Using Multimodal Biosignal Data from Wearables to Detect Focal Motor Seizures in Individual Epilepsy Patients

Sebastian Böttcher*
University Medical Center Freiburg
Freiburg, Germany

Nikolay V. Manyakov
Janssen R & D, LCC
Beerse, Belgium

Nino Epitashvili
University Medical Center Freiburg
Freiburg, Germany

Amos Folarin
Mark P. Richardson
King's College London
London, United Kingdom

Matthias Dümpelmann
Andreas Schulze-Bonhage
University Medical Center Freiburg
Freiburg, Germany

Kristof Van Laerhoven
University of Siegen
Siegen, Germany
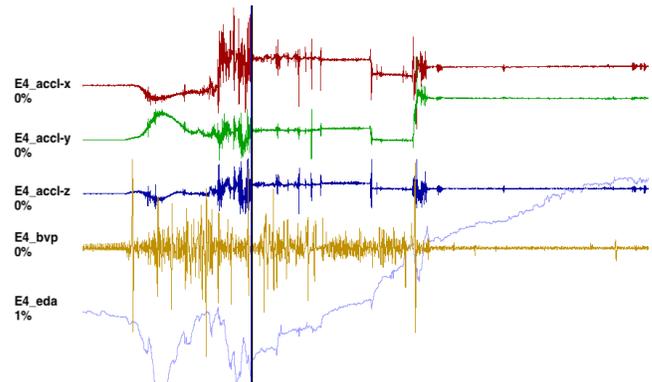
Figure 1: A video frame from our video-EEG epilepsy monitoring unit during a patient's focal motor seizure (left), with the timeseries over a 5 min segment from the patient's right wrist. The timeseries shows from top to bottom: 3D Accelerometry in x/y/z, blood volume pulse, and electrodermal activity, with the video frame's timestamp marked by the black line.

ABSTRACT

Epilepsy seizure detection with wearable devices is an emerging research field. As opposed to the gold standard, consisting of simultaneous video and EEG monitoring of patients, wearables have the advantage that they put a lower burden on epilepsy patients. We report on the first stages in a research effort that is dedicated to the development of a multimodal seizure detection system specifically for focal onset epileptic seizures. By in-depth analysis of data from three in-hospital patients with each having six to nine seizures recorded, we show that such seizures can manifest very differently and thus significantly impact classification. Using a Random Forest model on a rich set of features, we have obtained overall precision and recall scores of up to 0.92 and 0.72 respectively. These results show that the approach has validity, but we identify the type of focal seizure to be a critical factor for the classification performance.

*sebastian.boettcher@uniklinik-freiburg.de

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing**; • **Applied computing → Life and medical sciences**.

KEYWORDS

wearables, multimodal biosignals, epilepsy seizure detection

1 INTRODUCTION

Epilepsy is a chronic neurological disease that affects more than 50 million people worldwide, and is not only one of the most common neurological diseases, but also one of the oldest recognized conditions in this area. Research has identified several different types of epilepsy, which tend to manifest themselves by different symptoms and characteristically by seizures of varying severity. These seizures are typically involuntary movements of parts of or the whole body, sometimes accompanied by loss of consciousness [4, 9].

Patients with epilepsy are often treated in-hospital over the course of several days, in a video-EEG epilepsy monitoring unit,

which is the current gold standard for diagnosis and monitoring of the epileptic condition. At home however, patients are not objectively observed and usually resort to keeping a diary of seizures. These diaries often prove to be incomplete and unreliable, especially when epileptic seizures are accompanied with loss of consciousness [1, 3]. Since a 24/7 continuous video-EEG is unpractical for outpatient studies and personal monitoring, wearables have been studied as an attractive alternative to detect and log seizures of epilepsy patients in their day-to-day environment.

The few wearable devices that thus far have been used in epilepsy research are most commonly smartwatch-like devices or fitness trackers that record biosignals such as accelerometry (ACC), electrodermal activity (EDA), blood pulse via photoplethysmography (PPG), and electromyography (EMG). These biosignals have been shown to give sufficient indication towards epileptic seizures, with research focusing on monomodal and multimodal detection of Generalized Tonic-Clonic Seizures (or GTCS). GTCS are one type of seizure that involves both hemispheres of the brain and present themselves in violent bilateral muscle contractions of the whole body. These are very different from Focal Seizures (FS), which start in only one brain hemisphere and can present themselves in a number of different symptoms that are far harder to characterise. Other research has explored the detection of FS with wearable data, however a majority of these efforts have focused on detecting a specific type of FS only, often by using a single modality.

