Time-frequency analysis of accelerometry data for detection of myoclonic seizures

Time-Frequency Analysis of Accelerometry Data for Detection of Myoclonic Seizures

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***Abstract*—Four time-frequency and time-scale methods are studied for their ability of detecting myoclonic seizures from accelerometric data. Methods that are used are: the short-time Fourier transform (STFT), the Wigner distribution (WD), the continuous wavelet transform (CWT) using a Daubechies wavelet, and a newly introduced model-based matched wavelet transform (MOD). Real patient data are analyzed using these four time-frequency and time-scale methods. To obtain quantitative results, all four methods are evaluated in a linear classification setup. Data from 15 patients are used for training and data from 21 patients for testing. Using features based on the CWT and MOD, the success rate of the classifier was 80%. Using STFT or WD-based features, the classification success is reduced. Analysis of the false positives revealed that they were either clonic seizures, the onset of tonic seizures, or sharp peaks in "normal" movements indicating that the patient was making a jerky movement. All these movements are considered clinically important to detect. Thus, the results show that both CWT and MOD are useful for the detection of myoclonic seizures. On top of that, MOD has the advantage that it consists of parameters that are related to seizure duration and intensity that are physiologically meaningful. Furthermore, in future work, the model can also be useful for the detection of other motor seizure types.**

***Index Terms*—Accelerometry (ACM), model, seizure detection, time-frequency analysis.**

I. Introduction

EPILEPSY is a common neurological disorder that is characterized by recurrent seizures that are caused by hypersynchronous neuronal activity in the brain. The clinical signs of seizures depend upon the location and extent of the propagation of the discharging cortical neurons. Previously, we reported the potential value of accelerometry (ACM) for detecting seizures that have movement as the most important clinical manifestation, so-called *motor* seizures [1]. It was found that 95% of the motor seizures consisted of characteristic elementary patterns. These elementary patterns can be divided into three groups: myoclonic, clonic, and tonic patterns. It was found that 74% of the motor seizures detected consisted of at least one myoclonic element. Myoclonic seizures are brief, shock-like jerks of a muscle, or a group of muscles. Muscles of the face, the neck, shoulders, and arms can be involved. During a myoclonic seizure, the electrical activation of the muscles involved lasts less than 50 ms [2]. It is of clinical importance to detect these subtle seizures. Often a patient has many myoclonic seizures during the night and, thus, their sleep pattern can be disturbed. Severe motor seizures are often preceded by myoclonic seizures and, thus, the detection of myoclonic seizures could be used for early warning. Counting myoclonic seizures may also be an important measure for successful medical treatment, especially for patients for whom seizures persist after medical treatment. This paper presents a first approach for the detection of myoclonic patterns from ACM data. The purpose of the methods under study is to support off-line analysis for diagnostic and evaluation purposes. In our detection setup, a supervised learning approach is used, which requires the appropriate selection of features and classifier. Experience from more mature research areas, such as speech and audio, shows that the success of classification critically depends on the choice of features rather than on the complexity of the type of classifier [3]. Therefore, we focus on the study of suitable features rather than on classification methods. In ACM-literature, the choice for features depends on the type of activities that are to be detected. For distinguishing among normal daily activities, such as sitting, standing, lying, and movement in general, statistical properties of the amplitude of the signal such as mean and standard deviation seem to be effective [4]. When distinguishing between various complex movement patterns, features derived from time-frequency methods such as the short-time Fourier transform (STFT) [5] or a wavelet transform [6] are also applied. The dominant method of seizure detection described in literature is based on the EEG signal. Seizure detection based on the ACM-signal is new, and consequently new detection algorithms need to be developed. Nevertheless, from EEG-based detection methods, we can learn that features based on morphological characteristics of the patterns in the EEG signal associated with seizures, are more successful to detect epileptic seizures [7], [8]. Thus, also for ACM-based seizure detection, it is sensible to use features based on the shape of the ACM-patterns associated with epileptic seizures. Myoclonic seizures may be very subtle movements, and the amplitude in the ACM-signal during such a seizure can be very low. Nevertheless, a small, short "shock-like" pattern can be visible in the signal. A model was developed that describes the ACM output during a myoclonic seizure [9]. In this paper, this model

