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BRIEF COMMUNICATION

Convulsive seizure detection using a wrist-worn electrodermal activity and accelerometry biosensor

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Summary

The special requirements for a seizure detector suitable for everyday use in terms of cost, comfort, and social acceptance call for alternatives to electroencephalography (EEG)–based methods. Therefore, we developed an algorithm for automatic detection of generalized tonic–clonic (GTC) seizures based on sympathetically mediated electrodermal activity (EDA) and accelerometry measured using a novel wrist-worn biosensor. The problem of GTC seizure detection was posed as a supervised learning task in which the goal was to classify 10-s epochs as a seizure or nonseizure event based on 19 extracted features from EDA and accelerometry recordings using a Support Vector Machine. Performance was evaluated using a double cross-validation method. The new seizure detection algorithm was tested on >4,213 h of recordings from 80 patients and detected 15 (94%) of 16 of the GTC seizures from seven patients with 130 false alarms (0.74 per 24 h). This algorithm can potentially provide a convulsive seizure alarm system for caregivers and objective quantification of seizure frequency.

KEY WORDS: Seizure alarm, Electrodermal activity, Accelerometry, Wearable sensor, Epilepsy.

Although combined electroencephalography (EEG) and video-monitoring remain the gold standard for seizure detection in clinical routine, most patients are opposed to wearing scalp EEG electrodes to obtain seizure warnings for everyday use (Schulze-Bonhage et al., 2010). Accelerometry recordings offer a less-obtrusive method for detecting seizures with motor accompaniments (Nijsen et al., 2005). Previously, we showed that electrodermal activity (EDA), which reflects the modulation of sweat gland activity by the sympathetic nervous system, increases during convulsive seizures (Poh et al., 2010a). Herein we describe a novel methodology for generalized tonic–clonic (GTC) seizure detection using information from both EDA and accelerometry signals recorded with a wrist-worn sensor.

Methods

This study was approved by the institutional review boards of Massachusetts Institute of Technology and Children's Hospital Boston. We recruited patients with epilepsy who were admitted to the long-term video-EEG monitoring (LTM) unit. All participants (or their caregivers) provided written informed consent. Custom-built EDA and accelerometry biosensors were placed on the wrists (Fig. S1) such that the electrodes were in contact with the ventral side of the forearms (Poh et al., 2010b).

The various stages of the GTC seizure detector are depicted in Fig. 1A. A sliding window was used to extract 10-s epochs from both accelerometry and EDA recordings for each 2.5-s increment (75% overlap). The data were then preprocessed to remove nonmotor and nonrhythmic epochs. A total of 19 features including time, frequency, and nonlinear features were extracted from remaining epochs of the accelerometry and EDA signals to form feature vectors. Finally, each feature vector was assigned to a seizure or nonseizure class using a Support Vector Machine (SVM). We implemented a *non–patient-specific* seizure detection algorithm that excluded all data from a test patient in the training phase (double *leave-one-patient-out* cross-validation). To allow the SVM to learn from previous examples of seizures from the test patient if that patient had more than a single GTC seizure recording available, we also implemented double *leave-one-seizure-out* cross-validation. Because the detector was not trained solely on data from a

