Onset Detection of Epileptic Seizures From Accelerometry Signal

Shitanshu Kusmakar, Chandan K. Karmakar, Bernard Yan, Terence J.O'Brien, Ramanathan Muthuganapathy and Marimuthu Palaniswami

***Abstract*— Epileptic seizures are the result of any abnormal asynchronous firing of cortical neurons. Seizures are abrupt and pose a risk of injury and fatal harm to the patient. Epilepsy affects patients quality of life (QOL) and imposes financial, social, and physical burden on the patient. The unpredictability associated with seizures further adds to the reduced QOL and increases dependence on caregivers and family members. A seizure triggered alarm system can reduce the risk of seizure-related injuries and aid in improving patient's QOL. This study presents real-time onset detection of seizures from accelerometry signal. An automated approach based on statistical machine learning is employed to learn the onset of seizures. To search for the optimal parameter that simultaneously maximizes detection sensitivity while minimizing false alarms and latency, the epoch length is varied from $t = \{1, ..., 10s\}$. Linear and non-linear time-varying dynamical patterns were extracted from every epoch using Poincaré plot analysis. The correlation patterns were learned using a kernalized support vector data descriptor. The preliminary analysis on accelerometry data collected from 8 epileptic patients with 9 generalized tonic-clonic seizures (GTCS) shows promising results. The proposed algorithm detected all GTCS events (sens: 100%, FAR: $1.09/24h$) at $8s$ from onset. The proposed algorithm can lead to a sensitive, specific, and a relatively short-latency detection system for real-time remote monitoring of epileptic patients.**

I. INTRODUCTION

Epilepsy affects approximately 1% of the global population and approximately 50 million people are currently living with epilepsy [1]. Despite of the rapid advances in drug discovery and alternate treatment strategies for epilepsy, a large number of patients continue to have seizures. Patients with poor control of seizures lead a poor quality of life (QOL) due to passive coping styles, social consequences, and level of independence [2]. In addition, patients with poor control of seizures are more prone to epilepsy associated morbidity and mortality. Recent research, indicates that appropriate intervention following a seizure can reduce the risk of injury and harm [3]. In this study, we describe a framework of an algorithm for real-time onset detection of generalized tonic-clonic seizures (GTCS) from accelerometry signal. The proposed technique can provide a wearable remote monitoring seizure triggered alarm system.

S. Kusmakar and M. Palaniswami are with the Department of Electrical and Electronic Engineering, The University of Melbourne, Vic - 3052, Australia. skusmakar@student.unimelb.edu.au, palani@unimelb.edu.au

C. K. Karmakar is with Department of Electrical and Electronic Engineering, University of Melbourne, Vic - 3052, Australia and also with Deakin University Geelong, Vic - 3125, Australia. karmakar@unimelb.edu.au

B. Yan and T. O'Brien are with the Melbourne Brain Centre, Royal Melbourne Hospital, Dept. of Medicine, The University of Melbourne, Vic - 3052, Australia. Bernard.Yan@mh.org.au, obrientj@unimelb.edu.au

R. Muthuganapathy is with the Department of Engineering Design, Indian Institute of Technology Madras, India. mraman@iitm.ac.in

Accelerometers have been previously used in automated detection of GTCS events however, most systems suffer from high FAR or high latencies or both [4]. Several groups have also investigated the use of multi-modality systems to improve the specificity of the seizure detection system [5] [6]. However, these systems are optimized to detect the clonic phase of GTCS events and thus, result in a higher detection latency. Conradsen *et. al.* [7] proposed an algorithm for onset detection of GTCS event using surface electromyography (sEMG) zero-crossing rate. They detected all GTCS events from 11 patients with a mean detection latency of $13.7s$ while, the false alarm rate (FAR) was $1/24h$. Other approaches on onset detection of seizures are based on utilizing electroencephalography (EEG) or intracranial EEG (iEEG) recordings [8]. The best performing system are based on iEEG (sens: 97%, FAR: $0.6/24h$, latency: $5s$) [9] or EEG with 60 scalp electrodes (sens: 100%; FAR: $0.55/24h$; latency: $4s$) [10]. However, iEEG is an invasive procedure and is associated with a high risk of infection while, systems based on sEMG and EEG are susceptible to movement artifacts and can be uncomfortable during continuous use [4].