This work proposes a multimodal approach to detect Focal Seizures (FS), which has thus far been a new and underexplored avenue in epileptic seizure detection. It offers a first analysis into the challenges that lie ahead, especially in the analysis of the various subtypes of FS and the implications this holds for classification tasks in particular. In the following, the current state of the art in epileptic seizure detection with wearables is explored, followed by the introduction of a new data set of biosignal data from wearables worn by three in-hospital patients that were monitored with video-EEG in a medical epilepsy monitoring unit, along with wearable sensors. This paper focuses specifically on showing the difficulties that may arise when implementing a multimodal seizure detection pipeline for variable types of seizures, using common biosignals such as ACC, EDA and PPG. The detection of seizures from three selected patients is evaluated, and the results are analysed. Concluding, an outlook on the development of the detection pipeline is given.

2 RELATED WORK

We structure this section on research work in the detection of epileptic seizures along the two main types of seizures, Generalized Tonic-Clonic Seizures (GTCS) and Focal Seizures (FS), as most research to date has explicitly focused on one or the other. Monitoring these two types of seizures has also shown to require very different modalities.

Generalized Tonic-Clonic Seizures (GTCS). Due to the severe manifestation in body and especially limb movements, GTCS are relatively easy and straightforward to detect using standard wearable biosignals like accelerometry or electromyography (EMG). Moreover, GTCS are a significant risk factor in sudden unexpected death in epilepsy (SUDEP), raising interest in the automatic detection of this type of seizures, especially in an ambulatory setting [14].

There are various examples of GTCS detection in literature, both with monomodal and multimodal data.

One basic approach for example is evaluated by Kusmakar et. al. [7] who use accelerometry data from a wrist-worn wearable to detect short-length GTCS in 12 patients. Their approach with a support vector method and standard time domain features achieves a sensitivity of 95 % and false alarm rate (FAR) of 0.7/24 h. Halford et. al. [5] on the other hand use an upper arm wearable that records surface EMG signals on 199 patients with epilepsy. Their thresholding method detects 76 % of overall GTCS, with a FAR of 2.5/24 h. However they also distinguished between properly and improperly placed devices, reporting that among properly placed devices 100 % of GTCS were detected with a FAR of 1.4/24 h. They conclude that proper placement of the device is important. EDA and ACC signals are used for example by Poh et. al. [11] to detect 94 % of GTC seizures in a data set from 80 patients, with a FAR of 0.7/24 h. More recently, Regalia et. al. [13] also used EDA and ACC signals to detect GTCS, attaining a sensitivity of greater than 92 % with a FAR between 0.2 and 1 on varying data sets of inpatient and outpatient studies.

Focal Seizures (FS). Also known as partial seizures, FS are seizures that have their source in one of the brains hemispheres, as opposed to GTCS which spread over both. FS are therefore usually not accompanied by severe motoric reactions of the body like in GTCS, but rather manifest in a multitude of different symptoms: These can include autonomous reactions like heart rate increase (tachycardia), dyscognitive features like impaired awareness or unconsciousness, less severe motoric components, or so-called auras, which are sensory phenomenons such as deja vu sensations or dizziness. During the course of one FS, multiple of these symptoms may occur consecutively or simultaneously.

In literature, the detection of FS with wearables has been attracting more attention in the recent past. Some research studies have considered single modalities to detect FS of specific types. Jeppsen et. al. [6] for example look at heart rate variability from ECG for 17 patients, detecting 74 % of seizures with their method. Poh et. al. [10] on the other hand use an EDA sensor to analyze autonomic changes during and especially after FS and GTCS, concluding that the EDA response after GTCS is much more severe and prolonged than in FS. A different approach is taken by Vandecasteele et. al. [15], who compare wearable ECG and PPG devices in the detection performance of temporal lobe epileptic seizures, which are a type of FS. They report sensitivities of 70 % for ECG and 32 % for PPG detection, with FARs of 2.1/24 h and 1.8/24 h, respectively.

