KU LEUVEN

STADIUS
Center for Dynamical Systems, Signal Processing and Data Analytics

Citation/Reference	Van de Vel A., Milosevic M., Bonroy B., Cuppens K., Lagae L., Vanrumste B., Van Huffel S., Ceulemans B., ``Long-term accelerometry-triggered video monitoring and detection of tonic-clonic and clonic seizures in a home environment : pilot study'', *Epilepsy & Behavior Case Reports*, vol. 5, 2016, pp. 66-71.
Archived version	Final publisher's version / pdf
Published version	http://dx.doi.org/10.1016/ j.ebcr.2016.03.005
Journal homepage	http://www.elsevier.com/locate/ebcr
IR	url in Lirias https://lirias.kuleuven.be/handle/123456789/537435

(article begins on next page)

Epilepsy & Behavior Case Reports 5 (2016) 66–71

Contents lists available at ScienceDirect

Epilepsy & Behavior Case Reports

journal homepage: www.elsevier.com/locate/ebcr

Case Report

Long-term accelerometry-triggered video monitoring and detection of tonic–clonic and clonic seizures in a home environment: Pilot study

Anouk Van de Vel [a,*], Milica Milosevic [b,c,**], Bert Bonroy [d], Kris Cuppens [d], Lieven Lagae [e,f], Bart Vanrumste [b,c,g], Sabine Van Huffel [b,c], Berten Ceulemans [a,e]

[a] Department of Neurology—Paediatric Neurology, University Hospital, University of Antwerpen, Wilrijkstraat 10, 1650 Edegem, Belgium
[b] Department of Electrical Engineering (ESAT), STADIUS, KU Leuven, Kasteelpark Arenberg 10, Box 2446, 3001 Heverlee, Belgium
[c] iMinds IT Department, KU Leuven, Kasteelpark Arenberg 10, Box 2446, 3001 Heverlee, Belgium
[d] MOBILAB, Thomas More Kempen, Kleinhoefstraat 4, 2440 Geel, Belgium
[e] Rehabilitation Center for Children and Youth Pulderbos, Reebergenlaan 4, 2242, Pulderbos, Belgium
[f] Department of Child Neurology, University Hospital, KU Leuven, Herestraat 49, 3000 Leuven, Belgium
[g] Department of Electrical Engineering (ESAT), Advanced Integrated Sensing (AdvISe), KU Leuven, Kleinhoefstraat 4, 2440 Geel, Belgium

ARTICLE INFO

Article history:
Received 28 January 2016
Received in revised form 16 March 2016
Accepted 17 March 2016
Available online 06 April 2016

Keywords:
Epilepsy
Patient-specific algorithm
Nonpatient-specific algorithm
Semipatient-specific algorithm
Visual verification
Data storage

ABSTRACT

Purpose: The aim of our study was to test the efficacy of the VARIA system (video, accelerometry, and radar-induced activity recording) and validation of accelerometry-based detection algorithms for nocturnal tonic–clonic and clonic seizures developed by our team.
Methods: We present the results of two patients with tonic–clonic and clonic seizures, measured for about one month in a home environment with four wireless accelerometers (ACM) attached to wrists and ankles. The algorithms were developed using wired ACM data synchronized with the gold standard video-/electroencephalography (EEG) and then run offline on the wireless ACM signals. Detection of seizures was compared with semicontinuous monitoring by professional caregivers (keeping an eye on multiple patients).
Results: The best result for the two patients was obtained with the semipatient-specific algorithm which was developed using all patients with tonic–clonic and clonic seizures in our database with wired ACM. It gave a mean sensitivity of 66.87% and false detection rate of 1.16 per night. This included 13 extra seizures detected (31%) compared with professional caregivers' observations.
Conclusion: While the algorithms were previously validated in a controlled video/EEG monitoring unit with wired sensors, we now show the first results of long-term, wireless testing in a home environment.
© 2016 The Authors. Published by Elsevier Inc. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

1. Introduction

Epilepsy is a condition in which seizures often occur unprovoked and without warning. Mainly for safety reasons, many patients and their families are looking for a seizure detection system that is efficient, comfortable, and easy to use. This implies that such a system should have a high detection sensitivity (detect as many seizures as possible) and low false alarm rate; it should be unobtrusive, wireless, and in case of daytime use practically unnoticeable; and it should allow long-term use in a home situation without the presence of professionals.

