Katholieke Universiteit Leuven

Departement Elektrotechniek

ESAT-SISTA/TR 17-185

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March 2018
Published in Proc. of the 2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)

[1]This report is available by anonymous ftp from *ftp.esat.kuleuven.ac.be* in the directory *ftp://ftp.esat.kuleuven.be/pub/stadius/tdecooman/reports/SISTA_17_185.pdf*

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Acknowledgments: Research supported by imec: Strategic Funding 2017, ICON: HBC.2016.0167 SeizeIT; European Research Council. The research leading to these results has received funding from the European Research Council under the European Unions Seventh Framework Programme (FP7/2007-2013) / ERC Advanced Grant: BIOTENSORS (n 339804). This paper reflects only the authors views and the Union is not liable for any use that may be made of the contained information. Thomas De Cooman is supported by an FWO SBO PhD grant. Carolina Varon is a postdoctoral fellow of the Research Foundation-Flanders (FWO).

Comparison and Combination of Electrocardiogram, Electromyogram and Accelerometry for Tonic-Clonic Seizure Detection in Children

Thomas De Cooman[1,2], Carolina Varon[1,2], Anouk Van de Vel[3], Berten Ceulemans[3,4], Lieven Lagae[4,5], Sabine Van Huffel[1,2]

***Abstract*— Automated real-time detection of tonic-clonic seizures in a home environment can be done using different modalities. The algorithms from the literature have not been evaluated nor compared on the same dataset. In this study, 3 seizure detection algorithms using electrocardiogram, electromyogram and accelerometers are evaluated on a single dataset. In this dataset, 7 pediatric patients with tonic-clonic seizures are monitored during 224 hours using 7 sensors in total. All unimodal algorithms are evaluated and compared to each other using this dataset. The different unimodal algorithms are also combined using a late integration approach. The best unimodal algorithm was found to be the algorithm using the right wrist accelerometer, leading to 95.5% sensitivity and 0.70 false alarms per hour. The best combination of sensors was found to be electrocardiogram with the right ankle accelerometer with a sensitivity of 90.9% and 0.08 false alarms per hour. The results show that all combinations of multimodal sensors lead to at least 75% less false alarms, showing that such multimodal algorithms should be used in practice for tonic-clonic seizure detection.**

I. Introduction

Epilepsy is a neurological disease that affects around 1% of the people worldwide. In around 30% of the patients their seizures cannot be controlled by anti-epileptic drugs, so they continue to have seizures for the rest of their lives. One option to improve their quality of life in a home environment is to use a real-time warning system, which automatically detects ongoing seizures. In case of such an event, an alarm is given to the patient's relatives or friends, so they can give the proper treatment to the patient. Such a system is certainly of high demand for pediatric patients during nocturnal monitoring, as the parents are not able to keep an eye on their children during the night. They, however, keep wondering whether their child is having a seizure or not, strongly affecting their quality of sleep.

Automated seizure detection in a home environment in the literature has been investigated repeatedly during the last decades [1]. Extra focus went to the detection of tonic-clonic seizures, which are clinically the most severe type of seizures. The most chosen modalities to detect those seizures are accelerometers (ACM), electromyogram (EMG) and electrocardiogram (ECG). Although different algorithms are described in the literature, no comparison of the different modality algorithms has been performed on 1 database using different sensor placements. In this paper, three algorithms using the mentioned modalities will be compared to identify the strengths/weaknesses of each modality. Special attention will also go to the proper sensor placement, evaluating in total 7 sensors in this dataset.

Literature showed that in most cases unimodal algorithms lead to too many false alarms [2], [3]. Multimodal algorithms are therefore advised as they are assumed to lead to increased accuracy. The different unimodal algorithms will be combined using a late integration approach to illustrate the added value of each sensor on the detection of tonic-clonic seizures and which sensor locations are advised.