Recently, some studies have also expanded to multimodal detection of FS. Cogan et. al. [2] for example propose a multi-staged detection system that uses heart rate, arterial oxygenation, ACC, EDA and temperature data, detecting 100 % of FS in the sensor readings from nearly all 10 patients their data set consists of. However, they do not specify further what type of FS they worked with, only referring to the detected seizures complex partial, an older term for focal seizures. The work presented here is most comparable with that of Onorati et. al. [8], who use EDA and ACC data from 69 patients to detect GTCS as well as FS, comparing three different classification methods. Their best performing method reaches a sensitivity of 95 %, with a FAR of 0.2/24 h and a F-score of 0.67 in

cross-validation. However, their data set of 55 convulsive seizures only includes six focal seizures.

Among the above research works, there are several studies in literature that present monomodal and multimodal seizure detection on large data sets, however, these are often very generalized in what seizure types are included. The distinction between GTCS and FS is often made, but subtypes within FS are rarely investigated or separated in the annotation. The work presented here illustrates the breadth of FS by focusing specifically on the multimodal detection of three distinct types of focal motor seizures in three individual patients and therein identifies difficulties that may arise when analysing a larger data set of focal seizures. Furthermore, we explore a way of feature extraction that enables using multimodal data with multiple different window sizes per modality. In other studies only a single window size with a fixed overlap per modality is commonly used.

3   DATA SET

The evaluation presented here uses selected data that are taken from an ongoing clinical study. In this study, epilepsy patients that are continuously monitored in epilepsy monitoring units at two study sites (two academic hospitals) are recruited and asked to wear a wearable wristband device, the Empatica E4, and a wearable upper-arm device, the Biovotion Everion. Both sensor units are recording ACC (32 Hz/50 Hz), EDA (4 Hz/1 Hz), and PPG (64 Hz/50 Hz) data continuously. The goal of the study is to capture a variable set of seizures for a population of at least $n = 200$ patients, while recording at least one seizure for $m = 96$ patients. The study is divided across two clinical sites, King's College London (UK) and the University Medical Center in Freiburg (Germany).

The ground truth for seizure labeling is provided by a clinically trained expert, who browses through the video-EEG recordings from the epilepsy monitoring unit and manually marks seizure onset and offset, as well as timings of various seizure phases, such as tonic movement, clonic movement, tachycardia, or unconsciousness. Patients are typically recorded for stretches of 5 to 7 days, and tend to suffer from any type of epilepsy. At the time of this writing, the data set has collected data from 174 patients from both sites, with 276 complete seizures recorded from 70 patients, respectively.

3.1   Selection of three cases

For the preliminary evaluation presented here, only a select set of participants in the study is considered from a single site, as three representative cases that we wish to investigate. For each of the three patients in question, more than five FS with varying types of motoric components were recorded, and these patients were selected for their different seizure manifestations: One patient exhibits highly characteristic tonic arm movements that are clearly distinguishable on the raw ACC signal. The second patient has predominantly automatisms in their arms, which are often random movements of the limb that can be classified as neither tonic nor clonic. The third patient also has automatisms, however these are not located in the arms, but rather – more challenging for seizure detection – in the legs and also mouth region (oroalimentary). Among the three selected patients, a total of 22 seizures had motor features, and most of them also had autonomic or dyscognitive features, or
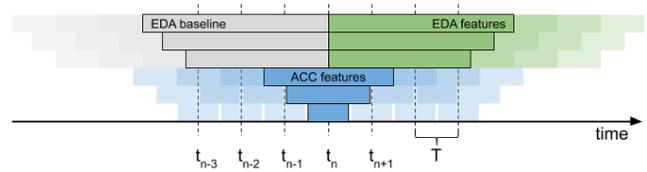
Figure 2: Graphical representation of the mixed EDA and ACC feature set used in the evaluation, with fixed feature points t_n and $T = 1$ s.

auras associated with them. Table 1 gives a concise overview of the main characteristics for the three selected patients. We focus on the ACC and EDA data from the Empatica E4 device in the following evaluation.

3.2   Feature Set

In order to be able to train a supervised model with multimodal data with differing sample rates, we chose to create a mixed modality feature set with variable window lengths per feature, but at fixed time intervals $T = t_{n+1} - t_n$. Thus, in this approach the window lengths and interval size are the determining factors of the feature set, contrary to the usual method of defining window lengths and overlap. Since it is unclear from existing literature what window lengths are best for specific modalities for epileptic FS detection, this approach gives us the opportunity to test several window lengths at the same time for later analysis of the best combination of features and window lengths. More specifically, the resulting tables of features will have values at the same time points for all modalities and all window sizes, allowing the feature data to be concatenated into one table for model training. Figure 2 shows a graphical representation of this mixed feature set.