Alarming for safety reasons or reassurance is already used in fall detectors for the elderly, babyphones (reacting to sound or movement), and glucose monitors for persons with diabetes [1,2]. In addition to being used for alarming, a detection system could allow offline storage or online streaming of selected data, allowing follow-up on treatment efficacy or summoning emergency support, respectively.

Our team is interested in the long-term observation of patients with epilepsy and detection of their seizures [3,4]. The focus lies on those convulsive seizures that can be dangerous because of their intensity (possible injuries), duration, or serious consequences such as brain damage, autonomic dysregulation, or suffocation. More specifically, we currently aim at the detection of nocturnal tonic–clonic and clonic seizures with patients remaining in one place, their bed, mainly because of the need for supervision at night and because seizures often occur during sleep.

As sensors need to be as unobtrusive as possible but still effective, small wireless accelerometers (measuring the acceleration of movement) are used and attached to the wrists and ankles of the patient.

* Correspondence to: A. Van de Vel, UZA, Paediatric Neurology, Wilrijkstraat 10, 2650 Edegem, Belgium. Tel.: +32 38215140.
** Correspondence to: M. Milosevic, KU Leuven, ESAT, Kasteelpark Arenberg 10, Postbus 2440, 3001 Heverlee, Belgium. Tel.: +32 16321130.
E-mail addresses: anouk.vandevel@uza.be (A. Van de Vel), mili.milosevic@gmail.com (M. Milosevic).

http://dx.doi.org/10.1016/j.ebcr.2016.03.005
2213-3232/© 2016 The Authors. Published by Elsevier Inc. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

The goal of this study was to test the efficacy of the VARIA (video, accelerometry, and radar-induced activity recording) system and algorithms for tonic–clonic and clonic seizures compared with that of semicontinuous monitoring by professional caregivers (keeping an eye on multiple patients), as well as the independence, robustness, comfort, and user-friendliness of the system. We therefore measure long term in a home environment without uncomfortable and stigmatizing electroencephalography (EEG) electrodes rather than in a video/EEG monitoring unit, and the system therefore needs to be able to store the data and to allow visual verification of detected events. This is why a camera is added to the accelerometer system.

2. Methods

2.1. Patients

Two patients were measured for one month in their rooms in an epilepsy center in Flanders, Belgium. As they returned home for the weekends and as the caregivers needed to get acquainted with the recording system, they were measured for a mean of 12 nights per patient.

Patient 1 is an 8-year-old girl with epilepsy e.c.i. and different types of seizures that typically last no more than 3 min: tonic–clonic seizures with or without faltering respiration, tonic seizures, and clonic seizures. All three occur symmetrically as well as asymmetrically. She also exhibits myoclonic jerks manifesting as (head) nods or facial contractions with eye deviation. Seizures are noticed based on semicontinuous video monitoring and when a scream or breathing problem is heard.

Patient 2 is a 9-year-old boy with lesional epilepsy due to herpes encephalitis, who is kept in bed with a restraining belt around the waist. He suffers from tonic–clonic seizures of various duration, tonic, clonic, and myoclonic seizures and (series of) spasms. The caregivers use a babyphone and semicontinuous video monitoring to keep an eye on him.

Approval by the Medical Ethical Commission of the Antwerp University Hospital, Belgium and signed informed consent forms from all parents were obtained prior to inclusion in the study, which was performed in accordance with the 1964 Declaration of Helsinki.

2.2. Measurement

The system uses video, accelerometry (ACM), and radar-induced activity recording and is therefore named VARIA. It consists of an AXIS M1011 camera (Axis Communications AB, Sweden) and a Hygrosens RAD-MOD motion sensor based on the radar principle (B + B Thermo-Technik GmbH, Germany). The camera and radar are attached to a tripod that is placed close to the patient's bed. The radar is added for detection of movements in the direction of the sensor and for measurement through sheets. Radar technology is also used for detection of falling, wandering, sitting, or getting up [5], so we expect it to detect large and slow epileptic and nonepileptic movements, also those caused by other persons in the room. Four Shimmer sensors with integrated three-axis ACM (Shimmer, Ireland), streaming wireless (Bluetooth) communication standards, are adjusted to allow recording of more than 10 h before batteries need recharging and are put in elastic bracelets worn around wrists and ankles. A laptop with a software application developed in LabVIEW (National Instruments Corporation, US) stores all movement data recorded by either camera, radar, or ACM (Fig. 1).

