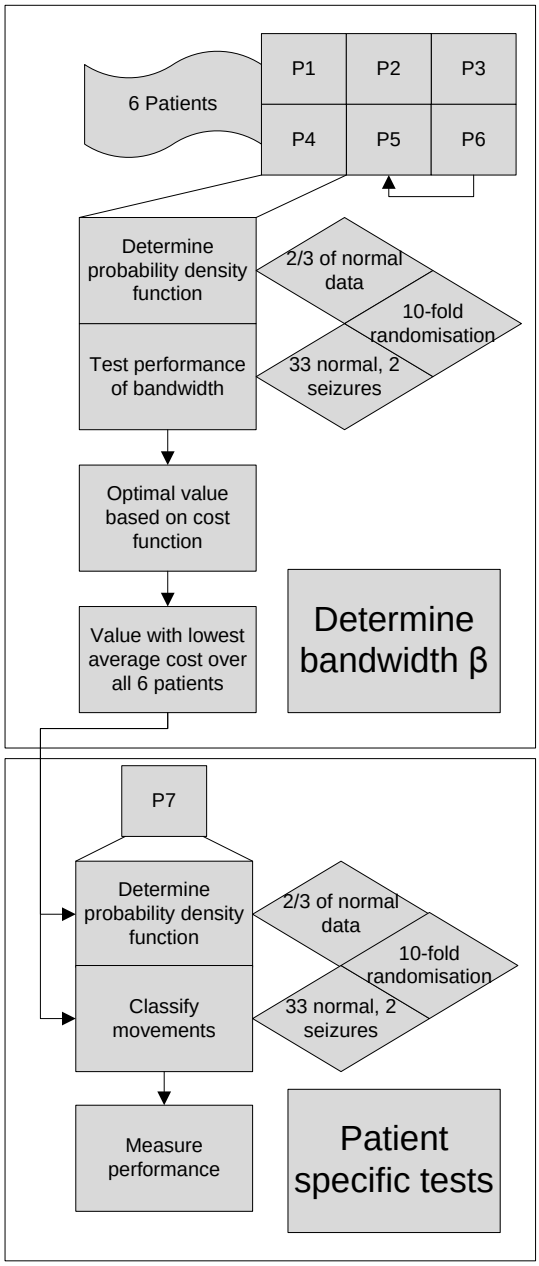

Fig. 4. Schematic overview of tuning β and the patient specific testing. Notice that two thirds of the normal movements are used to model the probability density function. Information of 6 patients is used to determine the optimal bandwidth in the 7^{th} patient.

This classification with an SVM is considered as the state-of-the-art approach and compared with the outlier detection.

D. Validation

As already mentioned, a leave one out approach is used to validate the models, meaning that the model hyperparameter β is estimated using information of 6 patients and then kept fixed for the remaining patient. For this 7th patient a performance score was computed using the same setup. For 10 randomizations a PDF of normal nocturnal movement based on two thirds of the normal movements of all nights of this patient is estimated (with fixed β). Next the sensitivity and

TABLE III
RESULTS OF VALIDATION. FOR EACH PATIENT THE SENSITIVITY (SENS), THE PPV AND THE SPECIFICITY (SPEC) ARE SHOWN, TOGETHER WITH THEIR RESPECTIVE STANDARD DEVIATION OVER 10 RANDOMIZATIONS

n°	sens. (%)	std. (%)	PPV (%)	std. (%)	spec. (%)	std. (%)
1	100.00	0.00	50.38	22.24	92.12	5.19
2	100.00	0.00	51.86	16.56	93.03	4.75
3	100.00	0.00	72.33	21.08	96.97	2.86
4	100.00	0.00	69.00	23.15	96.36	3.13
5	66.67	25.00	45.19	17.41	94.85	4.05
6	100.00	0.00	59.83	25.54	93.94	5.71
7	100.00	0.00	71.67	27.27	96.06	4.75
Total	*95.24*	*3.57*	*60.04*	*21.89*	*94.76*	*4.35*

PPV are computed on a set of 33 normal and 2 epileptic movements. Finally, the mean of the sensitivity and PPV over all the randomizations are used as validation measure.

III. RESULTS

The optimal parameter value for β is determined on a group of 6 patients excluding the patient for whom the performance measures are calculated. The cost over these 6 patients is averaged out, and the bandwidth related to the lowest cost is used for estimating the PDF. For all patients, a bandwidth of 8 gave the best result except for patient 3. But when testing with another threshold, the optimal bandwidth can change as both values are related.