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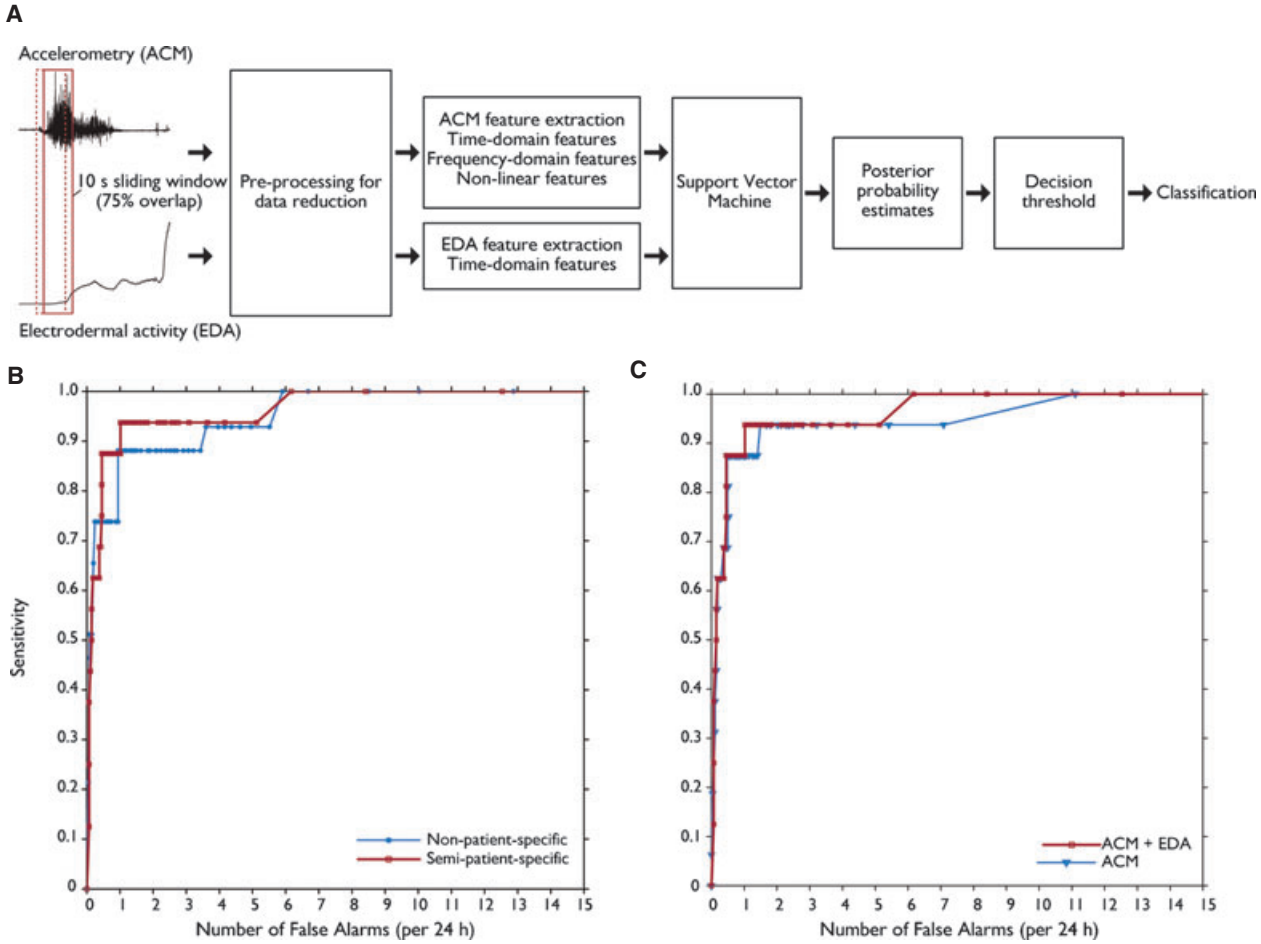

Figure 1.
(**A**) Overview of seizure detection architecture. EDA and accelerometry recordings were analyzed using a sliding window of 10 s to first discard nonmotor and nonrhythmic epochs for data reduction, and then extract various features (19 in total). SVM classifiers were constructed to produce posterior probability estimates for each feature vector. A decision threshold was applied to the posterior probability estimates to assign each epoch to a seizure or nonseizure class. (**B**) Receiver operating characteristic (ROC) curve analysis of two seizure detection modes tested on 688 h (29 days) of data from the seven patients with GTC seizures: a non–patient-specific (blue circles) and semi–patient-specific seizure (red squares) detector. (**C**) Comparison between semi–patient-specific seizure detectors using solely accelerometry features (blue circles) and using both accelerometry and EDA features (red squares).

particular test patient but included examples from all other patients, this approach was *semi–patient-specific*. For a full description of the data acquisition, preprocessing, feature extraction, model selection, and testing methodology, please see the Data S1.

Results

We included 80 patients (39 male, 10 ± 4.6 years, various epilepsy syndromes) in this study. A total of 16 secondarily GTC seizures were recorded from seven patients; the seizures occurred at different day and night times as well as during both awake and sleep states. The EDA and accelerometry recordings were obtained in a routine clinical environment and contained a wide range of activities of daily living. Because the EEG recording system could be placed in a backpack for (limited) data logging, patients were not constrained to staying in bed but could walk around the room, go over to a playroom nearby, engage in emotionally and physically activating games (e.g., Nintendo Wii), or leave the LTM for imaging studies and other tests.

Performance comparison of seizure detection modes

To visualize the performance of the non–patient-specific and semi–patient-specific seizure detection modes tested on 688 h (29 days) of data from the seven patients with GTC seizures, we performed receiver operating characteristic (ROC) curve analysis (Fig. 1B). The ROC curves depict the trade-off between sensitivity (percentage of recorded seizures that were identified by the detector) and false alarm

rate as the decision threshold is varied. At the optimal cut-off point that maximized sensitivity and minimized the false alarm rate (i.e., point nearest the top left-hand corner), the non–patient-specific detector achieved 88% (14/16 seizures detected) sensitivity with an average of one false alarm per 24 h. Two GTC seizures were missed1 (seizures 10 and 13 in Fig. S2). Overall, the semi–patient-specific seizure approach improved the performance. At the optimal threshold, 15 (94%) of 16 seizures were detected with one false alarm per 24 h.