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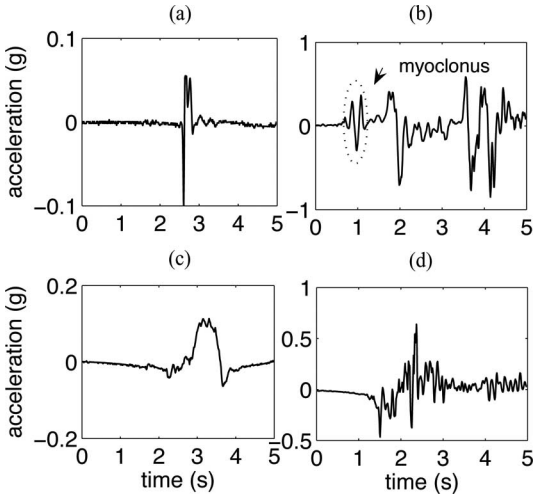

Fig. 1. (a) Isolated myoclonic waveform. (b). Myoclonic waveform in the presence of other pattern. (c) Slow movement. (d) Nonmyoclonic waveforms containing sharp peaks.

is used to formulate a matched wavelet transform (MOD). This MOD is used to derive features for the detection of myoclonic seizures. Furthermore, in this paper, three other time-frequency methods are studied for their feasibility to derive salient features for seizure detection, the STFT, the continuous wavelet transform (CWT), and the Wigner distribution (WD). All four feature sets are evaluated in a linear classification analysis setup on clinical data (see Section VII-A).

II. Accelerometric Waveforms

A myoclonus can affect muscles throughout the body but often only one limb is involved, in most cases the arm. Fig. 1 shows examples of ACM data during myoclonic seizures and other movements measured on the arm. A myoclonic seizure is a twitch-like contraction of an antagonistic muscle pair. Flexion is dominantly innervated over extension, so typically the limb involved flexes during the seizure. After the seizure, the limb suddenly stops. This sudden cessation results in a sharp peak in the ACM signal. Waveforms associated with myoclonic seizures have a short duration (0.5–2 s), are asymmetric and seem to damp out exponentially at the end. They can occur as isolated events [see Fig. 1(a)] or in a sequence of other movement patterns [see Fig. 1(b)]. Patterns associated with normal movements can have various appearances. Slow movements cause a block-shaped pattern in the ACM-signal [see Fig. 1(c)]. Rhythmic or jerky movements can cause sharp peaks in the ACM-signal [see Fig. 1(d)].

III. Model for Myoclonic Arm Movements

A model was developed that describes the ACM output—measured on the arm-during myoclonic seizures [9]. The model description consists of a mechanical part and a electrophysiological part. The electrophysiological part contains the definition of stimuli and a muscle response to these stimuli during the myoclonic seizure. The mechanical part is based on kinematic

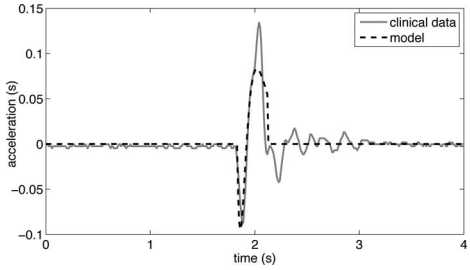

Fig. 2. Model fitted to real seizure waveform.