The technical aspects of the recording system will be published in more detail by Bonroy et al. and are briefly described in the Supplementary material.

2.3. Analysis

The algorithms developed by Milosevic et al. [6] for tonic–clonic and clonic seizures based on a large database of video/electroencephalography (EEG) data were used. Results of a patient-specific (algorithm trained only on data of the patient itself), a nonpatient-specific (algorithm trained on data not including those of the patient itself), and a semipatient-specific (algorithm trained on data also including those of the patient itself) approach were compared with the notes of professional caregivers. For a full description on how to implement these methodologies in practice, please see the Supplementary material.

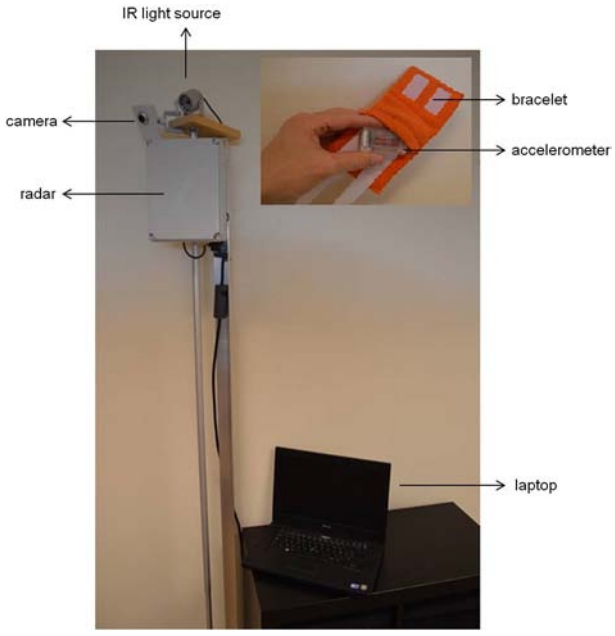

Fig. 1. Setup of VARIA system: video, accelerometry, and radar-induced activity recording. Camera and radar are attached to the tripod, accelerometers are worn in elastic bracelets around wrists and ankles, and a laptop receives and stores all movement data recorded by any of the three modalities.

Professional caregivers were asked to write down all seizures the patients had, with time and description in a form of a clinical report. They recognize epileptic seizures (one month training and yearly tuition), are awake during the whole night, know the patients, and are semicontinuously watching on average four patients with active epilepsy in front of a video screen, only leaving if one of them or one of the other (maximum) twelve patients need care.

The events detected with the algorithms were visually inspected by a pediatric video/EEG specialist and a pediatric neurologist using the screening tool which is a graphical user interface developed in MATLAB® (Mathworks Inc., US) (Fig. 2). The screening tool displays information on the number of movement events and on their duration. The ACM signals, a distribution graph, and the video images are depicted for each event. Also, radar and video signals are shown, as well as the fraction (percentage) of movement within the event. The graph at the lower left corner sets out amplitude of all events based on ACM signals and length of all events based on the three detection modalities. In other words, it shows the intensity and duration of the movement.

After the application of each of the three developed seizure detection algorithms and during postprocessing, the following logical reasoning was used:

Rule 1: A margin of error of 5 min has been taken into account for the seizure reporting. As the caregiver might write down the seizure after having attended to the patient, we assume the seizure may have been noticed 5 min before or after the actual time in the notes.

Rule 2: Only seizures longer than 10 s are considered as possibly dangerous and therefore candidates for the alarm system, hence shorter seizures are not counted when calculating detection performance.