In this study, we presents a generic non-patient specific algorithm for real-time onset detection of tonic-clonic seizures using wrist-worn accelerometer based device. The algorithm detects seizures by examining the correlation patterns derived from short-length signals characterizing the onset of events. The developed algorithm was tested on accelerometer data recorded from 8 patients undergoing video-electroencephalography monitoring (VEM). The preliminary results showed a higher seizure detection sensitivity and a lower detection latency in comparison to the state-of-art non-EEG ambulatory monitoring systems.

II. METHODS

The onset detection of seizures is framed as a binary classification problem that involves differentiation of seizure activity from non-seizure activity. Continuous monitoring accelerometer devices record a vast amount of daily living activities. Therefore, an algorithm was developed in the first stage to discard no movement or subtle movement activities. In the second stage, the epoch's are classified into seizure and non-seizure activities using Poincaré derived descriptors and kernalized support vector data description (SVDD) classifier. The following sections presents the details of the two stage seizure detection algorithm.

A. Experimental Design and Data Collection

A wrist-worn accelerometer based device was used to collect movement data from patients undergoing VEM monitoring at Melbourne Brain Center, Royal Melbourne Hospital, Melbourne, Australia. The device contains a 3D MEMS accelerometer sensor that continuously recorded movement activities with a sampling frequency of $50Hz$. Patients with a history of convulsive seizures were recruited in the study and every patient signed a informed consent form. A human research ethics approval was obtained from the Melbourne Health, Human Research Ethics Committee (HREC Project 300.259). The details of the collected data is shown in Table I.

TABLE I: Overview of the dataset

Patient	Age	Gender	#GTCS	Record duration
P_1	28	F	1	$86:17:53$
P_2	35	F	1	$93:36:17$
P_3	20	M	1	$64:32:54$
P_4	51	M	1	$86:00:19$
P_5	32	F	1	$87:17:21$
P_6	22	M	1	$64:53:48$
P_7	20	M	2	$85:38:30$
P_8	19	M	1	$50:28:09$
Total (#8 patients)	28.37 ± 10.23	3:5 (F:M)	9	$618:45:15$

The record duration is shown in $hh:mm:ss$ format, F: female, M:male.

B. Stage I: Detecting events

In real-time detection of seizures the parameter that controls the detection sensitivity and the false alarms is the number of consecutive epoch's required to be classified as seizure activity [5]. Whereas, the latency in detection of seizures is determined by the first epoch that is classified as seizure activity when compared to the onset of the seizure. Seizures are extremely heterogeneous in nature therefore, it is difficult to simultaneously maximize seizure detection sensitivity while, minimizing the false alarms and latency in detection. However, if the onset of seizure activity itself can be detected, and reliably differentiated from normal activity the trade-off between detection sensitivity, FAR and latency can be minimized. Therefore, in our search to find the optimal parameters such that onset of tonic-clonic seizures can be reliably detected we vary the epoch length used for analysis of the time-series data from $t = \{1, ..., 10s\}$.

In our previous work [11], we proposed the use of activity filtering strategies for data reduction. In this work we present a modified filtering approach that allows accurate detection of activities. The first step in the activity filtering is to discard the data corresponding to no movement or subtle movement activities. Epoch's of $t's$ with 50% overlap are considered and variance of the resultant ($r = \sqrt{a_x^2 + a_y^2 + a_z^2}$) accelerometry signal is calculated. Epoch's with variance lesser than $40mg$ are discarded from further analysis.

