Automated detection of tonic seizures using 3-D accelerometry

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Abstract— **A first approach is presented for the detection of accelerometry (ACM) patterns associated with tonic seizures. First it is shown that during tonic seizures the typical ACM-pattern is mainly caused by change of position towards the field of gravity and that the acceleration caused by movement is negligible. To this end a mechanical model of the arm and physiological information about muscle contraction during tonic seizures are used. Then six features are computed that represent the main characteristics of ACM-patterns associated with tonic seizures. Linear discriminant analysis is used for classification. For training and evaluation ACM-data are used from mentally retarded patients with severe epilepsy. It was possible to detect tonic seizures with a success rate around 0.80 and with a positive predictive value (PPV) of 0.35. For off-line analysis this is acceptable, especially when 42 % of the false alarms are actually motor seizures of another type. The missed seizures, were not clearly visible in the ACM-signal. For these seizures additional ACM-sensors or a combination with other sensor types might be necessary. The results show that our approach is useful for the automated detection of tonic seizures and that it is a promising contribution in a complete multi-sensor seizure detection setup.**

I. Introduction

Automated seizure detection can be important in mentally retarded patients that still have frequent seizures despite medical treatment and are institutionalized. Information about seizure frequency can be used for the management of daily care, to evaluate treatment effects and detections can be used to trigger an alarm during severe seizures that require medical assistance. It is known that in mentally retarded subjects, seizures often manifest themselves in movements (motor seizures) [1]. Therefore in mentally retarded subjects it is feasible to use accelerometers (ACM) for automated detection of epileptic seizures [2]. One type of motor seizures is the 'tonic seizure'. During tonic seizures a sudden sustained contraction of multiple muscle groups is seen and the patient stiffens. Often the limbs move slowly in one direction. In a previous clinical study, we found that 64% of all the motor seizures in our population consisted of a tonic element [2]. In ACM-signals a tonic seizure is characterized by a *block-like* pattern, that indicates a slow change of posture. On top of this pattern a small tremor can be visible. Figure 1 A. shows a tonic seizure. Figure 1 B. shows a tonic-clonic seizure. The block-like change of posture is very subtle and short and it evolves into a clonic phase with a higher amplitude and frequency. This paper presents a first approach for the detection of tonic patterns from ACM-signals measured with one 3-D sensor placed on one arm. The purpose of the methods under study, is to support off-line analysis for diagnostic and evaluation purposes.

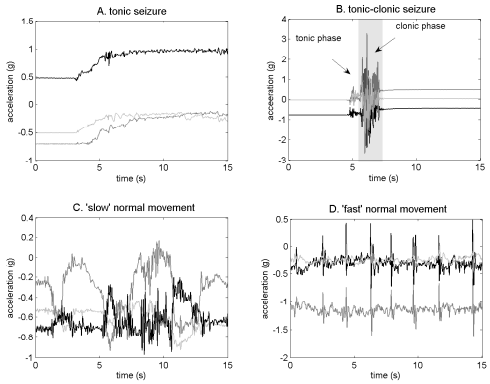

Fig. 1. Examples of typical ACM-patterns, measured with one 3-D sensor on an arm. A. Block-like pattern associated with tonic seizure. B. Tonic-clonic seizure. C. 'Slow' normal movement. D. 'Fast' normal movement.

II. Feature extraction

EEG-technicians can visually 'detect' tonic seizures from accelerometric (ACM) data based on three characteristics:

- There is a slow change in position of the limbs of the patients during a tonic seizure, that is slower than a normal change of posture.
- A small tremor of the limbs is visible, on top of the change of posture.
- Often more body parts can be involved, so the movement pattern is synchronously visible at more than one 3-D ACM-sensor.

Before exploring the combination of multiple ACM-sensors, this paper focusses on detection based on one 3-D sensor placed on one arm. To study the relations between all involved sensors, is a topic for future research. The arms are chosen since the characteristic patterns are best visible on the arm-sensors. In the next section a number of features is described that might contribute to the detection of ACM-patterns that are associated with tonic seizures. First a model is used to explain the ACM-patterns that can be seen during tonic seizures. Then a set of features is described, based on the descriptions of the experts. Tonic seizures usually have a duration between 10 and 20 seconds, but can vary between 2 seconds and 60 seconds [3]. For feature extraction therefore a time window of 10 seconds is chosen. All features are computed for the dominant arm sensor.