The feature set for this evaluation consists of 141 ACC features from the time and frequency domains (divided into 40 subgroups when grouping together x, y, z, and total features), and an additional 10 EDA features, some of which are also corrected for a baseline. With window lengths of 2 s, 10 s and 20 s for the ACC features and 5 min, 10 min and 20 min for the EDA features, a total of 453 features were calculated for each fixed time point. Note the large difference in window lengths for EDA vs. ACC; Since the EDA signal is primarily analyzed for tonic activity features, and the time frame of change in EDA signals is in the order of minutes, the window lengths for EDA were chosen like this. Furthermore, for this evaluation we used the fixed time interval of $T = 1$ s between time points. To avoid feature intervals with undefined values, feature extraction is only done on sections of the data where all modalities are present, i.e. where there is a data point in all modalities for a given timestamp.

4   EVALUATION

For evaluation, the described feature set was divided into sets per seizure per participant, each containing the feature data from the time interval $[s_{start} - 55 \text{ min}; s_{end} + 55 \text{ min}]$, where s_{start} and s_{end} refer to the seizure start and end, respectively, as labeled by the clinically trained expert via the video-EEG recordings. One seizure data set thus consists of 55 min before the seizure start and after

Table 1: The selected participants for this evaluation. n = amount of seizures recorded. Seizure type are the most common types among n, where seizures can have multiple sub-types. All seizures have the "motor" sub-type, indicating motoric components during the seizure. auto. = autonomic components, like tachycardia. dyscog. = dyscognitive components, like loss of consciousness. aura = aware seizure, usually with a specific associated feeling.

P	n	Data	Seizure Type	Comment
1	6	ACC/EDA	FS motor; FS auto.; FS dyscog.	Characteristic motor seizures with tonic/clonic arm movement
2	9	ACC/EDA	FS motor; FS auto.	Motor seizures with automatisms (most with arm movements)
3	7	ACC/EDA	FS motor; FS auto.; aura	Motor seizures with only automatisms (few with arm movements)

Table 2: Mean results (after 20 repetitions) of leave-one-seizure-out cross-validation using a Random Forest model ($t = 50$). Shown are precision (p), recall (r), and F1-score (f) for both sets of experiments and the three patients we have focused on in this paper (p1, p2, and p3).

	first experiment			second experiment		
	p_1	r_1	f_1	p_2	r_2	f_2
P1	0.78	0.5	0.56	0.92	0.7	0.77
P2	0.73	0.7	0.71	0.72	0.72	0.71
P3	0.29	0.22	0.19	0.42	0.28	0.28

the seizure end, as well as the duration of the seizure itself, which for the 22 seizures of the three selected patients had a mean of 1 min 55 s. Thus, one seizure accounts for approximately 112 min of data, amounting to approximately 41 h of data for all seizures of the three selected patients. The 55 min margin was chosen due to the large EDA window sizes and characteristically long EDA response time. Typical EDA response times can last up to an hour after the actual seizure has ended [10].

On these seizure sets per individual patient, binary leave-one-seizure-out cross-validation was performed, using a Random Forest model with $t = 50$ trees. The evaluation was done sample-wise, i.e. each time point is classified as either belonging to a seizure or not. The cross-validation for each patient was repeated 20 times to give a confident idea of the Random Forest model performance. Additionally, a second round of tests was done, where the interval for the feature data now is $[s_{start} - 55\,min; s_{end}] + [s_{end} + 5\,min; s_{end} + 55\,min]$, thus excluding data from detection for 5 min after a seizure was already recognized. This can be seen as the simulation of a post-detection pause of data analysis, which prevents false positive detections resulting from large uncertainty in data following immediately after a seizure.

Before the scoring of the tests, the predicted labels are smoothed by a hysteresis function with a threshold of 10 s. Effectively, this means all consecutive positive predictions of less than 10 s are disregarded, and all consecutive negative predictions of less than 10 s within a larger positive block are still regarded as positive. The results for all tests can be found in Table 2 and will be discussed in the following.

5 DISCUSSION

Since this is a sample-wise cross-validation, the scores from this evaluation give an overview of the performance of the Random Forest model with respect to the classification of seizure status for each second in the test data sets; As opposed to event-based classification which would give an overview of the performance with respect to the classification of overall seizure events. Furthermore, since for this sample-based evaluation the train and test sets are highly unbalanced, only precision, recall and F1-score are regarded as measures. The imbalance derives from the choice of seizure data set, i.e. data for one seizure includes 55 min of negative data before and after the seizure that typically has a length of < 5 min, with a mean of 1 min 55 s for our selected seizures, or 1.7 % compared to negative data.

