A wristband assessment of accelerometry and autonomic activity of epileptic patients

C Caborni*, F Onorati¹, G Regalia¹, M Migliorini¹, R Picardi²,*


*emails: cc@empatica.com or rp@empatica.com

Rationale

Electrodermal activity (EDA) is a physiological signal reflecting the activity of the sweat glands driven by the Sympathetic Nervous System. EDA and wrist acceleration (ACM) measurements can be used to automatically identify generalized tonic-clonic seizures (GTCs) [1].

Our prior work [2-3] showed that using 30 features from EDA and ACM, and a Support Vector Machine approach, it was possible to obtain a detector (SVM_30) with sensitivity (Se) of 98% and false alarm rate (FAR) of 2.02 events/day on a set of 38 GTCs from 18 epilepsy patients.

It is important to continue to test these methods on more patients, more seizures, more false-alarm-eliciting activities, and over longer periods of time.

Methods

In collaboration with top hospitals, we collected clinically labelled seizure data using video EEG (v-EEG), consisting of 192 recordings taken from 53 patients wearing an Empatica E3 or E4 wrist sensor recording EDA and 3-axis ACM (Figure 1(a)).

The data were analyzed off-line using proprietary software (Empatica, Inc.) to clean the data and extract signal features on a 10 seconds window every 2.5 seconds (overlap: 75%) (Figure 1(b)).

Next, SVM_30 was employed in order to evaluate the Se and FAR on this test set. The optimal decision threshold to discriminate between seizure and non-seizure epochs was selected by means of receiver operating characteristic curve analysis on a prior-collected training set (38 GTCs from 18 patients over 43 days).

Results

The SVM_30 classifier was tested on data from five new patients having more diverse seizures, using none of their data in the training set. The new test data consisted of 8 GTCs and 4 focal motor (FOCM) seizures from 5 patients over 378 hours (15.75 days). To further raise the difficulty, we also included test data of non-seizure wearable sensor recordings from 48 epilepsy patients over a total of 3564 hours (148.5 days) in order to mimic the realistic utilization of the wearable detector over a total of 164 days.

The classifier was able to provide an alarm before the seizure had finished in 100% of the cases, with a mean delay in the 12 cases of 29 seconds (SD=12 sec). As a percentage of the seizure duration, the detection occurred on average after 39% of the seizure had occurred. (Figure 2)

The SVM_30 automatically recognized 12/12 of the new seizures (Figure 3(a)), achieving for 164 days of recording from 53 patients, a sensitivity of 100% and FAR of 0.93 events/day. Of the 53 epilepsy patients, 40 patients (most of them) averaged less than or equal to 1 false alarm/day. Of these, 18 had no false alarms (Figure 3(b)). Six had a FAR higher than 2, while seven had from 1-2 false alarms/day.

Conclusions

In this work, the performance of an automated seizure detection system based on ACM and EDA features measured from the wrist was presented using clinical data collected from a total of 53 patients having two types of seizures.

The classifier we tested achieves a high seizure detection rate for GTC and FOCM seizures that had never been trained by the model (Se=100% on 12 new seizures) while maintaining an acceptable false alarm rate of 0.93/day on average over 164 days.

Furthermore, the method is efficiently integrated into a hardware platform to provide real-time alarms of seizures while they are occurring.

In the future, the model will be tested on data collected outside the clinic, where the test conditions are expected to be much more challenging.

References


We are grateful to Dan Friedman, Tobi Loddinlemper, Claus Ransberries, Rani Sarkis, and their teams at NYU, Boston Children’s Hospital, and Bingham & Womeans Hospital, Boston, and to Jonathan Biatelli and his teams at Emory and Childrens Healthcare of Atlanta Hospital, Atlanta, for their generous support collecting sensor data and labeling Video-EEGs.