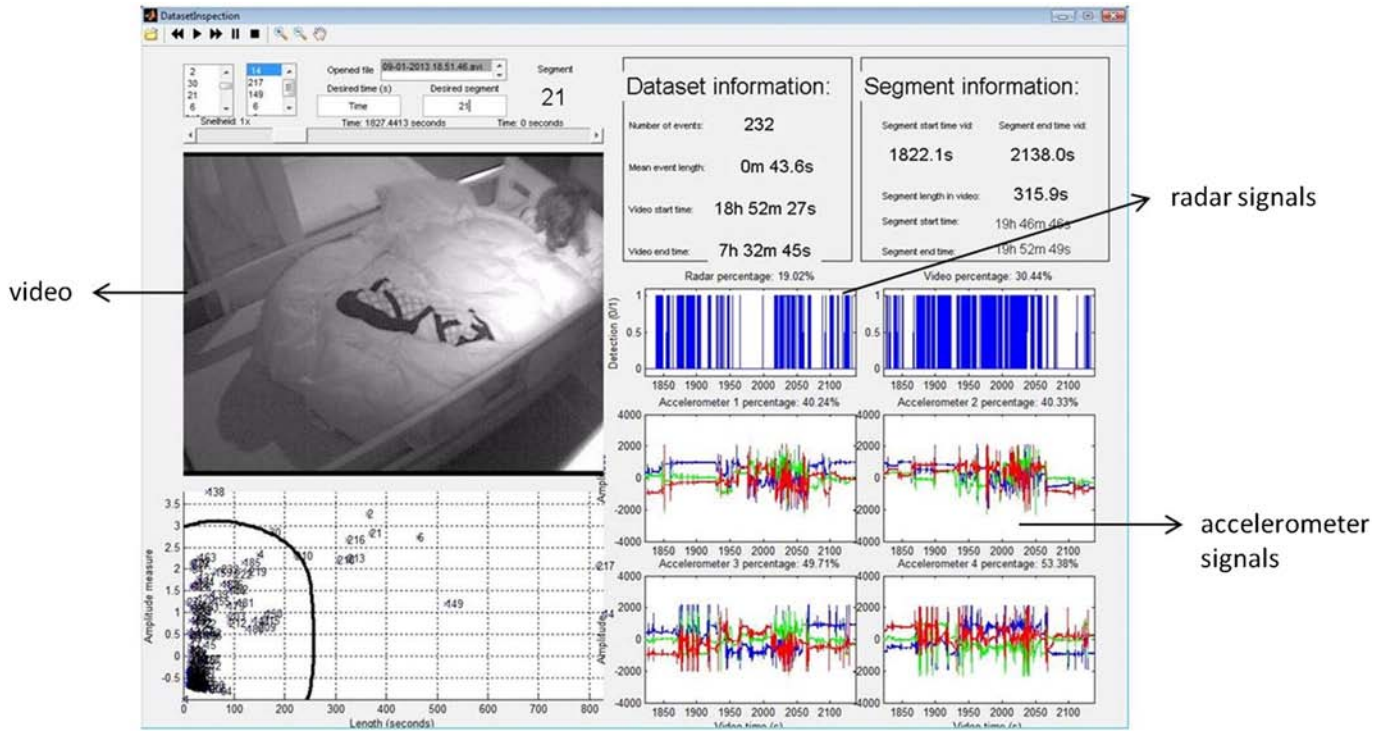

Fig. 2. Graphical user interface displaying radar and accelerometer signals per movement event. Video images of each event can be played. The graph at the lower left corner sets out amplitude and length of all events.

Rule 3: An alarm is set after 7 s of continuous positive detection. A margin of 3 s is left out since the beginning of tonic–clonic seizures is not typically detected by ACM; the tonic phase involves muscle contraction rather than limb movement.

Rule 4: An alarm within 1 min after a previous one is ignored. A future real-time alarm system should allow the system to be turned off by the caregiver when checking on an alarm, and 1 min is considered too short for the caregiver to have checked on and left the patient after the first alarm.

Rule 5: Alarms caused by the caregiver waking or handling the patient (medication administration) and installing (evening) or removing (morning) the system and ACM are ignored. Again, at these times, the future real-time alarm system should be turned off by the caregiver.

True positives (TP) are detected seizures with the extra seizures detected by the algorithm but not the caregiver mentioned in between brackets. False negatives (FN) are seizures reported by the caregiver but not detected by the algorithm. To calculate sensitivity, the formula TP / (TP + FN) was used. False positives (FP) are detections that were not seizures, which in some occasions were multiple alarms in one movement event. False detection rate (FDR) is calculated as the number of FP per night.

3. Results

Monitoring for 15 nights for patient 1 and nine nights for patient 2 resulted in 9586 movement events. In this first validation, 322 events (3.4% or 15 min) were discarded before algorithm application because the data of one or more accelerometers lasted less than 1 s or was completely missing.

The results of the nonpatient-specific and semipatient-specific approaches can be found in Table 1. The nonpatient-specific approach resulted in a sensitivity of 90% and FDR of one per night for patient 1 and a sensitivity of 33% and FDR of almost two per night for patient 2. The semipatient-specific approach gave somewhat better results with a sensitivity of 93% and FDR of a little over one per night for patient 1 and a sensitivity of 40% and FDR of one per night for patient 2.