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II. Methodology

A. Data

The different algorithms are evaluated on data acquired at the Pulderbos Revalidation Center for Youth and Adolescents. 7 pediatric patients were monitored for 224 hours during nocturnal recordings containing in total 22 tonic-clonic seizures with a duration of at least 10s. Seizures were annotated by expert clinicians using the gold video-electroencephalography (EEG) standard. Per patient, data is recorded from single-lead ECG, 2 EMG sensors placed on the left biceps (LB) and right biceps (RB) and 4 ACM sensors placed on both ankles (right (RA) and left (LA)) and wrists (right (RW) and left (LW)). Sensor locations were chosen because they are most often ictally activate. All signals were acquired with 250Hz sampling frequency.

B. Unimodal algorithms

Different unimodal algorithms from the literature are used for comparison and combination. Each unimodal algorithm uses only a single sensor as input. All algorithms use a similar classification approach.

1) Preprocessing and feature extraction: For the ECG-based seizure detection, the following preprocessing and feature extraction steps described in [2] are performed. First, the heart rate (HR) is extracted from the ECG by using an R peak detection algorithm based on dynamic thresholding on the derivative signal. Strong heart rate increases (HRIs) caused by sympathetic activations are then detected by HR slope analysis. Whenever such a strong HRI is detected,

feature extraction is performed. The obtained peak HR during this HRI and the average HR and standard deviation of the HR from 1 minute before the HRI are extracted and used for classification.

The preprocessing and feature extraction steps for the ACM and EMG sensors are based on [3]. ACM data were bandpass filtered between 0.2Hz and 47Hz with a Chebyshev type II filter. 2s windows with 75% overlap are then used in order to extract features from the ACM signals. The used features for classification are the number of local maxima in the signal, Shannon entropy of diagonal line lengths in a cross-recurrence plot, frequency of the first local peak in the spectrum and power within pseudofrequency range 9-22.5 Hz from a continuous wavelet transform.

The EMG signals are filtered using a Butterworth high-pass filter with 20 Hz cut-off frequency in order to remove movement artifacts and baseline noise contamination. 2s windows are used in order to extract the zero-crossing rate of the second derivative signal and the Wilson amplitude.

C. Unimodal classification

The features of all modalities are classified using a weighted support vector machine (SVM) classifier:

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C^+ \sum_{i=1|y_i=+1}^{N} \xi_i + C^- \sum_{i=1|y_i=-1}^{N} \xi_i \qquad (1)$$

such that

$$y_i(w^T \varphi(x_i) + b) \geq 1 - \xi_i, \qquad \xi_i \geq 1, \qquad i = 1, ..., N. \qquad (2)$$

with

$$C^+ = \alpha * \frac{N}{2 * N^+} \text{ and } C^- = \frac{N}{2 * N^-} \qquad (3)$$

with N^+ and N^- indicating the number of data points of seizure and non-seizure class and ξ the error of the classifier on data point x_i. The parameter α allows to train the classifier with more importance to sensitivity than specificity. The classifier is trained using a leave-one-patient-out procedure. In the unimodal approach, only data from that specific sensor is used during training. For the ACM and EMG sensors, only windows with a standard deviation higher than 30mg or 30μV are used in the training set in order to limit the class imbalance [3]. Unimodal ACM and EMG algorithms only lead to an alarm if 8 subsequent windows are classified as a seizure.

D. Multimodal seizure detection

A late integration approach is used for the combination of the different unimodal algorithms. Late integration is preferred here over early integration due to the lack of synchronization between the epileptic activations in the different modalities. EMG-based seizure detection is for example assumed to give an earlier warning than ACM-based seizure detection, as the first detects the tonic part of the seizure, whereas the latter alarms during the clonic part of the seizure.

Multimodal seizure detection is performed here by stating that a combination of 2 unimodal algorithms results in an alarm if both unimodal algorithms generate an alarm within a certain time window of each other. The length of the time window depends on which types of sensors are combined, an overview of the used values can be found in Table I.

TABLE I
OVERVIEW OF THE USED TIME WINDOWS FOR MULTIMODAL SEIZURE DETECTION.