The performance for P1 is acceptable in data set 1, without the simulation of a post-detection pause, and increases significantly in data set 2, where 5 min of data is cut off after a seizure. This behaviour is expected, as there often are detections right after the seizure in data set 1, as can be seen in Figure 3. Especially the precision score is affected by this, as primarily false positive classifications after a seizure are avoided. For P1 the recall score also improves significantly with data set 2, showing that the detection of clear and characteristic motor FS may benefit the most from this method.

Contrarily, for P3 recall scores improve less than precision. Overall however, the seizures of P3 are not detected as good as those of P1. This is expected considering that those seizures are not significantly represented in the motion data due to the seizure manifestation in automatisms not in the arm that the device was attached to. There is no significant change in scores for P2 after post-seizure classification pause, while the overall scores of that patient are comparable to those of P1. This may indicate that for the type of automatisms this patient was exhibiting, classification is invariant to post-seizure uncertainty, or – alternatively – that there is none.

Looking at the predictions from the point of view of event recognition, most predictions are in immediate proximity to the seizure ground truth, with only few false positives. Figure 4 for instance shows that while there are some false predictions immediately after a seizure, the rest of the 55 min before and after the seizure is, correctly, free from seizure predictions. The results in Table 3 were attained from examining a single run of the cross-validation for all patients and counting the event-wise true and false positives. In these results, a true positive is any ground truth event that overlaps with a predicted event, and a false positive is any predicted event that does not overlap with a ground truth event. The False Alarm Rates (FARs) for each patient are rough estimates, that were obtained by counting the false positives over the whole seizure data set, i.e. $FAR_{est} = n_{fp}/(112\,min \cdot n_{sz})$. These results show that even this basic Random Forest approach can already reach a performance comparable to that of current literature when regarding
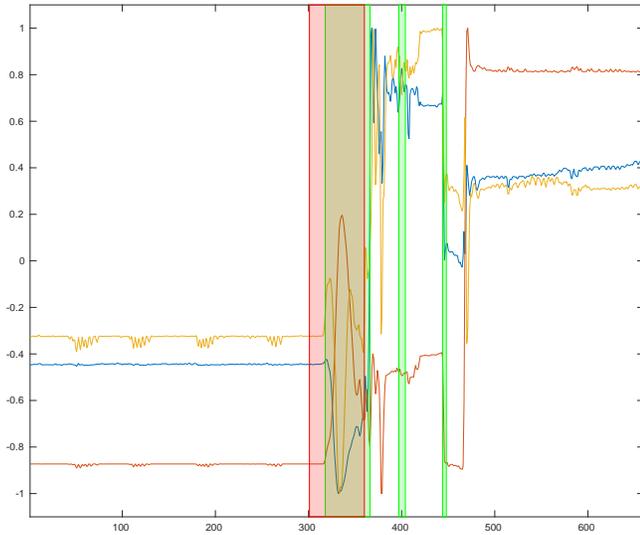
Figure 3: Example of the recognition performance on one seizure of P1, from a single cross-validation run on data set 1. Shown are the ACC means of each axis over a 2 s window. Overlay areas in red depict the ground truth, those in green mark the predictions. The interval spans 5 min before and after the seizure.
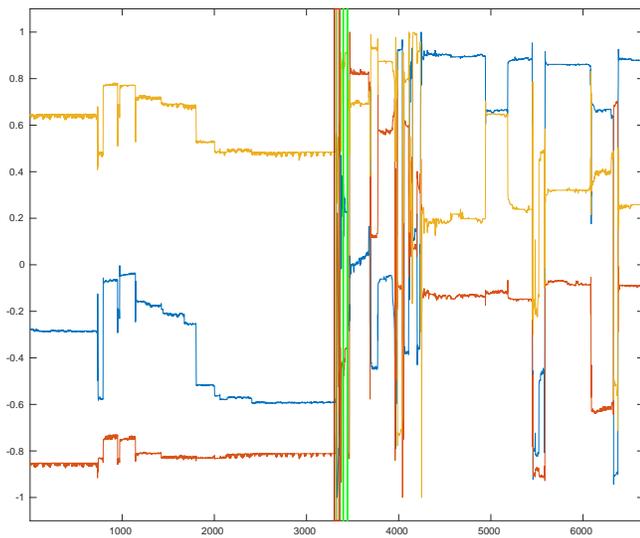
Figure 4: Timeseries of the data from the same seizure event as in Figure 3, but within a larger interval that includes 55 min before and after the seizure. This shows that the only positive predictions are in the immediate vicinity of the ground truth seizure (shown as green and red areas in the center of the timeseries plot).

only sensitivity, while estimated false alarm rates are still high, but may in reality be lower when testing on a whole patient recording.