Results of the patient-specific approach are not depicted as it was immediately clear that many seizures were missed, many false alarms occurred, and the approach was not stable in between trials (the results depended on which data were used for algorithm training).

Table 1
Results of nonpatient-specific and semipatient-specific algorithms with reference to the notes by the professional caregivers. extra = detected seizures not reported by the caregivers, FDR/n = false detection rate per night, FN = false negatives, FP = false positives, Sens = sensitivity, TP = true positives.

	Nonpatient-specific					Semipatient-specific				
	TP (extra)	FN	Sens (%)	FP	FDR/n	TP (extra)	FN	Sens (%)	FP	FDR/n
Patient 1 15 nights	29 (11)	3	90.62	15	1.00	30 (11)	2	93.75	20	1.33
Patient 2 9 nights	3 (1)	6	33.33	17	1.88	4 (2)	6	40.00	9	1.00
Mean			61.97		1.44			66.87		1.16

4. Discussion

In this work, we validated algorithms for the detection of tonic–clonic and clonic epileptic seizures with a new (wireless) system using video, wireless accelerometry (ACM), and radar-induced activity recording, which is placed in a home environment for a prolonged period of time. Three methodologies were tested: patient-specific, nonpatient-specific, and semipatient-specific algorithms.

It seems that combining a large amount of data of many (other) patients as in the last two methodologies, instead of using a limited amount of data of one specific patient as in the first approach, yields better classification results.

The semipatient-specific algorithm gave the best results, including 13 extra seizures detected (31%) and eight seizures missed (19%) compared with professional caregivers' observations. Of these eight, four were not even recorded in any of the movement data. Possible explanations include a temporary defect in the system, mistakes in reporting by the caregiver (one seizure was reported at 5:20 a.m. but found at 6:20 a.m.), or short seizures involving only the head (not attached to an ACM).

The limitations of our setup are discomfort (four accelerometers), noncontinuously recorded data (only movement events), and lack of gold standard (no electroencephalography or EEG).

The detection algorithms have their own limitations. They are not able to detect the tonic phase of tonic–clonic seizures (which involves muscle contraction rather than limb movement), so if the clonic phase is too short, the seizure will be missed: the alarm is set after 7 s of positive detection, so if the clonic phase lasts 6 s and this whole part is detected, the alarm will not be set off. Finally, asymmetric tonic–clonic or clonic seizures during which the movements of the limbs are not synchronized and seizures with a low frequency of clonic jerks are often missed, since the spatial and frequency content of these seizures differ from the majority of seizures in the training set (a large database of wired ACM data synchronized with video/EEG). Fig. 3 illustrates detected and nondetected seizures.

We compared the results of the semipatient-specific algorithm with those of the screening tool of Bonroy et al. [7] (submitted) where the most intense and longest movement events were visually inspected for seizures using the same datasets and the graphical user interface of Fig. 2. The screening tool can be used before a diagnosis is made to quickly and retrospectively look at a night and report abnormal nocturnal behavior, including seizures. Once the patient is diagnosed (with epilepsy), we can change the functionality of the same hardware into an alarming system. This implies that we have to reduce the false detection rate (FDR) and increase the sensitivity. The comparison results, presented in Table 2, show an increase of sensitivity from 58% to 66% (five seizures were missed, but 14 more were detected) and a decrease of FDR per night from 15 to 0.7. Because the method of Bonroy et al. selected a percentage of 'most abnormal' events irrespective of the number of movements or seizures that night, this automatically resulted in more false positives, so comparison of FDR is not relevant. Moreover, 11 of the 16 false positives in our approach were due to a system failure (broken channel or high-frequency noise), hence clustered alarms can be used to indicate this kind of events and reduce the number of false alarms.

Other publications reported on body-attached accelerometry for tonic–clonic and clonic seizure detection. Beniczky et al. [8] obtained a sensitivity of 89% by 20 patients with 39 seizures. Lockman et al. [9] reached a sensitivity of 87% testing 6 patients with (only) 8 seizures; however, Patterson et al. [10] only obtained a sensitivity of 31% (16 out of 51 seizures) with the same device. Schulc et al. [11] achieved a sensitivity of 100% but only used 3 patients and 4 seizures. It is difficult to compare with this study and obtained results, however, mainly because the gold standard video/EEG was not used to annotate the data. Furthermore, we did not review all video data (only where the algorithm or caregiver indicated a seizure), and some of the seizures reported by the caregivers were not even found in the (movement) data. Therefore, the presented results are an estimation of the performance of the algorithms.