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A. Model for motor seizures

We developed an analytical model that describes accelerometric patterns associated with myoclonic seizures [4]. The model was developed in such a way that it can be used for other motor seizure types. During a myoclonic seizure the innervation pattern of the muscles is a short pulse train, in the model this is represented by a single pulse. The muscle response to a pulse is defined by:

$$F_{ag}(t) = F_{sum}(\frac{t}{\tau})e^{\frac{-t}{\tau}} \ , \tag{1}$$

where $F_{ag}(t)$ is the agonistic muscle response, F_{sum} is a constant that indicates the force that can be produced by the muscle and τ is a general time constant for all motor units together. During tonic seizures the muscles are innervated with a long pulse train of high frequency [5]. For tonic seizures the muscle force response is modeled as:

$$F_{ag} = F_{sum}(1-(\tau t-1)e^{\frac{-t}{\tau}}) \ . \tag{2}$$

For the antagonist muscle the response is modeled as:

$$F_{ant} = AF_{sum}(1-(B\tau t-1)e^{B\tau}) \tag{3}$$

where A and B are dimensionless constants approximately equal to 1. Thus for $t >> \tau$ the net value of both muscles working together is approximated by $(1-A)F_{sum}$. A has a value close to 1 therefore the net muscle force is very small. Hence, the arm is moving very slowly in one direction. An accelerometer signal measured during human movement, consists of a part that represents accelerations due to the actual movements of the body and a part that represents the position of the sensor in relation to the gravity field. When there is no movement, the latter causes an offset in the signal between -1 and 1 g. During a change of posture, the position in relation to the gravity field can change, and thus the offset changes. For a simple 2-D planar rotation of the arm, in the field of gravity, the acceleration (A_t) in the direction of the movement then yields:

$$A_t(t) = -R\alpha(t) - gsin(\theta(t)); \tag{4}$$

where R is the distance between the elbow and the accelerometer, $\alpha(t)$ is the angular acceleration, g is the gravitational constant and $\theta(t)$ is the angular displacement. Using kinetic relations $\alpha(t)$ can be replaced by:

$$\alpha(t) = \frac{4.5}{BMBL^2}(F_{ag} - F_{ant}) \tag{5}$$

where BM is body mass and BL is body length. Using Eqs. 2–5 and $t >> \tau$ we get

$$A_t(t) = \frac{4.5}{BMBL^2}((1-A)F_{sum}) - gsin(\theta(t)) \ . \tag{6}$$

Now it can be seen that the acceleration caused by movement is much smaller as the acceleration caused by gravity. Thus the typical *block-like* pattern is mainly caused by the gravity component that slowly changes.

B. Features for block-like pattern

For the calculation of features that represent the block-like pattern, first we approximate the posture form the accelerometer signal. To this end each ACM-signal x_i is filtered with a first order low-pass filter with a cut-off frequency of 0.5 Hz, thus creating x_{islw}. x_i represents one of the three signals from a 3-D accelerometer, $i \in \{1,2,3\}$. Then the first derivative (jerk) and the variance from x_{islw} are determined as a measure for the change of posture. During a tonic seizure the movement is extremely slow, therefore the amplitude of the ACM-signal is between -1 and 1 g. During other movements there is more variation and the amplitude can be up to 2-3 g, therefore the distance between the minimal and maximal value of x_{islw} is also a good indicator for tonic seizures.

The jerk Jy_{slw} is defined as :

$$Jy_{slw}[n] = \sqrt{\sum_{k=1}^{3}\left(\frac{x_{kslw}[n] - x_{kslw}[n-1]}{\Delta t}\right)^2} \tag{7}$$

where Δt is the sampling interval.

During a tonic seizure the arm changes very slowly of position, thus the value of $J_{y_{slw}}$ is low. During other movement types the velocity of the position changes is much faster and thus also $J_{y_{slw}}$. Per segment of N samples we calculate the mean magnitude of the jerk $\overline{J_y}$. For a segment length of 10 seconds with a sampling frequency f_s of 100 Hz this means that $N = 1000$ samples.

$$\overline{J_{y_{slw}}} = \frac{1}{N}\sum_{n=1}^{N} Jy[n] \ , \ N = 1000 \ . \tag{8}$$

The magnitude Y_{slw} for the dominant arm sensor is:

$$Y_{slw}[n] = \sqrt{\sum_{1}^{3} x_{k\,slw}^2[n]} \ . \tag{9}$$

The variance of the magnitude $S^2_{Y\,slw}$ for each segment is:

$$S^2_{Y\,slw} = \frac{1}{N-1}\sum_{n=1}^{N}(Y_{slw}[n] - \overline{Y_{slw}})^2 \ , \ N = 1000 \ , \tag{10}$$

with $\overline{Y}$ the mean magnitude:

$$\overline{Y_{slw}} = \frac{1}{N}\sum_{n=1}^{N} Y_{slw}[n] \ , N = 1000 \ . \tag{11}$$

Since $J_{y_{slw}}$ is a linear measure and $S^2_{Y\,slw}$ quadratic, the square root of $S^2_{Y\,slw}$ is used. The hypothesis is that the change of posture is unnaturally slow, thus $S_{Y_{slw}}$ is lower for tonic seizures than for other movement types.