and kinetic relations for the lower arm modeled as a rigid body system. This part contains rigid body parameters that can be linked to body mass and body length. In the model, one agonistic muscle pair is included that is synchronously innervated during the seizure [2]. The ACM pattern $X(t)$ in the dominant movement direction, observed during a myoclonic seizure, can be analytically expressed by

$$X(t) = K\left(te^{\frac{-t}{\tau_0}} - \frac{t}{A}e^{\frac{-t}{B\,\tau_0}}\right)\chi_{[0,\infty)}(t) \quad t \in R \qquad (1)$$

where constant $K = (0.66(\mathrm{BM} \times \mathrm{BL}))(F_0/\tau_0)$, F_0 represents the intensity of muscle contraction, the relaxation time τ_0 is related to the duration of muscle contraction, BM represents the full body mass, and BL represents the full body length, A and B are dimensionless constants. Both A and B are > 1, in this way, an alternating positive and negative netto muscle movement is generated that is necessary to generate the typical myoclonic "shock-like" pattern. In (1), $\chi_{[0,\infty)}(t) = 0$ for $t < 0$ and $\chi_{[0,\infty)}(t) = 1$ for $t \geq 0$. Fig. 2 shows this model fitted to an ACM waveform associated to a myoclonic seizure. In a previous study, it was shown that the values of τ_0 varied between 20 and 70 ms, and that this corresponds to physiological values of motor units of a muscle responding to a twitch [9].

IV. Time-Frequency Methods

This section describes four different time-frequency methods which will be used to analyze ACM waveforms. One measure is based on the model described in Section III.

A. Short-Time Fourier Transform

For the STFT of signal f, the signal is multiplied by a window function h and then the Fourier transform of the product function is taken [10]. By translating the window along the signal, the STFT is able to analyze the frequency behavior of f during the time interval for which h is localized.

$$\mathrm{STFT}_h[f](t,\omega) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty} f(\tau)h^*(\tau - t)e^{-i\omega\tau}d\tau \qquad (2)$$

where $*$ denotes the complex conjugation. For $h(t)$, a Hanning window is chosen. A myoclonic seizure can last less than 1 s, therefore, a large time resolution is desirable. The sample frequency of the ACM signals used is 100 Hz, this limits the choice of window length. Since a myoclonic seizure typically lasts between 0.5 and 2 s, a window length of 50 samples is chosen. This corresponds to a frequency resolution of 2 Hz. A

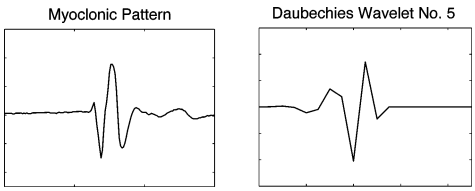

Fig. 3. Example of a myoclonic waveform in an ACM-signal and the fifth member of the Daubechies family.

shift of one sample with the STFT is chosen. A disadvantage of using the STFT for myoclonic seizure detection is the tradeoff between time and frequency resolution.

B. Continuous Wavelet Transform

The CWT of a signal $f(t)$, at the scale a and position t is defined as

$$\mathrm{CWT}_h[f](t,a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(\tau) h^* \left(\frac{t-\tau}{a} \right) d\tau \qquad (3)$$

where $h(t)$ is the mother wavelet and $*$ denotes the complex conjugation [10]. While the STFT uses a single analysis window, the wavelet transform uses short windows for analyzing high frequencies and long windows for analyzing low frequencies. As the scale changes, the wavelet is localized better in time, but worse in frequency and vice-versa. Nevertheless the use of various scales seems appropriate since movements can have various durations and intensities and, thus, take place on various scales. Furthermore, the shape of the pattern observed during a myoclonic seizure resembles a wavelet. A disadvantage of using the CWT for myoclonic seizure detection could be the bad time localization at higher scales. The CWT is calculated for scales 2–256. This choice is made because the lower boundary for frequencies in normal movements is approximately 0.3 Hz [11]. The scale of 256 corresponds to a frequency of 0.26 Hz. A mother wavelet is used, that is suitable for the signal pattern of interest and, thus, resembles the myoclonic waveform the most. Therefore, the fifth member of the Daubechies wavelet is used. This choice is motivated by the typical shape of a myoclonic waveform that is also depicted in Fig. 3. The central frequency of the wavelet used is 66 Hz.