Although setup without EEG is less optimal for seizure detection performance, it is optimal for testing the independence and robustness of the system and the patient-friendliness of the system in a long-term home environment. Also, the second part of the gold standard, namely video, is present in our system. Furthermore, a major advantage of our system is that it allows video storage for retrospective analysis. Of the commercially available seizure detection systems reported by Van de Vel et al. [12], some keep a log of the detected seizures: EpiWatcher [13] stores the time and duration of up to 20 detections, SmartWatch [9,10,14] keeps the time, duration, and movement patterns, EpiCare [8,15] saves the time and duration of an unspecified number of

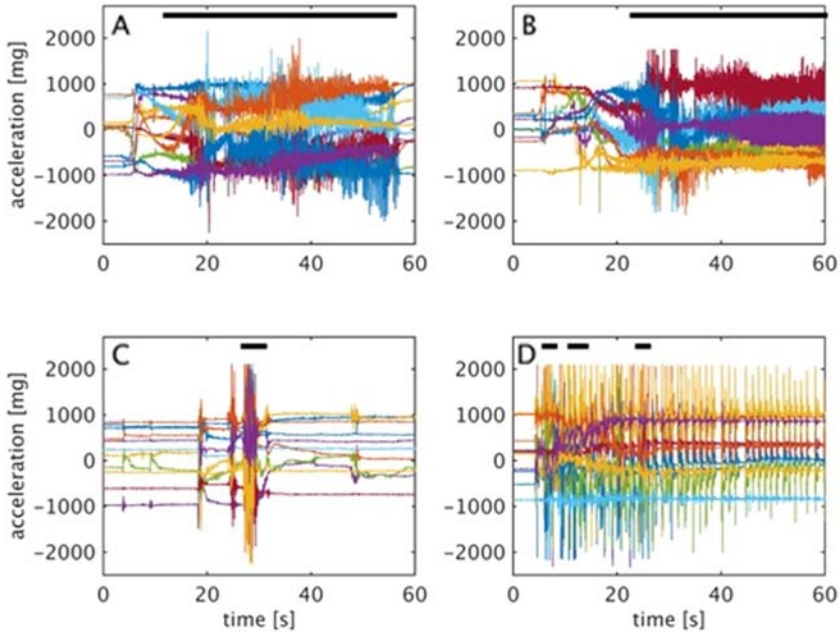

Fig. 3. Accelerometry signals (three orthogonal directions per limb) for (A) a detected tonic–clonic seizure, (B) a detected clonic seizure, (C) a nondetected tonic–clonic seizure with a too short clonic phase, and (D) a nondetected tonic–clonic seizure with jerks of too low frequency. The horizontal lines indicate detected seconds (nonpatient-specific algorithm).

Table 2
Comparison of the semipatient-specific algorithm with the screening tool (visual inspection of long and intense movement events using the graphical user interface of Fig. 2), method described in Bonroy et al. [7] (submitted). As Bonroy et al. only included 12 nights of patient 1, three nights were left out from the semipatient-specific analysis, and the same 12 nights were analyzed. Furthermore, as Bonroy et al. counted only one false positive per event, this was applied to our approach as well. extra = detected seizures not reported by the caregivers, FDR/n = false detection rate per night, FN = false negatives, FP = false positives, Sens = sensitivity, TP = true positives.

	Screening tool (Bonroy et al.)					Semipatient-specific algorithm				
	TP (extra)	FN	Sens (%)	FP	FDR/n	TP (extra)	FN	Sens (%)	FP	FDR/n
Patient 1 12 nights	13 (6)	11	54.16	244	20.33	25 (9)	2	92.59	7	0.58
Patient 2 9 nights	7 (3)	4	63.63	89	9.88	4 (2)	6	40.00	9	1.00
Mean			58.89		15.10			66.29		0.79

detections, and the mobile phone application EpDetect [16] logs the raw accelerometer data. None of them records and stores video data of the detected seizures. Some studies report on video-based seizure detection (so without ACM), but a disadvantage is the difficulty to measure through bed linen [17–19].

In order to improve the accuracy of the device, we are convinced that a multimodal approach is needed, and literature research as well as user questioning has persuaded us that the most important signals to be monitored are movement (often an early manifestation of seizures) and heart rate changes (indicating clinically relevant seizures and part of the pathophysiological mechanism leading to sudden unexpected death in epilepsy or SUDEP).