After the thresholding step, a 6^{th} order Butterworth bandpass filter with cutt-off frequency 2-25Hz is applied to remove any spurious spikes. A 256 point DFT is then calculated for the filtered epoch's. Epoch having a normalized highest peak magnitude above 0.009 were considered for further analysis. Further, it was noticed that seizures have a sustained activity which is not the cases in majority of normal movements. Therefore, a threshold based on the activity is applied (1) and thus, the name activity filter.

$$A_n = \frac{1}{10.F_s} \sum_{n=t_1}^{t_2} |sgn(\Delta_n r[n])| \tag{1}$$

where, A_n is the activity in the n^{th} epoch, F_s is the sampling frequency, $t_1 = (n-1).\frac{W_{len}}{2}.F_s + 1$, $t_2 = (n+1).\frac{W_{len}}{2}.F_s$, $W_{len} = t$ the window size, $\Delta_n r[n]$ is the approximate partial derivative ($\Delta_n r = r[n+1] - r[n]$), and sgn is the *signum* function.

In our previous work [11], we combined all the epoch's that were $\leq 20s$ apart as a single event. However, in this work we aim to distinguish the onset of seizure and normal activity. Therefore, we consider only the first epoch that characterizes the onset of an event while, all consecutive epoch's that are $\leq 20s$ apart are discarded as epoch's belonging to the same event. Thus, after activity filtering step we have several epoch's of length $t's$ that characterize the onset of movement activities. Now, the aim is to classify every epoch into normal or seizure activity.

C. Stage II: Feature Extraction and Classification

1) Feature Extraction and Selection: Our algorithm is based on detecting the short-term evolution of any movement activity. Therefore, the features have to be robust enough to detect hidden correlation patterns in short term signals. Poincaré plot analysis has shown to be an effective approach for analysis of short length signals [12]. Poincaré plot is a visual technique to represent a time-varying sequence as a $2D$ scatter plot in the Cartesian plane at embedding $lag = m$. The plot can be quantified by fitting an ellipse and standard parameters like SD_1, and SD_2 that represent the minor and the major axis of the ellipse can be derived as follows:

$$SD_1^2 = \frac{1}{\sqrt{2}} Var\big(r(n) - r(n+1)\big) \tag{2}$$

$$SD_2^2 = Var\big(r(n) + r(n+1) - 2\bar{r}\big) \tag{3}$$

where, $r(n)$ is the resultant accelerometer time series, $r(n+1)$ represents the sequence at $lag = 1$, and $\bar{r} = E[r(n)]$.

In addition to standard Poincaré descriptors we have also extracted non-linear descriptors like, $ratio = \frac{SD_1}{SD_2}$ and CCM [13].

2) Classification Algorithm: Seizures are rare events thus, long-term continuous monitoring accelerometer data is representative of a class imbalanced data. In this work, we employ kernalized support vector data description that can handle the class imbalance in the data [14]. Given a training set $X = \{x_1, x_2, ..., x_n\} \subset \mathbb{R}^d$, SVDD builds a hyperspherical description around the events of the majority class and any event lying outside the description is classified as an anomaly or outlier. The optimization problem in SVDD

can be described as the minimization of the radius of the hyperspherical decision boundary. To achieve this we require the center a and the radius R of the hypersphere and the optimization problem can be expressed as:

$$\min_{R,c,\xi_i} \quad R^2 + C\sum_{i=1}^{n}\xi_i$$
$$s.t \quad ||x_i - a||^2 \leq R^2 + \xi_i, \quad \forall \quad \xi_i \geq 0 \tag{4}$$

where, ξ_i is the slack term, and C is the cost of misclassifying an event.

