Detection of Generalized Tonic-Clonic Seizures Using Short Length Accelerometry Signal

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***Abstract*— Epileptic seizures are characterized by the excessive and abrupt electrical discharge in the brain. This asynchronous firing of neurons causes unprovoked convulsions which can be a cause of sudden unexpected death in epilepsy (SUDEP). Remote monitoring of epileptic patients can help prevent SUDEP. Systems based on wearable accelerometer sensors have shown to be effective in ambulatory monitoring of epileptic patients. However, these systems have a trade-off between seizure duration and the false alarm rate (FAR). The FAR of the system decreases as we increase the seizure duration. Further, multiple sensors are used in conjugation to improve the overall performance of the detection system. In this study, we propose a system based on single wrist-worn accelerometer sensor capable of detecting seizures with short duration ($\geq 10s$). Seizure detection was performed by employing machine learning approach such as kernelized support vector data description (SVDD). The proposed approach is validated on data collected from 12 patients, corresponding to approximately $966h$ of recording under video-telemetry unit. The algorithm resulted in a seizure detection sensitivity of 95.23% with a mean FAR of $0.72/24h$.**

I. INTRODUCTION

Epileptic seizures are caused due to a asynchronous firing of neurons. This burst of electrical activity can be restricted to a part or can spread to the entire brain. Epileptic seizures are characterized by their unpredictable nature and can occur at anytime. Seizures can be convulsive involving convulsions of a part or the complete body thus, convulsive seizures have a higher risk of injury or harm to a person during a seizure event. Generalized tonic-clonic seizures (GTCS) have shown to be the major contributor to sudden unexpected death in epilepsy (SUDEP) [1]. Thus, creating a need for monitoring patients with epilepsy in their own environment. Various ambulatory monitoring devices have been proposed earlier [2]. However, devices based on accelerometry have gathered more interest as they are less obtrusive and are not susceptible to movement artifacts or the discomfort due to continuous use of electrodes as might be the case in systems based on electroencephalography (EEG), surface electromyography (sEMG) and electrocardiography (ECG) [3].

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Seizure detection systems have shown varying performance for detection of GTCS events across different studies [4] [5] [6]. The minimum seizure duration varied from 10-60s across the studies. However, as the minimum duration of the seizures to be detected is increased, the seizures with duration lesser than the minimum duration will be missed by the system. This seizure duration is also related to the false alarm rate (FAR) of the system [6]. Similarly, a relationship exists between the number of accelerometer sensors and overall performance. As the number of sensors increases the overall performance of the system increases [6]. However, for an ambulatory monitoring system it is important that it offers no hindrance and is comfortable to wear over long duration especially during nights, as an epileptic person is more susceptible to injury in an unwitnessed seizure. Thus, a system with minimum number of sensors would be an ideal system as it will be more comfortable for the patient.

In this study, we have proposed a seizure detection system based on single-wrist worn accelerometer sensor. The minimum seizure duration is kept at $\geq 10s$ therefore, the system is capable of detecting all seizures with duration $\geq 10s$. GTCS events are generally accompanied with unconsciousness and the person might need immediate help from a caregiver in case of an event. Therefore, it is important to detect all seizures irrespective of their duration. A novel algorithm for automated detection of GTCS events is presented here. A new set of time domain features with advanced learning technique like kernalized support vector data description (SVDD) is used [7]. The algorithm is developed and tested on data collected from 12 patient with GTCS.

II. METHODS

Ambulatory monitoring accelerometer based devices collects a high volume of data. Thus, pre-processing steps are important for systems based on supervised learning. Seizures are rare event and the accelerometry data is dominated by non-seizure moves. Thus, accelerometry data is representative of an imbalanced data. Algorithms that can handle the imbalance in the data will be more suitable to seizure detection problem as conventional statistical classifiers are based on optimizing the overall accuracy which can even be high if the events of minority class are misclassified. Cuppens *et. al.* [8] proposed an algorithm based on modeling the non-seizure moves. They used a manual threshold to characterize events that are outliers as seizures. In this study, we have proposed an automated algorithm based on kernalized SVDD that can handle imbalanced data. A leave-

one-patient-out (LOPO) approach is used for training the classifier.

A. Data Collection

Patients with history of epileptic seizures admitted to the video-telemetry unit of the Royal Melbourne Hospital in Melbourne, Australia were included in the study. Patients with absence seizures and patients with severe psychological disorder in addition to patients with intracranial monitoring were excluded from the study. All the patients were requested to sign an informed consent form to participate in the study. An ethical approval for the study was obtained from the Melbourne Health, Human Research Ethics Committee at the Royal Melbourne Hospital (HREC Project 300.259). Two devices with MEMS accelerometer sensor with a sensitivity of $\pm 2.5g$ were strapped to both the wrist of the patient. The devices were time synchronized with the video-telemetry unit and the data was collected for the whole duration of video-telemetry recording. A total of 12 patients with 21 GTCS events were recorded. All events with duration $\geq 10s$ were included in the study. The data was annotated for supervised learning by expert epilepsy scientists.

B. Pre-Processing

The pre-processing steps are extremely important to prepare the data for supervised learning, considering the large volume of the recorded movement data. The 3D accelerometer data is collected with a sampling frequency of $50Hz$. The data is first filtered using a 6^{th} order Butterworth low pass filter with 25Hz as the cutoff frequency. The cutoff frequency has been selected in consultation with the clinical experts. The data is then filtered using a 6^{th} order Butterworth high pass filter with 1Hz as the cutoff frequency to remove the effect of static gravity. After these filtering steps, the resultant accelerometer signal is calculated in short time windows of $10s$ with 50% overlap. A threshold of $0.2g$ is then used to discard movement data as obvious non-seizure move. The movement data is again discarded if the activity within a time window is less than 50%. After the thresholding steps, the data is in the form of several movement epoch's. Therefore, the epoch's that are lying $< 20s$ apart are clustered as one event to obtain movement epoch's of variable duration. The minimum length of any movement epoch will be $10s$ thus, all events $\geq 10s$ will be captured by the algorithm. Time domain features are then extracted from all movement epoch's in windows of $2.56s$ for supervised learning.