It is clear that the number of sensors should be reduced to one or two at the most. Attachment of a seizure detection device to the upper arm is less comfortable than to the lower arm [20] and can easily move when for example changing clothes or not tightly attached; so for the moment, we will continue our research with wrist-attached devices.

Detection of respiration changes is certainly useful, but these changes occur probably almost simultaneously with heart rhythm changes, respiration is a very slow signal, and heart rhythm changes are very easy to detect, which is why more studies focus on cardiac- than respiration-based detection [21,22].

Oxygen saturation measurement and electrodermal activity (EDA) seem promising, but changes are detected more slowly than heart rhythm changes [22,23], and EDA is measured using electrodes (as are ECG and EMG), which cause potential skin irritation, and there is a risk of losing the signal due to electrodes falling off or a bad contact with the skin [24,25].

Furthermore, EMG and respiration cannot be measured at the wrist, and oxygen saturation cannot be measured yet without adding a finger cuff, even though reflectance oximetry might be an option in the future [23].

All of these arguments lead us to focus our future research on movement detection by ACM in combination with heart rate detection by PPG (photoplethysmography).

The algorithm should be robust and independent of the number and functionality of used sensors, so that there is no rejection of the data, and to be able to use our future device patient-independently, we will be concentrating on adaptive (learning) algorithms.

Not only efficacy of the device will be important but also comfort (including the reduction of sensors), user-friendliness (less setup steps), and therapeutic (e.g., medication changes) and social (e.g., quality of life including the impact of false alarms) impact. Therapeutic impact can be examined by using the logging function of a seizure detection device, but in order to look into social impact, the device obviously needs to allow online use (with real-time alarming). The latter brings along additional challenges such as the need for fast computation time, low energy consumption, large storage capacity, and miniaturization of the device, which we need to address.

Finally, it would be interesting to compare the performance with that of commercially available seizure detection bracelets using accelerometry, such as SmartWatch or EpiCare Free, also tested in a home environment.

5. Conclusion

This study demonstrates the first clinical results of an algorithm for the detection of tonic–clonic and clonic seizures tested on two patients with epilepsy monitored in a long-term home environment with the VARIA system (video, accelerometry, and radar-induced activity recording) developed by our team. Compared with the professional caregivers' observations, a mean sensitivity of 61.97% and false detection rate of 1.44 per night were obtained with the nonpatient-specific approach and a mean sensitivity of 66.87% and false detection rate of 1.16 per night with the semipatient-specific approach.

We believe that, while privacy protection needs to be taken into account, the addition of video to accelerometry allows a seizure detection system not only to alarm the family or (informal) caregiver but also allows retrospective (offline) or emergency (online) verification of detected events.

Much work remains to develop a multimodal, learning, comfortable, and user-friendly device.

Acknowledgments

This research was funded by TBM grant 070713 of the agency for Innovation by Science and Technology in Flanders (IWT-Vlaanderen) and an educational grant 21NLL24 for A. Van de Vel by Cyberonics, Inc.

M. Milosevic and S. Van Huffel were sponsored by the Research Council KUL: GOA MaNet, PFV/10/002 (OPTEC), and the Belgian Federal Science Policy Office: IUAP P7/19/(DYSCO, 'Dynamical systems, control and optimization', 2012–2017) and FWO projects G.0427.10N (integrated EEG–fMRI) and G.0108.11 (compressed sensing).

The authors would like to thank the caregivers of the involved epilepsy center for their help with measurements and feedback.

Conflict of interest

None of the authors have any conflicts of interest related to the submitted manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ebcr.2016.03.005.

References

[1] Chaudhuri S, Thompson H, Demiris G. Fall detection devices and their use with older adults: a systematic review. J Geriatr Phys Ther 2014;37(4):178–96.
[2] Eron L. Telemedicine: the future of outpatient therapy? Clin Infect Dis 2010;51(S2): S224–30.
[3] Cuppens K, Vanrumste B, Chen CW, Wong KBY, Aghajan H, Tuytelaars T, et al. Integrating video and accelerometer signals for nocturnal epileptic seizure detection. Conf Proc ICMI; 2012. p. 161–4.
[4] Van de Vel A, Cuppens K, Bonroy B, Milosevic M, Van Huffel S, Vanrumste B, et al. Long term home monitoring of hypermotor seizures by patient-worn accelerometers. Epilepsy Behav 2012;26:118–25.
[5] Applied radar technology website. Available at: http://www.artbv.com [last accessed March 10th, 2016].