To solve for the center a and the radius R, we use the Lagrange multiplier technique to obtain the dual programing form:

$$\min_{\alpha} \quad \sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j x_i^T x_j - \sum_{i=1}^{n}\alpha_i x_i^T x_i \tag{5}$$

$$s.t \quad \sum_{i=1}^{n}\alpha_i = 1 \quad 0 \leq \alpha_i \leq C \tag{6}$$

The hypersphere center a and radius R can then be determined using the Lagrange multiplier α_i. Only samples x_i with $\alpha_i > 0$ are needed to define the description and are termed as support vectors of the description $(SV's)$.

$$a = \sum_{i=1}^{n}\alpha_i x_i \tag{7}$$

$$R^2(x_{SV}) = x_{SV}^T x_{SV} - 2\sum_{i=1}^{n}\alpha_i x_{SV}^T x_i + \sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j x_i^T x_j \tag{8}$$

3) Model Estimation and Validation: A generic non-patient specific system will be an ideal solution as it can be used by any patient. Therefore, we performed the model estimation and validation in a leave-one-patient-out (LOPO) approach. In LOPO approach, data corresponding to one patient is randomly left out while, the data from the rest of the patients is used for training the classifier. Let the data corresponding to all patients be represented by T_{total}, and the data corresponding to the left out patient be P_{LO}. The training data will then be represented by T_{total} - P_{LO}. For, tunning the SVDD parameters (C, and kernel parameter γ) two-third of the training set was randomly chosen as learning set and one-third as validation set. This procedure was repeated in ten randomizations and the best model is selected based on the cost function (9).

$$cost(\nu,\gamma) = -w \times sensitivity(\nu,\gamma) - ppv(\nu,\gamma) \tag{9}$$

A higher weight ($w = 2$) is placed on the sensitivity as missing a seizure is more costly. The model parameters with the least cost are then used to test the performance on the left-out patient P_{LO}.

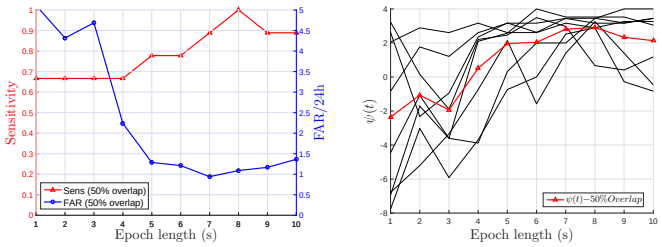
4) Selection of Optimum Parameters: Assuming that variation of sensitivity and FAR with epoch length ($t = \{1, ..., 10s\}$) follows a exponential distribution, we define a function $\psi(t)$ to select the optimum epoch length. We select the maxima of $\psi(t)$ as the optimum operating point.

$$\max_{t} \quad \psi(t) = W_1 \times Sens(t) - W_2 \times FAR(t) \tag{10}$$
$$where \quad \psi(t) \in (-\infty, 0)$$

where, $W_1 = 4$ and $W_2 = 1$ are weights that balances the trade-off between sensitivity and FAR.

III. Results and Discussion

In this preliminary study, we ought to investigate onset detection of tonic-clonic seizures from accelerometry signal. We present the evaluation of a real-time seizure onset detection algorithm on data collected from 8 patients who had 9 tonic-clonic seizures during the monitoring period. In the search of the optimum epoch length a detector was developed corresponding to every epoch size of $t's$. The classification performance of the system is then evaluated for all epoch length ($t = \{1, ..., 10s\}$) in term of sensitivity and FAR, as shown in Fig. 1.



(a) Variation of sensitivity and FAR with epoch length

(b) Variation of $\psi(t)$ with epoch length

Fig. 1: (a) The performance of the proposed approach in terms of seizure detection sensitivity ($red\ (-\Delta-)$ curve) and FAR ($blue\ (-\circ-)$ curve) corresponding to different epoch lengths. (b) The variation of function $\psi(t)$ with epoch length as shown for individual patients and the mean variation over all patients as shown in ($red\ (-\Delta-)$ curve). The optimum operating point corresponds to an epoch length of $8s$ that corresponds to a detection latency of $8s$.