C. Wigner Distribution

The WD involves the signal quadratically and aims at an energetic description of the signal in time and frequency without windowing. This windowing limits the resolution of the time-frequency decomposition in case of the STFT and the CWT [10]. To our knowledge, the application of this technique to ACM signals is new in literature. It is known that the WD, among other favorable properties, achieves the best results in terms of spread in the time-frequency plane, compared to other quadratic time-frequency distributions that belong to the same class [12]. The WD of f at a point (t,ω) is the response at frequency ω of the τ-function $f(t+(\tau/2))f^*(t-(\tau/2))$

$$\mathrm{WD}[f](t,\omega) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f\left(t+\frac{\tau}{2}\right) f^*\left(t-\frac{\tau}{2}\right) e^{-i\omega\tau} d\tau \,. \qquad (4)$$

In contrast to the STFT and the CWT, the WD is a nonlinear operation. An advantage of the WD is that there is a good time-frequency resolution. Since the WD is an energy distribution, a link can be made to mechanical energy, that is expected to be different between normal and epileptic movements. A disadvantage is that artifacts occur when multicomponent signals are analyzed, because of the quadratic character of the distribution. These artifacts are known as cross terms. These cross terms can interfere with the actual signal terms and make it difficult to interpret the time-frequency plot. To avoid interference terms between positive and negative frequencies, the signal is transformed to its analytical version [13].

D. Model-Based Matched Wavelet Transform

The model described in Section III can be used as a MOD. In this case, the mother wavelet $h(t)$ is taken to be

$$h(t) = t\left(e^{-t} - \frac{1}{A} e^{\frac{-t}{B}}\right) \chi_{[0,\infty)}(t) \quad t \in R. \qquad (5)$$

The parameters A and B are positive, and so is τ. In particular, the case is considered when $A \approx B^2$. In the case that $A = B^2$, the signal in (5) is admissible [14]–[16] as a wavelet since then

$$\int_0^{\infty} \left(te^{\frac{-t}{\tau}} - \frac{1}{A} te^{\frac{-t}{B\tau}} \right) dt = \tau^2 \left(1 - \frac{B^2}{A}\right) = 0. \qquad (6)$$

In a previous study, where the model is fitted to clinical data, it is shown that this condition is met [9]. From this study, the value 1.023 for B is obtained. For the MOD, the wavelet transform is performed with a time reversed version of $h(t)$. In this case, the highest value occurs when the signal waveforms best match the model. The scale a is proportional to τ_0. A scale of 1 corresponds to a value of τ_0 =10 ms. Therefore, for this wavelet, the central frequency is 100 Hz. It was found that the values for τ_0 in a myoclonic seizure vary between 20 and 70 ms, therefore, scales from 2 to 7 are important for the analysis of myoclonic seizures. For the distinction between other movements that are longer in duration, the higher scales are also important. In our analysis, we include scales up to 50.

V. Patient Data

For analysis and evaluation, ACM data were used from 36 mentally retarded patients who suffer from refractory epilepsy. The patients were monitored with the setup described in our previous clinical study [1], with five 3-D sensors placed on the limbs and the sternum. The sampling frequency f_s of the ACM signals is 100 Hz. For each patient, at least one and a maximum of three video fragments per seizure type (myoclonic, tonic, and clonic) were selected. Video fragments were selected only if the patients were within the field of view of the camera. This resulted in 156 video fragments with a total duration of 3.6 h. Three experts divided the corresponding ACM signals into classes using both video and ACM information. These classes were: no movement, myoclonic seizure waveform, tonic seizure waveform, clonic seizure waveform, normal movement, and unclear. For the evaluation study, only events where at least two experts agreed on a particular classification were selected. Events

