Using Wearable Sensors for Semiology-Independent Seizure Detection - Towards Ambulatory Monitoring of Epilepsy

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***Abstract*— Epilepsy is a disease of the central nervous system. Nearly 70% of people with epilepsy respond to a proper treatment, but for a successful therapy of epilepsy, physicians need to know if and when seizures occur. The gold standard diagnosis tool video-electroencephalography (vEEG) requires patients to stay at hospital for several days. A wearable sensor system, e.g. a wristband, serving as diagnostic tool or event monitor, would allow unobtrusive ambulatory long-term monitoring while reducing costs.**

Previous studies showed that seizures with motor symptoms such as generalized tonic-clonic seizures can be detected by measuring the electrodermal activity (EDA) and motion measuring acceleration (ACC).

In this study, EDA and ACC from 8 patients were analyzed. In extension to previous studies, different types of seizures, including seizures without motor activity, were taken into account. A hierarchical classification approach was implemented in order to detect different types of epileptic seizures using data from wearable sensors. Using a k-nearest neighbor (kNN) classifier an overall sensitivity of 89.1% and an overall specificity of 93.1% were achieved, for seizures without motor activity the sensitivity was 97.1% and the specificity was 92.9%. The presented method is a first step towards a reliable ambulatory monitoring system for epileptic seizures with and without motor activity.

I. INTRODUCTION

Epilepsy is a disease of the central nervous system, with 50 million patients worldwide [1]. The most important symptom associated with epilepsy are epileptic seizures, i.e., episodic events where the patient is struck by various symptoms such as loss of consciousness or involuntary movements. Differences in clinical manifestations of epileptic seizures depend on the location of the seizure onset in the brain, i.e., the epileptogenic zone [2].

For therapy, physicians need to know if and when seizures occur. Many medical decisions depend on detailed information about the seizure type and its origin in the brain. The gold standard for the diagnosis of epilepsy is video-electroencephalography (vEEG) monitoring. A vEEG investigation usually provides the aforementioned information, allowing a diagnosis of epilepsy and a detailed seizure characterization in order to determine therapeutic options, especially in absence of a response to medication [3].

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The standard vEEG examination takes up to several days. Consequently, a patient is required to stay at hospital and to keep electrodes placed at his scalp during that time. An easier and more applicable diagnostic tool would facilitate long-term monitoring at home, reduce the burden on patients as well as the financial and medical staff expenditure and would be helpful for a first diagnosis. In cases of already diagnosed epilepsy it could serve as event monitor, especially if it is applicable both inside and outside the vEEG environment.

In previous research, various biomedical signals were analyzed and tested for applicability in home monitoring. Wearable sensor systems measuring biomedical signals were used to develop automatic detection tools. Most of the systems were based on measurements of motor activities [4], [5]. Furthermore, changes in electrodermal activity (EDA) in particular for generalized tonic-clonic seizures (GTCS) and complex partial seizures (CPS) were analyzed and showed an increased EDA amplitude [6], [7]. EDA is a measurement of the skin conductance reflecting the activity of the sympathetic nervous system [8]. Recent studies proposed that combining the measurement of EDA with acceleration (ACC) data could improve the performance of such detection systems [7].

Wearable sensor systems measuring motor activity are applicable for seizures with striking movement patterns, e.g. GTCS. For seizure types that do not show prominent movements, a motor based system would fail. It was shown that seizures with motor activity can be detected by measuring ACC and EDA.

In this study, different types of seizures, including seizures without motor activity, were taken into account. The purpose of this paper is to detect different types of epileptic seizures. The measured ACC and EDA data were analyzed in order to determine significant characteristics and differences between seizure types. We show that characteristic EDA changes can be measured for seizures with and without striking movement patterns. We propose a hierarchical seizure classification algorithm as a first step towards an ambulatory event monitor.

II. METHODS

A. Measurement Devices

The ACC and EDA signals were measured using the *Empatica E3* (Empatica Inc., Milan, Italy) wristband, which was worn bilaterally at the distal forearm. It contained a three-axes accelerometer measuring with a sampling frequency of 32 Hz. EDA was measured by applying a generated alternating current through two silver-coated electrodes placed at the

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ventral side of the distal forearm [9]. EDA data was collected with a sampling frequency of 4 Hz. A vEEG monitoring unit served as reference data.