The optimum parameters for onset detection of seizures are the ones that allows simultaneous maximization of sensitivity while minimizing FAR. The optimum epoch length corresponds to $t = 8s$ as seen from Fig. 1b, which corresponds to mean sensitivity of 100% and an FAR of $1.09/24h$. In addition, 7 of 9 tonic-clonic seizures could be detected at $5s$ from onset which shows the efficacy of the proposed approach. The lowest false alarm corresponds to an epoch length of $7s$, which resulted in a total of 23 false alarms (FAR: $0.94/24h$) and a sensitivity of 0.88 (detected 8 of 9 tonic-clonic seizures). Further, the sensitivity of the algorithm increases with the epoch length until $t = 8s$ and starts to decrease as the epoch length is increased further. A possible explanation for the decreases in sensitivity after $t = 8s$ can be attributed to the physiological phenomenon of motor manifestation in GTCS events. Tonic-clonic seizures start with a tonic phase that involves stiffing movements and

lasts a few second before the clonic phase. The duration of the tonic phase varies across patients and among different seizures of the same patient. Therefore, as the epoch length is increased the correlation among Poincaré derived patterns decreases as the epoch length would have exceeded the tonic-phase and involves two distinct phases with no correlation. This also explains why, existing seizure detection systems have high latencies as they are sensitive to clonic phase of GTCS events.

The LOPO validation results corresponding to the epoch length of $t = 8s$ are shown in Fig. 2. The proposed algorithm detected all GTCS events with 30 false alarms across 8 patients. Patient P_2 had the highest FAR of $3.58/24h$ (13 false alarms) while, the rest of the patients had an FAR significantly lesser than or equal to the mean FAR of $1.09/24h$ (Fig. 2). On reviewing the video recording for P_2 it was observed that movements corresponding to restlessness like continuously changing postures while lying down, swinging and crossing arms contributed to false alarms. In future studies activities causing false alarms can be modeled to incorporate additional filter in the activity filtering step.

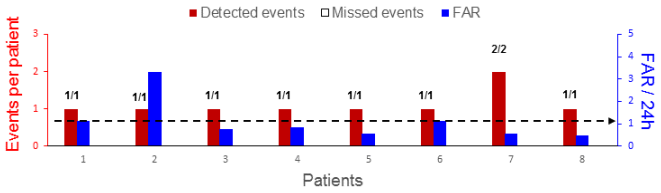


Fig. 2: The detected events and the FAR per patient, shown for epoch length of $t = 8s$. The algorithm detected all GTCS events and the FAR per patient is lesser than or equal to mean FAR (shown by $(--)$), except for patient P_2.

The results of this preliminary study indicates that onset of tonic-clonic seizures can be detected from accelerometry signal. The key to our detectors high accuracy is the robust feature set that captures the short-time evolution of seizure activity as recorded by a wrist-worn accelerometer sensor.

TABLE II: Comparison of the proposed algorithm with state-of-art non-EEG seizure detection systems.

Author	Sensor¶	Sensitivity (%)	FAR¶	Latency (s)
Milošević et. al. [6]	2 ACM + 2 sEMG	91	1	10.5
Poh *et. al.* [5]	1 ACM + 1 EDA	94	0.74	31.4
Conradsen *et. al.* [7]	1 sEMG	100	0.96	13.7
Proposed Approach	1 ACM	100	1.09	8

¶ ACM: accelerometer sensor, EDA: electrodermal activity, sEMG; surface electromyography; FAR: false alarms per $24h$.

In comparison to the existing state-of-art ambulatory monitoring systems [5] [7] [6], our algorithm results in a comparable overall performance (sens: 100%; mean FAR: $1.09/24h$) with a much lower detection latency of $8s$ (Table II). The results indicate the potential of the proposed approach however, the approach has to be tested on a larger patient cohort. In addition, the generalizability in terms of false alarms has to be evaluated on patients without seizures.

IV. Conclusion

In this study we have demonstrated the feasibility of early and accurate real-time detection of tonic-clonic seizure onset from accelerometry data. The algorithm detected all 9 tonic-clonic seizures at $8s$ from onset with a mean FAR of $1.09/24h$. The proposed algorithm will enhance the utility of wearable accelerometer based devices in real-time monitoring of epileptic patients, especially when early detection has to be balanced with low false alarm rate.