TABLE I
COMPOSITION OF TRAINING AND TEST DATA

A. Training data			
Type	♯ events	total duration (min)	mean duration (min)
no movement	116	56.2	0.48
movement	72	32.8	0.46
myoclonic	29	0.89	0.03
tonic	39	8.38	0.21
clonic	13	1.9	0.15
B. Test data			
Type	♯ events	total duration (min)	mean duration (min)
no movement	98	50.7	0.52
movement	39	20.3	0.52
myoclonic	35	1.1	0.03
tonic	30	4.8	0.16
clonic	7	2.3	0.32

marked as "unclear" were also excluded from the evaluation. In total, 30 min of data were excluded. The four time-frequency methods were tested for their suitability to detect myoclonic seizures in a linear classification setup. The data were divided into a training and a test set. In order to ensure a robust inter-patient classification, individual patient's data were used, either in the training set or the testing set, but not both. Data from the first 15 patients were used for algorithm training (100.17 min). Data from the remaining 21 patients were used for the test set (79.2 min). The datasets are further specified in Table I. Since our model-based approach is based on a model for arm movements, only data from the arm sensors are included. From the two 3-D arm sensors automatically the measurement direction on which the movement has the greatest amplitude reading was chosen automatically. The sensor selected per event can vary per patient and per seizure. From the video footage, it has been observed that during a myoclonic seizure the movement in the direction of the thumbs, the x-direction of the accelerometer, is typically the most dominant movement direction. The characteristic waveform is most clearly visible and has the highest amplitude in this direction. Analyzing all signals measured on both arms during myoclonic seizures confirmed this hypothesis.

VI. TIME-FREQUENCY ANALYSIS ACCELEROMETER PATTERNS

A. Myoclonic Waveforms

Fig. 4 shows time-frequency and time-scale representations that are typical for ACM patterns associated with myoclonic seizures. For each method, the absolute value is plotted.

The ACM signal that yields this output is depicted in Fig. 1(a). Data points that have high values for $|\mathrm{STFT}|$ form a clear distinct area. Most of the power is concentrated in the 4–6 Hz frequency range. In the plot of the WD, there is also a distinct area, but there are more high frequencies present. The frequencies where most of the power is concentrated varies between 5 and 8 Hz. For the CWT, the observations are similar, the highest values of $|\mathrm{CWT}|$ lie in the 8–60 range of scales. The scale where $|\mathrm{CWT}|$ is maximal lies in a range of 9–39 for all the seizures. For MOD, the highest values of $|\mathrm{MOD}|$ lie in the 2–8 scale range. This corresponds to the findings presented in [9].

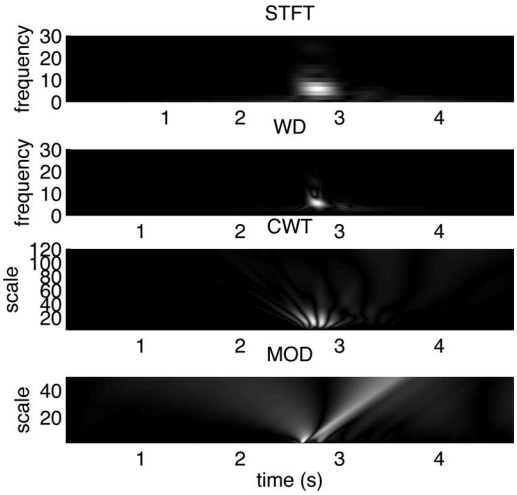

Fig. 4. Time-frequency/scale representations of myoclonic pattern.

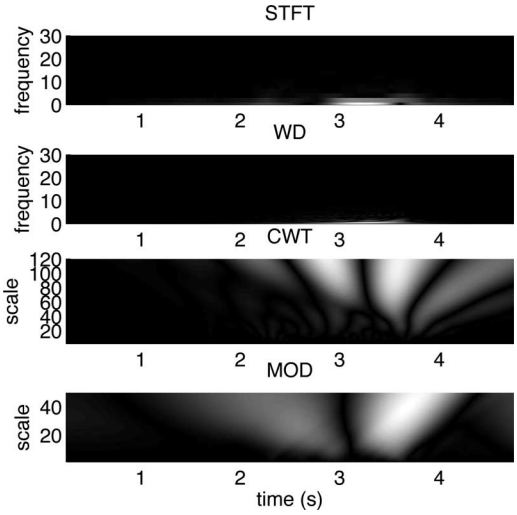

Fig. 5. Time-frequency/scale representations of normal movement.