For the distance between minimum and maximum signal values, the range R_y is defined as:

$$R_y = \sqrt{\sum_{k=1}^{3} |max(x_{k_s}lw[1:1+L]) - min(x_{k_s}lw[1:1+L])|^2} \ . \tag{12}$$

The range $R_{y_s}lw$ between the maximum and minimum value is in a smaller range for tonic seizures than for other movement types.

C. Features for tremor

The block-like pattern is often accompanied by a subtle tremor, therefore also the fast signal component x_{ifst} is used, to calculate features that are indicative for tremor. To create x_{ifst}, x_{islw} is subtracted from the original signal x_i. Then the variance is also calculated for this fast component ($S_{Y_{fst}}$).

D. Features for other movements

For a discriminative feature set, features need to represent characteristics of both tonic seizures and other movement types, this can also be motor seizures of another type. Therefore features based on our model for myoclonic and clonic seizures are included. The continuous wavelet transform (CWT) of a signal $f(t)$ at scale a and position t is defined as:

$$CWT_h[f](t,a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(\tau) h^* \left(\frac{t-\tau}{a} \right) d\tau \ , \qquad (13)$$

where $h(t)$ is the wavelet base and $*$ denotes the complex conjugation.

In this case the wavelet base $h(t)$ is formed by our model:

$$h(t) = t(e^{-t} - \frac{1}{A} e^{\frac{-t}{B}}) \ . \qquad (14)$$

This function satisfies the admissibility condition if $A = B^2$, see [6] for more details.

Then the scalograms

$$SC_h[x_i](n,a) = |CWT_h[x_i](n,a)|^2 \ , \qquad (15)$$

of the three 1-D sensors are summed

$$SCT(n,a) = \sqrt{\sum_{i=1}^{3} SC_h[x_i](n,a)} \ . \qquad (16)$$

Frequencies of movements during daily activities, dominantly lie between 0.3 and 3.5 Hz. Frequencies of clonic seizures typically lie in the range of 2–5 Hz [3] and accelerometer patterns of myoclonic seizures lie in the range of 4–6 Hz.

For myoclonic (and clonic) seizures most of the power is in the range of scales 2-10. Our hypothesis is that during tonic seizures the power is concentrated in the higher scales (≤ 0.5 Hz) because of the slow change of posture. Hence the model based wavelet is used to calculate a scalogram for the scales 1-50. For the detection of tonic seizures the ratio between the power in scale 2–10 and the total power (ER_{high}) and the ratio between the power in scale 20–50 and the total power (ER_{low}) can be useful features:

$$ER_{high}[n] = \frac{\sum_{a=2}^{10}(SCT(n,a))}{\sum_{a=1}^{50}(SCT(n,a))}, \qquad (17)$$

$$ER_{low}[n] = \frac{\sum_{a=20}^{50}(SCT(n,a))}{\sum_{a=1}^{50}(SCT(n,a))} \ . \qquad (18)$$

ER_{high} is chosen because it is expected to be an important feature to discriminate between tonic movements and myoclonic, clonic and fast normal movements, and ER_{low} because it is an important feature to distinguish slow (block-like) movements from the other movements. Per segment of 1000 samples the mean values of ER_{high} and ER_{low} are determined:

$$\overline{ER_{high}} = \frac{1}{N} \sum_{n=1}^{N} ER_{high}[n] \ , N = 1000 \ , \qquad (19)$$

and

$$\overline{ER_{low}} = \frac{1}{N} \sum_{n=1}^{N} ER_{low}[n] \ , N = 1000 \ . \qquad (20)$$

III. Classification

To establish their value for the detection of tonic seizures the features are evaluated in a 'two-class' detection setup. The two classes are: 'tonic seizure', and 'other movements'. Hence, myoclonic, clonic, and normal movements are regarded as one class. As classification method Fisher's linear discriminant analysis is used [7].