B. Data Collection

Data collection took place at the Epilepsy Center in the Department of Neurology of the University Hospital Erlangen. The study was approved by the local ethic commission. Only patients who were regularly scheduled for a vEEG monitoring at the Epilepsy Center Erlangen with a pre-diagnosed clear cut epilepsy syndrome were asked to participate. The study data was collected additionally to the standard examination. Each patient participating in the study was informed and asked to sign consent.

The duration of the data collection varied for each patient from 24 hours to several days, depending on the length of their stay and the occurrence of epileptic seizures. The examined vEEG data, provided by the Epilepsy Center and annotated by a medical expert (B.K.), was used to determine the data of interest, i.e., time of seizure onset, duration of the seizure, EEG pattern of the seizure and a possible movement pattern during the seizure. The seizure types were grouped according to their movement patterns. Tonic-clonic seizures and seizures with hypermotor and complex motor symptoms were grouped as *predominantly motor* seizures. Dialeptic seizures and seizures with automotor and hypomotor symptoms were grouped as *predominantly non-motor* seizures.

Before and after each measurement period a temporal alignment of the sensor and the vEEG system was performed by producing an artificial artifact on the two wristbands simultaneously and manually marking the corresponding time stamp in the vEEG recording.

C. Preprocessing

EDA is a slow-moving signal that might contain motion artifacts [10]. For this reason a low pass filter was used to reduce high frequency components. Analogously to earlier studies, a cutoff frequency of 1.5 Hz was chosen [10]–[12].

The EDA signal as a measurement of the skin conductance was decomposed into two components: the tonic skin conductance level and the phasic skin conductance response [13]. The EDA signal was decomposed using *Ledalab*, a Matlab-based software that provided an implementation of the continuous decomposition analysis (CDA), an algorithm based on deconvolution [14].

D. Feature Extraction

For the feature extraction, sliding windows of 10 s with 50% overlap and 5 min with 80% overlap were used to extract features of the ACC and EDA data. 26 features were extracted with 10 s windows. 16 of these features were time, frequency and nonlinear features computed from the ACC data, already introduced in a previous study [7], [11]. Ten features proposed in different studies were determined from EDA, skin conductance level and skin conductance response data [7], [11], [15]–[17]. In order to determine changes of the signal, further 26 features indicating the difference of the value of each 10 s window feature to its value 60 s before were calculated. To obtain information about the distribution of the EDA signal and to capture low frequency components of the EDA signal, another four features were used to compute mean, variance, skewness and kurtosis in a 5 min window. Accordingly, we ended up with 56 features in total. Before training and testing, each feature was scaled to the interval [0;1] on the training and test data sets.

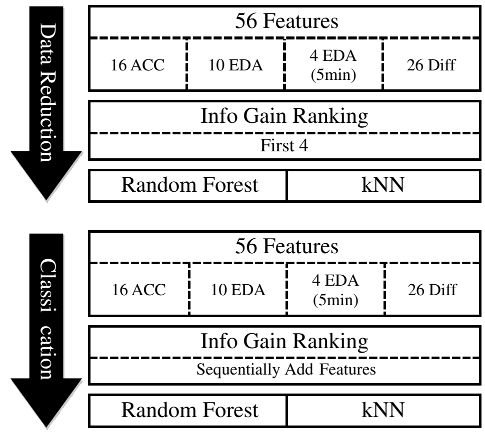

Fig. 1. Overview of the hierarchical classification approach. Firstly, data was reduced using the four best features of the information gain rank on the training set to detect possible seizures and discard non-seizure data. Secondly, with another information gain rank, the best feature set achieving the best classification results was determined.

E. Hierarchical Classifcation

A hierarchical classification system was used to firstly detect possible seizures and discard non-seizure data and secondly classify the remaining data. Figure 1 illustrates the process of the hierarchical classification, which will be described in the following.