Combination	Time window (s)
EMG+EMG	5
ACM+ACM	15
ACM+ECG	20
ACM+EMG	20
ECG+EMG	30

E. Evaluation metrics

Seizure detection algorithms can be evaluated with different metrics. The sensitivity (Se) shows the percentage of detected seizures, whereas the false alarm rate (FAR) illustrates how many false positives (FP) are generated in time (expressed as FP/hour). The positive predictive value (PPV) indicates the percentage of correct alarms. The PPV and Se can be combined in one metric by using the F_β score:

$$F_\beta = (1 + \beta^2) * \frac{Se * PPV}{(\beta^2 * Se) + PPV} \qquad (4)$$

The F_3 score is used here instead of the standard F_1 score in order to give more importance to the sensitivity than to the FAR [2]. A seizure is said to be detected if an alarm is generated between 30s prior and 90s after the EEG onset [2]. The detection delay indicates the time difference between the generated alarm and the EEG seizure onset.

III. RESULTS

Table II gives an overview of the found unimodal results. All algorithms led to sensitivities of at least 80%. Because the sensitivity and FARs vary between the different algorithms, the ROC curves of all algorithms are shown in Figure 1, which allows to give a better algorithm comparison. From this figure, it can be seen that the ACM-RW and the EMG-RB sensor result in better overall performance compared to the rest. Based on the F_3 scores in table II, also the ECG is seen as one of the better unimodal algorithms as it is able to reach 100% sensitivity with a relatively low FAR.

If for every patient the best unimodal algorithm is used, an overall sensitivity of 100% would be found with on average 0.25FP/h. In this case, 5 different sensors would be taken as best sensor, with only the ECG and ACM-RW sensor to be chosen twice as the best sensor. Overall, the inter-patient variability showed to be high for most unimodal algorithms (standard deviation$>$1.4FP/h), except for the wrist ACM sensors and the ECG ($<$0.8FP/h).

The EMG-based algorithms led to the lowest detection delay with an average delay of $\pm$8s compared to the EEG onset. The ACM-based algorithms showed to be the slowest on average (15.0-19.3s).

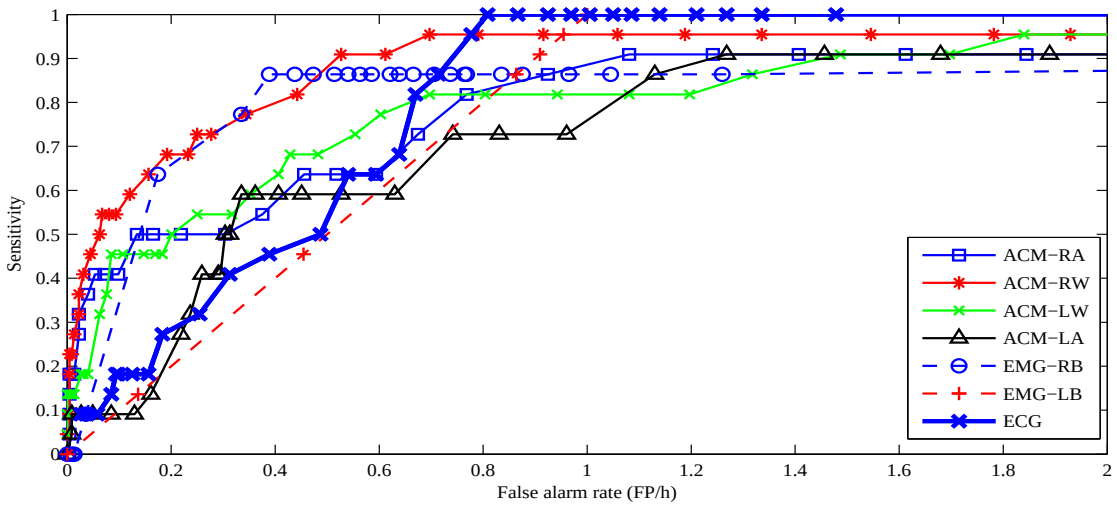


Fig. 1. Sensitivity over false alarm rate ROC curve for all unimodal seizure detection algorithms.