B. Normal Movements

Fig. 5 shows time-frequency and time-scale representations that are typical for ACM patterns associated with normal movements. For each method, the absolute value is plotted. The ACM signal that yields this output is depicted in Fig. 1(c). Most of the power of $|\mathrm{STFT}|$ is concentrated below 2 Hz. In the case of the WD, the frequency resolution is better and the power is mainly concentrated below 0.8 Hz. For $|\mathrm{CWT}|$, the highest values occur in the scales ranging from 74 to 256. For the model-based wavelet, the range is 10–50. For normal movements that are more rhythmical and contain sharper peaks, it was observed that high power values up to 30 Hz occur in the plot of $|\mathrm{STFT}|$. For the WD, a complicated pattern is visible which contains a broad spectrum of frequencies (interference). For both wavelets, high values of $|\mathrm{CWT}|$ or $|\mathrm{MOD}|$ occur also in the lowest scales. These observations suggest that sharp peaks due to normal movement differ from peaks induced by myoclonic seizures. They posses a pulse-like broader frequency pattern, and they have higher wavelet coefficients at lower scales.

TABLE II
FEATURES USED IN EVALUATION FOR EACH METHOD

Method	features	number of features
STFT	$\|STFT_h[f](t,\omega)\|$	50
WD	$\|WD[f](t,\omega)\|$	50
CWT	$\|CWT_h[f](t,a)\|$	255
MOD	$\|MOD_h[f](t,a)\|$	50

Myoclonic seizures have a more isolated frequency pattern (4–10 Hz) and higher wavelet coefficients in an isolated range of scales 8–60 or 2–8 depending on the wavelet used.

VII. EVALUATION OF TIME-FREQUENCY FEATURES IN DETECTION SETUP

A. Detection Setup

To evaluate the value of the time-frequency methods for the detection of myoclonic seizures, a "two-class" classification setup was used. The two classes were: "myoclonic seizure," and "other." Tonic, clonic, no movement, and normal movements were regarded as one class. The choice of only two classes can potentially result in some of the false positives actually belonging to one of the two other motor seizure types. In the future, however, we aim for a detection setup that consists of a number of "two class" modules, with each module designed for a specific movement type. Eventually, all the modules together will provide a detection system consisting of more classes. Table II lists which features were used and the number of features used for each method. For the STFT and the WD, the magnitude of the spectral powers are used as features. For CWT and MOD, the absolute wavelet coefficients are tested as features.

The features are calculated for each sampling point in the data, thus, for each 10 ms in the signal a feature value is calculated and classification in performed. Then, the classification outputs of all segments are again aligned in time and compared to the judgement of the signal by experts. Fisher's linear discriminant analysis (FLDA) is used as a classification method [17]. This classification method projects the multidimensional feature space onto one line. The projection maximizes the distance between the means of the two classes while minimizing the variance within each class. Classification is performed in the 1-D space that is created. A threshold is set by optimizing a cost function on training data, which takes into account the distance between the means of the two classes and the variance within each class. The performance per feature set (for the optimal threshold) is expressed in the percentage of myoclonic seizures correctly classified (SEN), the number of false detections, the positive predictive value (PPV), which is the ratio between correct detected myoclonic seizures and all events that are classified as a myoclonic seizure, and the specificity (SPEC), that is the percentage of the data without myoclonic seizures that is correctly discarded. A receiver operating characteristic (ROC) analysis is performed to study the influence of a varying threshold on the results, thus, also other thresholds than the one that was found by optimizing the cost function are used. Sensitivity (SEN) is plotted versus 1 - SPEC as the discrimination threshold is varied. Classification results are compared with experts score in the signal over time. It is to be expected that precise onset and offset times for a particular event will vary between the detection algorithm and the experts. Taking this into account, a timing difference of 0.3 s or less in the onset of an event is tolerated. When the algorithm or the experts score a different number of events within the same time interval, these events are considered as one event if the timing difference between the separate events is within 0.3 s.