For data reduction, features were ranked according to their information gain [18]. The first four features of the ranking were selected and used for data reduction. To handle the skewed class distribution, an oversampling technique was applied. With the applied oversampling technique, the data set used for training was repartitioned to 80% seizure and 20% non-seizure data [19], [20]. Then, a classifier deciding for a possible seizure or non-seizure sample was trained using the repartitioned data. As classifiers, the machine learning algorithms Random Forest with 10 trees [21] and k-nearest neighbor classifier (kNN) with $k = 5$ were tested [22], [23].

The remaining data set, i.e., the data classified as possible seizure, was again ranked according to the information gain [18]. This time, the result of the information gain was used to sequentially add a feature to the classifier in order to determine the feature set with the best classification results. For this approach, the kNN and Random Forest algorithm were tested again. Allowing the classifier to detect different types of seizures, different labels were used for epileptic seizures with and without motor activity. The seizure type (predominantly motor or non-motor) was determined accord-

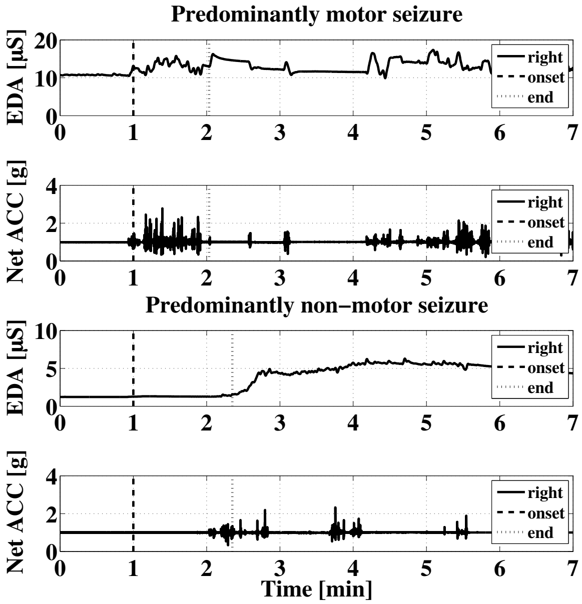

Fig. 2. Example of a predominantly motor seizure with complex motor symptoms (top) and of a predominantly non-motor seizure with hypomotor symptoms (bottom).

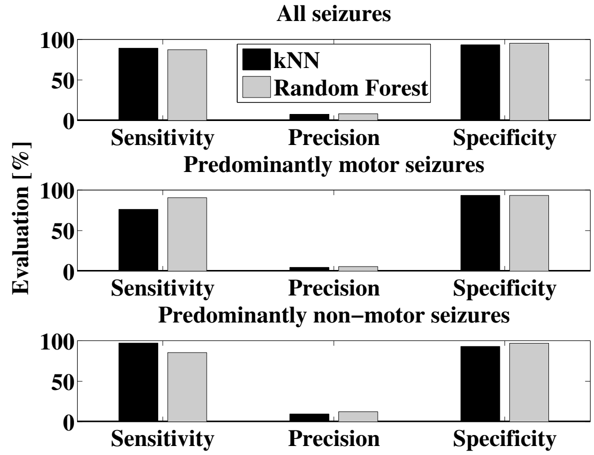

Fig. 3. Best result for Random Forest and kNN classifier. The Random Forest classifier achieved the best results with the 26 first features of the information gain rank and the kNN with the eleven first features.

ing to the video data and the course of the seizure described by the medical experts. In order to avoid losing important information of the measured signals just before or after the indicated seizure time, the signals five minutes before the seizure onset were considered and labeled as preictal and the signals five minutes after the seizure offset were considered and labeled as postictal.

F. Evaluation

In order to account for statistic variations induced by the randomness of the oversampling process, the data reduction was repeated 10 times and the average of the results for the different settings was used for comparison. For the evaluation, sensitivity, precision and specificity were estimated using an exhaustive leave-one-subject-out cross-validation [24]. The specificity and precision indicate the reliability of the detector. The sensitivity specifies how many clinical seizures were detected. A seizure was considered as detected, if any seizure label was set within the preictal, ictal or postictal phase. Measurements of the right and left side were considered separately.

III. Results

Considering the measurements on the right and left side separately, 55 epileptic seizures were measured within 540 hours. Four of eight patients had seizures with striking movement patterns (21 seizures), the remaining four patients had predominantly non-motor seizures (34 seizures).