Table II also shows the multimodal results for all potential combinations of 2 sensors. The best combinations were ECG+ACM-RA and ACM-RA+EMG-LB. The first combination resulted in 90.9% sensitivity with on average 0.076FP/h and an average detection delay of 22s. If these 3 most successful sensors are combined together, an overall sensitivity of 86.4% is found with no false alarms in the entire dataset.

Combinations of different modalities led on average to better performances than when sensors of the same modality are combined (78.7% F_3 score versus 64.4%). If only looking to combinations of different modalities, all combinations led to a decrease in FAR with at least 75%, and 59% of these combinations led to a FAR decrease of more than 90%. This way the PPV values often changed from around 10% towards values up to 50%. In 18/21 multimodal combinations, the sensitivity remained higher than 80%.

The detection delay in the multimodal algorithms is defined by the slowest modality used. Therefore the combination of 2 EMG's or ECG+EMG led to the fastest detection delays (respectively 11.7s and $\pm$15s) compared to combinations including ACM ($\pm$20s on average).

TABLE II

OVERVIEW OF THE UNIMODAL AND MULTIMODAL RESULTS. BOLD VALUES INDICATE THE BEST VALUE FOR A SPECIFIC EVALUATION METRIC FOR THE UNIMODAL AND MULTIMODAL ALGORITHMS.

Sensors	Se (%)	FP/h	Delay (s)	F_3 score (%)
ECG	**100.0**	0.87	14.7	51.7
ACM-RW	95.5	0.70	15.8	**54.6**
ACM-LW	86.4	1.32	15.0	35.9
ACM-RA	90.9	1.24	19.3	39.0
ACM-LA	90.9	1.46	15.3	35.5
EMG-RB	86.4	**0.64**	8.7	51.5
EMG-LB	95.5	0.89	**8.3**	48.8
ACM-RW+ACM-LW	86.4	0.19	20.9	72.5
ACM-RW+ACM-LA	86.4	0.20	16.3	72.0
ACM-RW+ACM-LW	86.4	0.27	18.6	67.6
ACM-LW+ACM-RA	77.3	0.32	20.8	58.4
ACM-LW+ACM-LA	86.4	0.37	18.1	62.5
ACM-LA+ACM-RA	86.4	0.82	22.2	46.1
EMG-RB+EMG-LB	81.8	0.15	**11.7**	71.4
ECG+ACM-LW	81.8	0.11	20.5	74.1
ECG+ACM-RW	86.4	0.08	19.8	80.8
ECG+ACM-LA	86.4	0.11	21.2	78.5
ECG+ACM-RA	90.9	0.08	22.0	**84.7**
ECG+EMG-RB	86.4	0.14	14.6	75.7
ECG+EMG-LB	**95.5**	0.18	15.4	80.1
ACM-RW+EMG-RB	81.8	0.04	17.6	79.6
ACM-RW+EMG-LB	90.9	0.08	19.1	84.0
ACM-LW+EMG-RB	77.3	0.09	18.7	72.0
ACM-LW+EMG-LB	81.8	0.17	17.8	70.3
ACM-RA+EMG-RB	86.4	**0.03**	21.9	84.4
ACM-RA+EMG-LB	90.9	0.08	20.3	84.0
ACM-LA+EMG-RB	77.3	0.05	20.2	74.6
ACM-LA+EMG-LB	86.4	0.10	18.9	83.3

IV. DISCUSSION

The ROC curves in Figure 1 show that most ACM and EMG sensors are able to reach a mediocre sensitivity (40-50%) with a very low FAR (<0.1FP/h). This shows that these clinically clear seizures can be detected very efficiently with these algorithms. The clinically less clear seizures are however much harder to detect. Most of the ACM/EMG algorithms can only reach sensitivities higher than 80-90% by also resulting in a much higher FAR. During some seizures, some limbs are either not activated or are obstructed, causing no clear seizure pattern in these sensors. Also some seizures had a very short tonic or clonic part (<5s), making it very hard to detect them with only an EMG or ACM sensor. The ECG algorithm is not able to combine a mediocre sensitivity with such a low FAR, but is able to get 100% sensitivity with a lower FAR than the other modalities. The ECG is normally activated during both phases, and obstruction is not an issue. However, motion artifacts are the cause of a big portion of the generated false alarms [2].