TABLE III
DETECTION PERFORMANCE FOR EACH FEATURE SET

Feature set	SEN	PPV (FD)	SPEC
$STFT$	0.71	0.16 (136)	0.89
WD	0.34	0.15 (67)	0.93
CWT	0.80	0.16 (148)	0.87
MOD	0.80	0.15 (155)	0.85

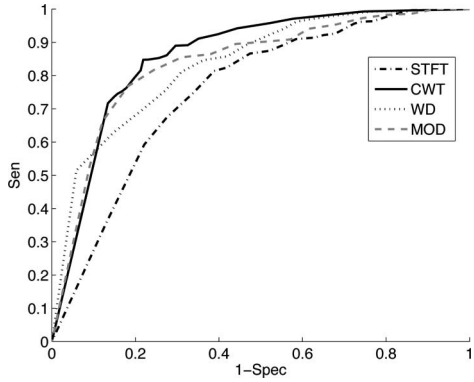

Fig. 6. ROC analysis for four feature sets.

B. Detection Results

Table III shows the performance for each method for the optimal threshold. The highest SEN are seen with the CWT and the model-based MOD. The SEN of the WD is poor. The performance of the STFT is in between the results of the wavelet methods and the WD. All four methods have a similar value for the PPV. SPEC obtained using these methods varies between 85% and 93%. These are the percentages of data without myoclonic seizures that are correctly discarded. The ROC analysis in Fig. 6 is in agreement with these results, the curves of STFT and WD lie below CWT and MOD. Furthermore, we can see that shifting the threshold found by FLDA either leads to a too low SEN or too many false positives. Table IV shows the number of false positives and total duration of the false positives per movement type. It can be seen that STFT, CWT, and MOD detect all the clonic seizures in the dataset. WD detects five out of seven clonic seizures. Furthermore, some of the false detections occur at the onset of a tonic seizure. Most of the false detections are in the normal movement periods. The analysis of these patterns reveals that these events translate to sharp peaks in normal movements, that occur during a jerky movement or when the patients' arm bumps into a surrounding object. Slow normal movements are successfully distinguished from myoclonic-motor activity.

TABLE IV
FALSE DETECTION NUMBER AND TOTAL DURATION PER MOVEMENT TYPE

	STFT		*WD*	
Movement type	♯	duration (min)	♯	duration (min)
movement	91	4.6	45	3.6
no movement	26	1.3	9	0.4
clonic	7	2.1	5	1.5
tonic	12	0.5	8	0.35
	CWT		*MOD*	
Movement type	♯	duration (min)	♯	duration (min)
movement	92	6.0	101	6.8
no movement	37	1.5	35	1.6
clonic	7	2.2	7	2.2
tonic	12	0.61	12	0.66