The result of the validation is given in Table III. For all the patients, the sensitivity, the PPV and the specificity are given with the according standard deviation over the randomizations. In all patients except in patient 5, the sensitivity is 100.00% and the PPV is more than 50%.

Figure 3 shows the probability density functions of patient 2 (A) and patient 5 (B), together with the epileptic activity from one randomization in red. The black decision line gives the 95% threshold that separates normal and epileptic movement. This decision line and the PDF are calculated on only two features (in contrast to the 6 features we use in our approach) for visualization purposes. Feature 1 and 2 are used in this figure, which represent the maximal resultant over both arms and the mean standard deviation over all channels, respectively. From this figure it is clearly visible that the normal and epileptic activity is well separable for patient 2 but not for patient 5 as the normal and epileptic activity overlap in this patient.

When comparing the results of the outlier detection to the state-of-the-art SVM approach, we can say in general that for patient 2 and 6 the sensitivity is comparable (95.00%) and the PPV is higher (83.33%). Only the results for patient 5 are worse, with a sensitivity of 30.00% and a PPV of 35.93%. The standard deviation over the randomizations of the SVM approach is high (the mean std on the sensitivity is 19.33% and on the PPV the mean std is 30.39%). This indicates that the generated SVM models are not robust over the different randomizations.

IV. DISCUSSION

The advantages of the PDF classification are the possibility to train the model without positive training examples (no labeling needed) and the flexibility to adjust the model with an increasing number of data. In this way, when we install the system in a real home situation, a better model of normal movement can be learned over time, when more and more data becomes available. This is also further discussed in a next paragraph.

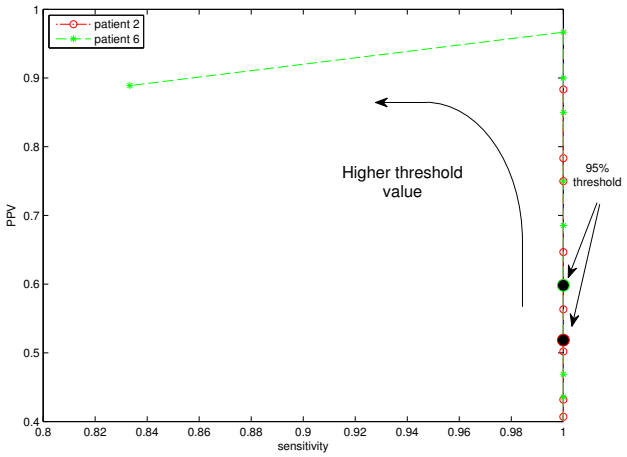

Fig. 5. Performance of PDF approach when using different threshold values (between 0.25 and 0.999). The full black dots indicate the 95% threshold. We clearly see that an improvement is possible compared to the 95% threshold.

In our results section, we evaluated the method on the different patients, using the same number of seizures (2) and normal movements (33) in the test set. This makes a comparison between patients fairer. It also allows us to calculate and average sensitivity and PPV over all patients. However, for some patients, the balance between normal and epileptic movements is different when we would consider all the patient's data, which has an influence on the performance. We observed that the PPV value decreases when a relative larger number of normal movements occur with respect to the number of seizures. The influence of the balance on the PPV value is also explained in a next paragraph.

In the PDF approach we use a rather conservative threshold in a way that in all patients but one, all the seizures are detected. We prefer to use a conservative threshold to be sure no seizures are missed. However, a more optimal result of the PDF classification can be achieved when choosing the threshold in a better way, for example when making use of prior knowledge of the relative number of seizures that occur. We see in Figure 5, which shows the performance for different values of the threshold, that for patient 2 and 6 a sensitivity and PPV value of more than 90% can be achieved when choosing the best threshold value.