Figure 2A shows the true positive detections declared on each test patient under the semi–patient-specific mode. Only one seizure was missed (Patient 4, seizure 10 in Fig. S2). There were 28 false alarms during the 688 h of testing (0.98 per 24 h). The average false alarm rate across patients was 1.05 ± 0.71 per 24 h (Fig. 2B). The electrographic and clinical latencies for each seizure are illustrated in Fig. 2C. In all seizures, the electrographic onset preceded its clinical onset; hence the electrographic detection latency (delay between EEG onset of seizure and first epoch classified as seizure) was longer compared to the clinical detection latency (delay between onset of outwardly visible physical or cognitive symptoms and first epoch classified as seizure). Three seizures had a particularly long nonmotor lead in (seizures 10, 11, and 12 in Fig. S2), and seizure 10 was not detected. The median electrographic latency was 42.95 s; median clinical latency was 31.42 s.

EDA features improve performance

To evaluate the utility of combining accelerometry and EDA, we compared the performance of two semi–patient-specific seizure detectors. One detector included features from both the accelerometry and EDA recordings (original feature set), and the other incorporated features from only the accelerometry recordings. The overall performance was lower when only accelerometry features were included (Fig. 1C). The optimum performance achieved was 94% sensitivity with a higher average false alarm rate of 1.5 per 24 h compared to the detector utilizing both accelerometry and EDA features (1 per 24 h).

False alarms in patients with no GTC seizures

After training the SVM using data from the seven patients with GTC seizures, we tested the seizure detection algorithm for false alarms on 3,525 h (147 days) of recordings from the 73 patients who did not experience GTC seizures. On average, each patient was tested over 48 ± 35 h of data. There were 102 false alarms during the 3,525 h of testing (0.69 per 24 h). The average false alarm rate across patients was 0.98 ± 2.61 per 24 h (Fig. 2D), which is similar to the rate observed in the seven patients with GTC seizures. The majority of patients (77%) had <1 false alarm per 24 h. Of the 73 patients, 46 (63%) did not trigger any false alarms during the entire monitoring period, resulting in a median