However, the purpose of this paper is not to compare performance to the current state of the art, but to analyse the challenges in

Table 3: Event-based results for a single run of the cross-validation. TP = true positives, FP = false positives. False alarm rates (FAR) are rough estimates, calculated from the number of FP over the whole duration of the seizure data sets combined, for each patient.

	TP (%)	FP	estimated FAR
P1	6/6 (100)	2	4.3/24 h
P2	7/9 (78)	2	2.9/24 h
P3	3/7 (43)	11	20.2/24 h

the multimodal classification of epileptic focal seizures, and specifically those with motor features. These motor features can manifest themselves in many different ways. As the selection of patients in this work shows, there are motor features that are not captured by data from a single wearable. Even with multimodal ACC and EDA data, seizures that manifest themselves for example in a limb that the wearable is not directly attached to may be missed. While an additional modality like features from PPG may help with this, it is essential that the wearable collecting data is attached to the body part that the seizure is most predominantly located in, with respect to individual patients.

Post-seizure movement is another factor that makes some FS difficult to detect accurately. Especially in a hospital environment, patients may move in a way that makes accelerometry models less accurate, for example due to nurse intervention. A further modality next to ACC may help with this, but the large timeframe in which EDA changes happen make it less ideal for that specific purpose. One way to counteract this is also to stop looking for seizures for some time after one was already detected, which is shown here to help with detection accuracy. Furthermore, multiple detections that are located within a certain time frame should be counted as one event, to reduce false alarm rates.

Lastly, due to the nature of epileptic seizures and their infrequent occurrence, the available data is highly imbalanced towards the negative class. The evaluation shown here tries to alleviate this problem somewhat, by segmenting out the seizures within a certain time interval. Yet, other measures could be taken to counteract the imbalance. For example, data during sleep may be cut out by looking for periods of very little activity in accelerometry data. In the end however, this problem remains somewhat unsolved in seizure detection with wearable data.

6 CONCLUSIONS

We have presented in this paper findings from ongoing work that focuses on the multimodal detection of focal seizures (FS) from wearable sensor data. We argue in this paper for such a multimodal approach by examining the data from three patients which exhibit different types of FS, showing that these manifest themselves very differently in both the sensor signals and classification performance measures. This heterogeneity will inherently hinder accurate recognition of any FS from wearable assessment data, and needs to be taken into account when designing a learning model for seizure detection.

While the experiments shown here are promising for further work, it is clear that this is only a first step in building a system

for multimodal detection of FS using biosignal data from wearables. The results in Table 2 show that while this approach may work for individual patients with characteristic, motoric seizure manifestation, it may not work for patients exhibiting other seizure types. Furthermore, comparing the results of the first and second experiments shows that ignoring a certain amount of time after a seizure detection can significantly improve the detection performance. While the evaluation shown here is based on sample-wise scoring, a fully implemented system has to be based on events, i.e. consecutive positive predictions must be consolidated into one seizure event, which would be scored as a hit if it has some overlap with a ground truth event. An outlook on such a system is given by the results in Table 3, showing the performance of the presented system when scored on an event basis.

The selection of three specific patients with focal motor seizures illustrates some core problems that a more advanced detection system needs to deal with. In the future, the cross-patient seizure detection of such a system needs to be evaluated as well. While individual based detection is one possible approach, the need for generalized models is apparent, and current state-of-the-art moves in the direction of individual-invariant models. Furthermore, a system's performance on different types of seizures like autonomic or dyscognitive FS needs to be evaluated. Therefore, PPG features need to be considered in addition to the ACC and EDA features already implemented. Multi-class classification of seizure types, and specifically recognition of phases within focal seizures are reasonable goals that may be achieved by a detection system that takes into account the high variance in focal seizure manifestations shown in this paper.

ACKNOWLEDGMENTS

DISCLAIMER

This communication reflects the views of the RADAR-CNS consortium and neither IMI nor the European Union and EFPIA are liable for any use that may be made of the information contained herein.

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