IV. Evaluation

A. Patient data

For evaluation ACM-data are used from 36 mentally retarded patients who suffer from refractory epilepsy. The patients are monitored with the setup described in our previous clinical study [2]. Three experts divided the corresponding ACM-signals into classes using video and accelerometric information. Available classes were: no movement, myoclonic seizure waveform, tonic seizure waveform, clonic seizure waveform, normal movement, and unclear. The interrater agreement is computed for each pair of experts. For the evaluation study, only events were selected, where two experts agreed on. Events marked as 'unclear' were excluded from the evaluation. For a seizure event to be included, the seizure needed also to be visual in the EEG-signal. This resulted in a data set containing data of 18 patients, 27 tonic seizures, 10 clonic seizures, 16 myoclonic seizures and 36 normal movements. The data is divided into three groups. We aim for an approach that is robust among patients. Therefore the groups have no overlap in patients. From these three groups, three training sets are created that are composed of data of two groups. For each training set, the data of the remaining third group of patients is used for testing. The three training sets are also used for the determination of the optimal combination of features. To this end per training set the detection performance of each combination of features is calculated. The optimal feature set, is the feature set where all training sets obtain a PPV > 0.4 and where lowest sensitivity of the three training sets is maximal.

B. Performance measures

The performance per feature set is expressed in the sensitivity (SEN) the percentage of myoclonic seizures correctly classified, the number of false detections (FD), and the positive predictive value (PPV), which is the ratio between correct detected tonic seizures and all events that are classified as a tonic seizure. Detected events are defined in a similar way as in [8], but with a the time-basis of 10 seconds instead of one second.

V. Results

A. Interrater agreement

Annotations were made based on information from both video and ACM. With a mean value of 0.50 the agreement of our experts can be considered moderate [9]. This results is in agreement with the findings of Parra et al. [10].

B. Detection performance

Table I shows the detection performance on the training data itself with the optimal feature set. It was found that the optimal feature set contains all features, except ER_{high}. This feature did not contribute much extra to the performance of the algorithm. This feature was added to describe the characteristics of fast normal movements as well, but this feature appears to be redundant. Sensitivities are high. All tonic seizures except one are detected. The positive predictive values lie around 0.40. Table II shows the detection performance on the three test sets. The values for SEN and PPV are slightly lower than in the training phase. 80 % of the tonic seizures is detected with a PPV of 0.35. Analysis of the false detections shows that 42% of the false positives is also a seizure.

TABLE I
DETECTION PERFORMANCE RESULTS ON TRAINING SETS

Training set	TP	FN	FD	Sen	PPV
1	7	1	14	0.88	0.33
2	12	0	19	1.00	0.39
3	14	0	18	1.00	0.44
overall	33	1	51	0.97	0.40

TABLE II
DETECTION PERFORMANCE RESULTS ON TEST SETS

Test set	TP	FN	FD	FD_{sz}	Sen	PPV
1	11	3	13	4	0.79	0.46
2	7	2	14	5	0.78	0.33
3	6	0	18	10	1.00	0.25
overall	24	5	45	19	0.83	0.35

VI. Discussion

This paper shows the first quantitative results for the detection of tonic seizures based on 3-D accelerometry (ACM) recordings. It was possible to detect tonic seizures with a success rate around 0.80 and with a positive predictive value (PPV) of 0.35. Four of the five tonic seizures that were missed, did not have the characteristic block-like appearance in the ACM-signals. During a tonic seizure both agonist and antagonist muscles contract heavily. Usually there is still a net force effect in one direction, and then the affected limbs move slowly, but it can also happen that the net effect is zero and that there is no movement effect. It can also be the case that the movement is blocked, because the limbs are fixed (for example against the body, or against furniture). In these cases, where the seizures are not clearly visible in ACM-signals, the measurement of the EMG might be more useful. The other missed seizure was very short in duration ($<$ 1 s) and therefore difficult to detect with a window of 10 seconds. A positive predictive value of 0.35 implies that one out of three alarms is genuine. For off-line analysis this is acceptable, especially when 42 % of the false alarms are actually motor seizures of another type (myoclonic or clonic). Previously we reported that there are three characteristic pattern types visible during simple motor seizures [2]. It was also shown that a seizure can consist of a combination of these 'elementary' patterns. In our seizure detection setup we have chosen for a modular approach, where patterns associated with myoclonic, tonic and clonic seizures are separately handled. Nevertheless there is a percentage of seizures that manifests in patterns that are a mix of the three types. Thus a part of the false positives from the separate modules will point to other motor seizure types. For automatic analysis this is not a problem, since these are events that are also clinically relevant. To separate these mixed forms (if this is of clinical interest) from the purely elementary movements is possible in a post processing step using features like duration of event or amplitude. The false positives that were not of a mixed seizure type, were movements that can not be distinguished from tonic seizures based on information from one sensor alone. Experts had all five 3-D ACM-signals, video and EEG available. Using information from accelerometers placed on the other limbs might contribute to a higher SEN and PPV in these cases. In conclusion, the results show that our approach is useful for the automated detection of tonic seizures based on 3-D accelerometry and that it is a promising contribution in a complete multi-sensor seizure detection setup.

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