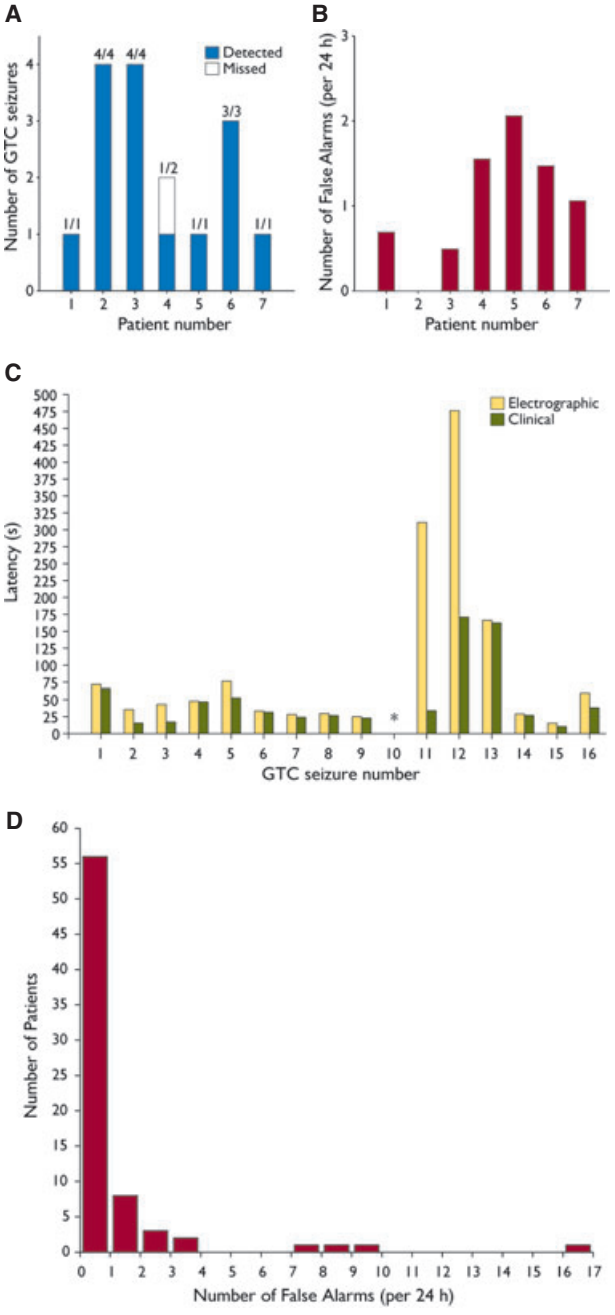

Figure 2.
Semi–patient-specific seizure detection performance tested on 688 h (29 days) of data from the seven patients with GTC seizures. (**A**) Number of GTC seizures detected per patient. (**B**) Number of false alarms per 24 h per patient. (**C**) Latency of detection for each GTC seizure. *Seizure 10 (patient 4) was not detected by the algorithm. (**D**) Histogram of false alarm rates after testing on 3,525 h (147 days) of recordings from 73 patients who did not experience GTC seizures. A 63% of patients did not raise any false alarms, 77% of patients had <1 false alarm per 24 h, and four patients had a high rate of false alarms.

false alarm rate of zero. On the other hand, four patients had an unusually high rate of false alarms (see Discussion below).

Discussion

We described a novel sensor and algorithm for GTC seizure detection. Previous work on wrist-worn GTC seizure detectors focused primarily on accelerometry as the input signal (Table S1). Our study illustrates how a seizure detector that combines information from both EDA and accelerometry recordings can perform better than a detector that relies only on accelerometry. Moreover, we evaluated the algorithm on recordings from 80 patients containing a wide range of ordinary daily activities to test for false alarms. EDA is a unique signal that reflects purely sympathetic activity (Boucsein, 1992; Critchley, 2002). Several cortical structures with recognized seizure potential (e.g., the frontal cortex or cingulate gyrus) have direct or indirect connections with autonomic centers from the medulla oblongata (Sevcencu & Struijk, 2010) and electrical stimulation of such structures can induce changes in EDA (Mangina & Beuzeron-Mangina, 1996; Lanteaume et al., 2007). Therefore, incorporating EDA measurements in a seizure detector can improve detection performance as well as provide a quantitative measure of the autonomic impact for each seizure (Poh, 2011).

The proposed algorithm failed to detect one of the test seizures because that seizure produced only mild motor convulsions and little change in the EDA signal (seizure 10 in Fig. S2). It is possible that with more training examples that resembled the missed seizure, the algorithm would have produced the correct classification. The relatively low number of seizure examples represents one of the limitations of this study, but the extensive amount of real-world activity nonseizure data allowed a good estimation of the false alarm rate. Of all 80 patients, only 4 patients had a relatively high amount of false alarms. Based on analysis of the video recordings, the false alarms occurred only when patients were awake (mainly during daytime) and were typically triggered by forceful, rapid, and rhythmic motions during activities such as dice shaking, hand flapping (several patients were on the autism spectrum), juggling, and motion-controlled gaming (Nintendo Wii, Redmond, WA, U.S.A.). More examples of these harder cases in the training set may improve the decision boundary and performance. Alternatively, the addition of other physiologic signals that are influenced by a seizure (e.g., heart rate acceleration, changes in the RR interval series or ECG morphology, and electromyography) or positioning the sensor on the lower leg instead of the wrist may provide better discriminability of these cases.

Timely detection of seizures allows caregivers to monitor their severity and determine whether immediate treatment is necessary. This could help prevent sudden unexpected death in epilepsy, which occurs mainly during or shortly after a seizure, and the deaths are largely unwitnessed (Surges et al., 2009). Our findings suggest that this algorithm can automatically detect convulsive seizures with high sensitivity and a low false alarm rate. Future work should involve longitudinal home ambulatory studies to evaluate the algorithm's performance during everyday use.

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Disclosures

Dr. Loddenkemper serves on the Laboratory Accreditation Board for Long Term (Epilepsy and ICU) Monitoring (ABRET), performs video-EEG long-term monitoring, EEG studies, and other electrophysiologic studies at Children's Hospital Boston and bills for these procedures, and receives funding from the Epilepsy Foundation of America, CIMIT, NIH, PPSQ at Children's Hospital Boston, and from a career development grant from Harvard Medical School and Children's Hospital Boston. Dr. Picard is Cofounder, Chief Scientist, and Chairman of Affectiva, Inc, a company that has commercialized the MIT sensors used in this study. All other authors report no disclosures. We confirm that we have read the Journal's position on issues involved in ethical publication and affirm that this report is consistent with those guidelines.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Data S1. Methods.

Figure S1. Data collection from patients with epilepsy.

Figure S2. Electrodermal activity (EDA) and net acceleration recordings of individual generalized tonic–clonic seizure (GTCS) from seven patients.

Figure S3. Time-frequency mapping of the accelerometry signal during a tonic–clonic seizure (63 s long).

Figure S4. Example of recurrence plots for various events.

Table S1. Comparison of wrist-worn convulsive seizure detectors.

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