Figure 2 depicts the changes of the EDA and ACC signal for an epileptic seizure with (top) and without motor activity (bottom).

The four best ranked features used for data reduction are the four EDA distribution features mean, variance, skewness and kurtosis. Using the kNN classifier for data reduction resulted in 58.2% remaining data, with a sensitivity of 96.4%. The Random Forest classifier reduced the data to 40.8%, with a sensitivity of 93.5%. Since it was aimed to detect all seizures, further calculations were done based on the data set with the highest sensitivity (96.4%), obtained by the kNN classifier.

Figure 3 presents the results of the second classification step. In the top plot the best results of the kNN and Random Forest classifier are displayed. A sensitivity of 89.1%, a precision of 7.5% and a specificity of 93.1% was achieved using the kNN classifier trained by the eleven first features of the information gain rank. This was the highest sensitivity obtained by the kNN classifier. The highest sensitivity of the Random Forest classifier (87.3%) with a precision of 8.2% and a specificity of 95.2% was obtained by using the 26 first features of the information gain rank.

The corresponding results for all seizures with motor activity and all seizures without motor activity are shown in the middle and on the bottom of Figure 3. The kNN classifier with eleven features detected 97.1% of predominantly non-motor seizures (9.6% precision, 92.9% specificity) and 76.2% of predominantly motor seizures (4.6% precision, 93.4% specificity). The Random Forest classifier detected 90.5% seizures with motor activity (5.6% precision, 93.3% specificity) and 85.3% without motor activity (12.3% precision, 96.8% specificity).

IV. Discussion

A visual inspection of the raw signals of EDA and ACC already indicated significant changes for predominantly motor and non-motor seizures (see Figure 2). Furthermore, it was shown that changes of the ACC and the EDA signal were different for epileptic seizures with motor activity compared to those without. Besides the expected differences in the ACC signal, there were also differences in the EDA signal. While the EDA signal of seizures with complex and hypermotor symptoms started with the seizure onset and showed an alternating curve, the changes of seizures with automotor and hypomotor symptoms started with a delay and they were characterized by a slow increase of the amplitude. Concerning the delay, it was important to consider the postictal phase. Having various different characteristics, the usage of two different classification systems, suitable for solving different classification problems, could improve the classification results.

Since the four best ranked features used for data reduction were calculated with a 5 min window and an overlap of 80%, the features for the data reduction only had to be computed every 60 s. This reduced computational costs. The volume of reduced data is still high compared to previous studies reducing data based on motor activity [11]. This might be one reason for the low precision.

The sensitivity achieved in this study is slightly better compared to a similar non-patient-specific detector, that achieved a sensitivity of 88% [7], [11]. While in the aforementioned study only one false alarm per day was encountered, we encountered a high number of false alarms [7], [11]. The false alarms decreasing the specificity and precision of the presented hierarchical classification system might be explained by several facts. One main challenge was the varying EDA signal. EDA changes occur during various daily activities and even while sleeping. For this reason there are many similarities between daily arousals and epileptic seizures. In addition, the amplitude of the changes was relatively small compared to other daily changes [11]. In previous studies it was already mentioned that using another biomedical signal that provides further significant characteristics of epileptic seizures, e.g. the heart rate, might improve the classification results [11]. Furthermore, a different classifier might improve the results.

Regarding the results for predominantly motor and non-motor seizures, it was shown that seizures without movement pattern are as good detectable as seizures with motor activity.

The proposed method does not provide the same diagnostic information that can be obtained from vEEG recordings, e.g. the location of the seizure onset. For this reason it cannot replace the vEEG monitoring. Instead, it is a first step towards a reliable long-term ambulatory monitoring system.

V. CONCLUSIONS

In this study, wearable sensors measuring EDA and ACC were used to detect epileptic seizures, including such with and without striking movement patterns. It was shown that both seizure types could be detected using EDA and ACC data. Furthermore, methods detecting predominantly motor and non-motor seizures were proposed and achieved a high sensitivity. This work is a first step towards a reliable ambulatory monitoring system for predominantly motor and non-motor seizures.

Due to a low precision, the main challenge in future will be to distinguish characteristics evoked by epileptic seizures from other daily EDA arousals. Therefore, it should be considered if another biomedical signal or a different classifier could improve the detection.

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