When we look at the manifestation of the seizures in patient 5, we see that they are short in duration and subtle in intensity and are clearly different from the seizures in the other patients. After a more thorough inspection, we can conclude that 20 of the 26 seizures included arm movements, 10 contained leg movements. In 5 seizures, the patient sits up in bed, in 7 seizures the patient turns over, and 2 seizures look like normal nocturnal movements. The seizures are typically shorter than

10 seconds, and clearly less violent compared to the seizures of the other patients. This makes it hard for the algorithm to detect them correctly, which explains the lower performance for this patient. This is also visible in the optimal number of features determined by Lasso on this patient. At the minimal mean squared error (MSE), the number of features for patient 5 is 10, compared to an average of 7.7 over all patients. At the largest λ value for Lasso where the MSE is within 1 standard deviation of the minimum, the number of components is still 6 in patient 5, compared to an average of 2.7 over all patients. When we use the 10 features from the optimal feature set for patient 5 determined by Lasso in the outlier detection approach, the performance increases to a sensitivity of 70.00% and a PPV of 49.00%.

Observing the differences between the means of the normal and epileptic normalized data for all patients and for all features, we can see that this difference for patient 5 is maximal 1.87 whereas for the other patients this is at least 3.49 (and 5.39 on average). And although a combination of features with a weak discriminative power, potentially has a high discriminative power, this is an indication that the univariate discriminative power of the 6 features that are used is low for patient 5. To be able to increase the performance, probably other features are required that are not yet included in our overall feature set.

Novelty detection works well in situations where the occurrence of abnormal events is very low. In this case the distribution of normal events can be constructed from all the data available. If the occurrence of abnormalities is low enough, these will not influence the distribution too much. Another advantage of this approach is that in the learning phase, the events should not be labeled, as all the events are used for estimating the PDF. In our case this would mean that, given a group-specific determined β and τ, we can immediately install the detector in the room of the child. Movement data can continuously be collected for updating the PDF. This does not require any other human action. Initially a subset of normal movement from other patients can be used, which is gradually replaced by patient specific movements as more data is collected from that patient.

A possible extension of the method could be integrating an adaptation of the PDF over time. We can make the algorithm robust against a change of normal movements of the patients over time (a change in behaviour). This could be done by discarding the older movement events that were used for building the PDF and replacing them by new movements that are observed.

The obtained value for the PPV depends on both the threshold, and the balance between both classes. This can easily be explained using the following reasoning: consider the case that both classes are separable, so there is no overlap between classes, and that the threshold is set in a way that all seizures are detected, with a certain number of false positives. Let B be the balance, the positive examples (seizures) divided by the total number of movements (seizures + normal movements). Let n be the total number of data points, and T the threshold, which in our case would be 95%. We can state that:

$$PPV = \frac{TP}{TP + FP} = \frac{B.n}{(1-T).n} = \frac{B}{1-T}. \qquad (8)$$

As we assume that all seizures are detected, we can say that $TP = B.n$. To get a high PPV, $1 - T$ should be a good estimation of B. Note that $B <= (1 - T)$, otherwise seizures are missed, we get false negatives, and the ideal case we assumed would not hold anymore. Thus the threshold could be optimized in function of the balance.

We now have tested the algorithm on one type of seizure, but the detection based on accelerometers can be extended to other types of seizures that contain motor components. At least if the seizures do not occur too often throughout the night. Indeed, if the patients suffer from too many seizures, the probability density function will be influenced too much, and seizures will not be regarded as an abnormal event anymore. So in this case many seizures will be missed, unless the threshold is set lower, which leads to more false positives. Furthermore, for seizures with no motor component, this detection system will not work. Hence, this system is restricted to detection of convulsions (seizures with a motor component) only.

To improve the performance for example for the seizures that are visually not distinguishable from normal movements such as some seizures in patient 5, extra modalities can be integrated. For example the tensioning of the arm muscles can be measured using EMG. But also sensors such as ECG, audio, video or skin conductivity, can increase the performance. However, there is a trade-off between the number of applied sensors and the patient's comfort, unless contactless sensors are used.

The results we have are initial results on a group of seven patients. To make more reliable conclusions we will have to test the system and algorithm on a larger group. Furthermore, the system should also be tested in a real home situation. For now it is only tested in a hospital setting. However, when we test it at home, we will lose the EEG information, and a labeling based on the gold standard is not possible for validation.

V. Conclusion

We proposed a method to detect nocturnal hypermotor seizures in pediatric patients. First, we segment the raw data in movement events and extract the features with the highest discriminative power. Afterwards we estimated a non-parametric patient specific probability density function based on normal movement to distinguish epileptic activity from normal activity. This resulted in an average sensitivity of 95.24% and a PPV of 60.04% for 7 patients.

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