[6] Milosevic M, Van de Vel A, Bonroy B, Ceulemans B, Lagae L, Vanrumste B, et al. Detection of epileptic convulsions from accelerometry signals through machine learning approach. Conf Proc IEEE MLSP; 2014. p. 1–6.
[7] Bonroy B, Van de Vel A, Cuppens K, Milosevic M, Van Huffel S, Verhaert K et al. A home monitoring tool for offline screening of nocturnal behavior in children with convulsive epileptic seizures. Unpublished results. [Submitted for publication].
[8] Beniczky S, Polster T, Kjaer TW, Hjalgrim H. Detection of generalized tonic–clonic seizures by a wireless wrist accelerometer: a prospective, multicenter study. Epilepsia 2013;54(4):e58–61.
[9] Lockman J, Fisher RS, Olson DM. Detection of seizure-like movements using a wrist accelerometer. Epilepsy Behav 2011;20(4):638–41.
[10] Patterson AL, Mudigoudar B, Fulton S, McGregor A, Poppel KV, Wheless MC, et al. SmartWatch by SmartMonitor: assessment of seizure detection efficacy for various seizure types in children, a large prospective single-center study. Pediatr Neurol 2015;53(4):309–11.
[11] Schulc E, Unterberger I, Saboor S, Hilbe J, Ertl M, Ammenwerth E, et al. Measurement and quantification of generalized tonic–clonic seizures in epilepsy patients by means of accelerometry — an explorative study. Epilepsy Res 2011;95(1–2):173–83.
[12] Van de Vel A, Cuppens K, Bonroy B, Milosevic M, Jansen K, Van Huffel S, et al. Non-EEG seizure-detection systems and potential SUDEP prevention: state of the art. Seizure 2013;22:345–55.
[13] EpiWatcher is a device by Vahlkamp. Website available at: http://www.vahlkamp.nl [last accessed March 10th, 2016].
[14] SmartWatch is a device by Smart Monitor Corp. Website available at: http://www.smart-monitor.com [last accessed March 10th, 2016].
[15] EpiCare is a device by Danish Care. Website available at: http://danishcare.dk/uk [last accessed March 10th, 2016].
[16] EpDetect is a mobile phone application. Website available at: http://www.epdetect.com [last accessed March 10th, 2016].
[17] Cuppens K, Chen CW, Wong KB, Van de Vel A, Lagae L, Ceulemans B, et al. Using spatio-temporal interest points (STIP) for myoclonic jerk detection in nocturnal video. Conf Proc IEEE EMBS; 2012. p. 4454–7.
[18] Karayiannis NB, Xiong Y, Tao G, Frost Jr JD, Wise MS, Hrachovy RA, et al. Automated detection of videotaped neonatal seizures of epileptic origin. Epilepsia 2006;47(6):966–80.
[19] Rémi J, Cunha JP, Vollmar C, Topçuoğlu ÖB, Meier A, Ulowetz S, et al. Quantitative movement analysis differentiates focal seizures characterized by automatisms. Epilepsy Behav 2011;20(4):642–7.
[20] Szabó CÁ, Morgan LC, Karkar KM, Leary LD, Lie OV, Girouard M, et al. Electromyography-based seizure detector: preliminary results comparing a generalized tonic–clonic seizure detection algorithm to video-EEG recordings. Epilepsia 2015;56(9):1432–7.
[21] Jansen K, Varon C, Van Huffel S, Lagae L. Peri-ictal ECG changes in childhood epilepsy: implications for detection systems. Epilepsy Behav 2013;29(1):72–6.
[22] Ryvlin P, Nashef L, Tomson T. Prevention of sudden unexpected death in epilepsy: a realistic goal? Epilepsia 2013;54(Suppl. 2):23–8.
[23] Cogan D, Nourani M, Harvey J, Nagaraddi V. Epileptic seizure detection using wristworn biosensors. Conf Proc IEEE Eng Med Biol Soc; 2015. p. 5086–9.
[24] Teohari V-M, Ungureanu C, Bui V, Arends J, Aarts RM. Epilepsy seizure detection app for wearable technologies. AmI 2014.
[25] van Andel J, Ungureanu C, Aarts R, Leijten F, Arends J. Using photoplethysmography in heart rate monitoring of patients with epilepsy. Epilepsy Behav 2015;45:142–5.