References

[1] World Health Organization, "Epilepsy: Fact sheet," http://www.who.int/mediacentre/factsheets/fs999/en/, February 2017.

[2] A. Jacoby, D. Snape, and G. A. Baker, "Determinants of quality of life in people with epilepsy," *Neurologic clinics*, vol. 27, no. 4, pp. 843–863, 2009.

[3] O. Devinsky, T. Spruill, D. Thurman, and D. Friedman, "Recognizing and preventing epilepsy-related mortality a call for action," *Neurology*, vol. 86, no. 8, pp. 779–786, 2016.

[4] A. Ulate-Campos, F. Coughlin, M. Gaínza-Lein, I. S. Fernández, P. Pearl, and T. Loddenkemper, "Automated seizure detection systems and their effectiveness for each type of seizure," *Seizure*, vol. 40, pp. 88–101, 2016.

[5] M.-Z. Poh, T. Loddenkemper, C. Reinsberger, N. C. Swenson, S. Goyal, M. C. Sabtala, J. R. Madsen, and R. W. Picard, "Convulsive seizure detection using a wrist-worn electrodermal activity and accelerometry biosensor," *Epilepsia*, vol. 53, no. 5, pp. e93–e97, 2012.

[6] M. Milošević, A. V. de Vel, B. Bonroy, B. Ceulemans, L. Lagae, B. Vanrumste, and S. V. Huffel, "Automated detection of tonic clonic seizures using 3-d accelerometry and surface electromyography in pediatric patients," *IEEE Journal of Biomedical and Health Informatics*, vol. 20, no. 5, pp. 1333–1341, Sept 2016.

[7] I. Conradsen, S. Beniczky, K. Hoppe, P. Wolf, and H. B. Sorensen, "Automated algorithm for generalized tonic–clonic epileptic seizure onset detection based on semg zero-crossing rate," *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 2, pp. 579–585, 2012.

[8] S. Ramgopal, S. Thome-Souza, M. Jackson, N. E. Kadish, I. S. Fernández, J. Klehm, W. Bosl, C. Reinsberger, S. Schachter, and T. Loddenkemper, "Seizure detection, seizure prediction, and closed-loop warning systems in epilepsy," *Epilepsy & behavior*, vol. 37, pp. 291–307, 2014.

[9] A. Kharbouch, A. Shoeb, J. Guttag, and S. S. Cash, "An algorithm for seizure onset detection using intracranial eeg," *Epilepsy & Behavior*, vol. 22, pp. S29–S35, 2011.

[10] G. R. Minasyan, J. B. Chatten, M. J. Chatten, and R. N. Harner, "Patient-specific early seizure detection from scalp eeg," *Journal of clinical neurophysiology: official publication of the American Electroencephalographic Society*, vol. 27, no. 3, p. 163, 2010.

[11] J. Gubbi, S. Kusmakar, A. Rao, B. Yan, T. O'Brien, and M. Palaniswami, "Automatic detection and classification of convulsive psychogenic non-epileptic seizures using a wearable device," *IEEE Journal of Biomedical and Health Informatics*, vol. PP, no. 99, Jun 2015.

[12] S. Kusmakar, C. K. Karmakar, B. Yan, T. J. O'Brien, R. Muthuganapathy, and M. Palaniswami, "Detection of generalized tonic-clonic seizures using short length accelerometry signal," in *Engineering in Medicine and Biology Society (EMBC), 2017 39th Annual International Conference of the IEEE*. IEEE, 2017, pp. 4566–4569.

[13] C. K. Karmakar, A. H. Khandoker, J. Gubbi, and M. Palaniswami, "Complex correlation measure: a novel descriptor for poincaré plot," *Biomedical engineering online*, vol. 8, no. 1, p. 1, 2009.

[14] D. M. Tax and R. P. Duin, "Support vector data description," *Machine learning*, vol. 54, no. 1, pp. 45–66, 2004.