The ACM-RW algorithm performed better than the ACM-LW, which is in contrast with the results of [3]. The main

reason for this is that only ACM-LW data is used for the training of ACM-LW classifier. We however noticed that the LW data showed less non-seizure data variability compared to the RW, leading to a better trained RW classifier. If however the RW classifier is used on the LW data, the performance of the RW is nearly achieved by using LW data.

Table II shows that the combination of different modalities leads to better results. It can also be seen that if the sensors originate from different parts of the body, the performance is also higher. If the used sensors are placed on the same limb, motions causing noise/actions in one sensor automatically will also trigger the other sensor, causing less added value of the extra sensor due to more overlap in unimodal false alarms. In practice, sensors on different locations lead to better performance, but also mean a less comfortable system for the patient to use as it requires the patient to wear 2 devices. It should be investigated further if the added value of the extra device is sufficiently large in order to justify this. The mentioned ECG-based algorithm relies completely on HR analysis and could thus also be implemented by using photoplethysmography (PPG). That way it can be combined together with an ACM or EMG sensor into 1 device. However, PPG showed to be more sensitive to noise compared to ECG [4], and the added value will be lowered if PPG is measured on the same location as the ACM/EMG.

A late integration approach was used here for the combination of the different algorithms by assuming the unimodal algorithms alarm within a certain time window of each other. The time windows shown in Table I were chosen based on the seizures found in the available dataset. It might be that for adult patients, the time windows need to be broadened further as there might be longer delays between seizures of longer duration and secondary generalized tonic-clonic seizures. In this dataset however, changing the values of Table I to any other value under 60s had relatively little effect on the multimodal performances. More advanced late integration approaches will be considered in future work.

The best combination of 2 sensors led to 90.9% sensitivity with just more than 1FP every two nights. This is a big improvement compared to the unimodal algorithms, but a lower FAR is advised for usage in practice. A relative high FAR is found here compared to other multimodal studies [5]. One of the reasons for this is the fact that children are evaluated here, whereas most other studies only look into adults. For adults, the tonic-clonic patterns are clearer and often last longer than the ones found in children. Therefore they are harder to detect, and a higher FAR is required to reach a sufficiently high sensitivity. For comparison, only 41% of tonic-clonic seizures in the used database have the stereotypical EMG pattern described in [6], meaning they are not that stereotypical in children. The results of Figure 1 however show that the stereotypical tonic-clonic seizures can be detected with low FAR using unimodal ACM or EMG.

In this study, 3 different patient-independent algorithms are used for evaluation. Making the algorithms patient-specific is advised in order to achieve a better performance. Specially for the ECG-based seizure detection algorithm a big performance increase can be found if patient-specific algorithms are used due to the large patient-dependency of the HR [7]. Similar adaptations should be made for all unimodal algorithms, and also the combination and the sensor choice should be done for each patient individually. The big challenge here is how to make these adaptations and sensor decisions automatically with a limited amount of annotated patient data. This is however left for future work.

V. Conclusion

Unimodal pediatric tonic-clonic seizure detection algorithms using different modalities and sensor placements were compared on a single dataset. Not one single sensor/modality really outperformed all others in terms of performance. Adding an extra sensor from a different modality leads to a strong decrease in false alarms by at least 75%. Sensors of different modalities on different locations on the body should be used in order to get the best possible performance for seizure detection, and this combination should be chosen for each patient.

Acknowledgment

Research supported by imec: Strategic Funding 2017, ICON: HBC.2016.0167 SeizeIT; European Research Council. The research leading to these results has received funding from the European Research Council under the European Union's Seventh Framework Programme (FP7/2007-2013) / ERC Advanced Grant: BIOTENSORS (n 339804). This paper reflects only the authors' views and the Union is not liable for any use that may be made of the contained information. Thomas De Cooman is supported by an FWO SBO PhD grant. Carolina Varon is a postdoctoral fellow of the Research Foundation-Flanders (FWO).

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