VIII. DISCUSSION

Detecting myoclonic seizures from ACM signals is an entire novel research topic. As a first step, ACM signals measured in patients with epilepsy were analyzed using the STFT, the WD, the CWT, and a newly introduced model-based MOD. It was found that ACM waveforms associated with myoclonic seizures have similar time-frequency characteristics across all patients. The purpose of the methods under study is to support offline analysis for diagnostic and evaluation purposes. In the future also a real-time alarm system is pursued. Therefore, our criterium for SEN and PPV are 90% and 50%, respectively [1]. Using the STFT leads to a SEN of 71% but a PPV of only 16%. There were 136 false positives detected. This is mainly caused by the fact that most of the difference between the movement types occurs in the 0–2 Hz frequency band which corresponds to just one bin for the STFT. The WD performs poorly, only 34% of the myoclonic seizures is detected. The PPV was 15% and 67 false positives were detected. This poor performance could be caused by the cross terms that are introduced by the WD. In the literature much can be found about solutions to decrease the contribution of these cross terms [18]. Applying such a solution could contribute to a valuable set of features. Using the CWT leads to a SEN of 80% with a PPV of 16% and 148 false positives. The model-based method MOD has a similar performance with an SEN of 80%, a PPV of 15% and 155 false positives. As we can see all the methods have a similar PPV, and both wavelet methods, CWT and MOD, have the best SEN for detecting myoclonic seizures. MOD was designed to match a myoclonic waveform and this is shown in the high SEN. The Daubechies wavelet used was specifically chosen because it resembles a myoclonic pattern the most, therefore, also here a high SEN is shown. The results obtained for CWT and MOD are similar, but an advantage of our newly introduced model is that it contains parameters that have a physiological meaning related to seizure pathophysiology. It was especially designed for the detection of myoclonic seizures. In this setup, we used 50 scales and obtained similar results as with the CWT using 255 scales. Further research should focus on the optimization of feature selection for these methods and then perhaps the superiority of one of these two methods can be shown. Future research should also focus on increasing SEN and decreasing the number of false positives. From ROC analysis, it can be concluded that for these feature sets the optimal results were obtained. Therefore, an increase of SEN can only be achieved by using an other combination of features or extra features. For all methods, the large number of frequencies or scales is not ideal. From the analysis in Section V, it can be observed that for the wavelets mainly the lower scales and the highest scales are important. Future research should, therefore, first focus on the optimal subsection of features for each method. After analysis of the false positives, it was observed that some of the false positives were actual motor seizures. STFT, CWT, and MOD detected all clonic seizures in the set. The WD detected five out of the seven clonic seizures. Per definition clonic seizures consist of myoclonic jerks recurring at a regular repetition rate [19]. The clonic events are longer in duration and the ACM amplitude is higher than that during a myoclonic seizure. As a result, we decided to treat them as two different classes. Nevertheless, these results imply that similar features can be used for the detection of clonic patterns. This will be a topic for further research. Tonic seizures are more block shaped in appearance, more like slow normal movements, but in some cases also a FD was seen at the onset of a tonic seizure. This corresponds with findings of a clinical study that shows that 67% of the tonic seizures observed started as a myoclonic seizure but evolved into a tonic seizure [1]. The majority of the false positives were sharp peaks during normal movements. Slow normal movements are never falsely detected. This could be expected since the analysis results showed that the characteristics of slow movements vary distinctly from myoclonic patterns. Sharp peaks in normal movements, on the other hand, can resemble myoclonic seizures. In our analysis, we observed some difference in the higher frequencies and lowest scales but our experimental results at this stage do not confirm this observation. In future work, we could focus on features that distinguish between sharp peaks in normal movements and myoclonic seizures. On the other hand, clinically, these sharp peaks could be interesting. They coincide with the arm bumping into a surrounding object or an abrupt jerk. These are both situations that can be seizure related.

IX. CONCLUSION

This paper discusses the use of four time-frequency and time-scale methods for detecting myoclonic seizures in ACM data: the STFT, the WD, the CWT and a method based on a newly introduced model-based matched wavelet (MOD). The choice for time-frequency and time-scale methods was made because of the nonstationary character of the signals of interest. To our knowledge, this is the first attempt to detect myoclonic seizures based on ACM recordings. This paper demonstrates that time-frequency and time-scale methods can contribute to the detection of myoclonic waveforms from ACM data from epilepsy patients. Wavelet-based features demonstrate an especially high SEN for seizure detection. An extra advantage of our model-based matched wavelet is that it consists of parameters that are related to seizure duration and intensity and are physiologically meaningful. The model can also be adapted so that it is useful for other motor seizure types. Our model-based matched wavelet is a promising tool for the detection of myoclonic seizures from ACM signals, and may be extended to make part of a real-time alarm system.

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