C. Feature Extraction and Selection

Time domain features have shown to be effective in differentiating seizure and non-seizure moves [8]. GTCS events manifest as violent and vigorous burst of activity on the accelerometer data. Whereas, non-seizure moves are generally more representative of subtle repetitive activity. Features from individual accelerometer channel might not be discriminating alone as seizures involve complex motor manifestation. Therefore, features are extracted from all four channels including the three Cartesian co-ordinates and the resultant signal. Time domain features such as measures of dispersion (inter-quartile range, standard deviation, and amplitude) can capture the violent burst like activity for GTCS events. Features such as zero crossing rate (ZCR) of the accelerometry signal can capture the sudden burst of activity due to convulsions. Whereas feature such as mean amplitude over time in every short time window over an event can capture the sudden jerk like patterns associated with seizures [6]. In addition to simple time domain features we further calculated Poincare descriptors such as $SD1$, $SD2$, $Ratio$, and CCM which, are also capable of capturing non-linear patterns in time-domain. To the best of our knowledge Poincare based features have not yet been investigated in seizure detection problem based on accelerometry. The best features are then selected based on the area under the ROC curve (AUC) analysis. All features above a threshold of 0.9 ($AUC \geq 0.9$) are selected to train the classifier. The selected features are: 1) standard deviation over all channels, 2) mean of the means calculated for resultant signal in short time windows, 3) ZCR for the three Cartesian co-ordinates, 4) total average power of the signal over all channels and 5) all four Poincare descriptors.

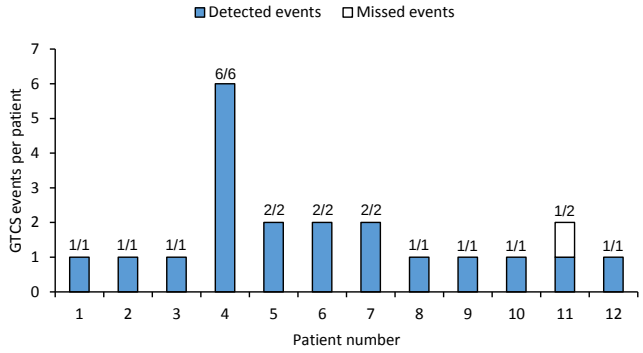
D. Support Vector Data Description

Seizures are rare events and seizure moves can be detected as abnormality or outliers in the data. SVDD is an algorithm that builds a description around the target samples and any event lying outside this description is classified as anomaly. SVDD build a hypershperical boundary around the target samples such that the volume of the hypersphere is minimized to allow all anomalies to be outliers. Let $\{x_1, x_2, \ldots, x_l\} \in \mathcal{X} \subset R^d$ represent the $i.i.d$ target sample. If $\phi(\cdot)$ maps the features to a d dimensional space, then we have to find a hypersphere with center c and radius $R > 0$ such that it encloses all the target samples. The optimization problem can thus be framed as minimizing the volume of the spherical region.

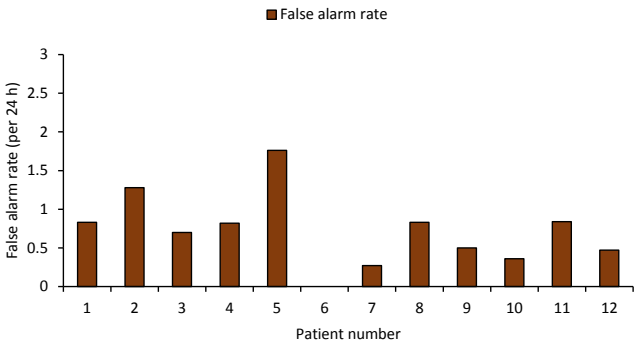
$$\begin{aligned} \min_{R,c,\xi_i} \quad & ||\phi(x) - c||^2 + \frac{1}{\nu l}\sum_{i=1}^{l}\xi_i \\ s.t \quad & ||\phi(x_i) - c||^2 \leq R - \xi_i, \quad \forall \xi_i \geq 0 \end{aligned} \tag{1}$$

Here, $\nu \in (0, 1)$ controls the percentage of points that can be classified as outliers and ξ_i is the penalty associated with sample x_i to be classified as outlier. On replacing the scalar product $\langle x, y \rangle$ with kernel function $K(x, y)$ the dual problem can be represented as:

$$\begin{aligned} \max_{\alpha} \quad & \sum_{i=1}^{l}\alpha_i K(x_i, x_i) - \sum_{i=1}^{l}\sum_{j=1}^{l}\alpha_i\alpha_j K(x_i, x_j) \\ s.t \quad & 0 \leq \alpha_i \leq \frac{1}{\nu l}, \quad \sum_i \alpha_i = 1 \end{aligned} \tag{2}$$



(a) Number of detected and missed events per patient



(b) False alarm rate per patient

Fig. 1: The validation results shown for each patient. (a) Shows the number of seizures detected correctly and the number of missed seizures per patient. Only one seizure event is missed for patient no. 11. (b) Shows the false alarm rate obtained per patient. The mean FAR over 12 patients is $0.72/24h$.

The solution of the primal problem can then be represented using the dual

$$c = \sum_{i=1}^{l} \alpha_i \phi(x_i), \quad R = ||\phi(x_j)||^2 - 2(c \cdot \phi(x_j)) + ||a||^2 \tag{3}$$

where, $||\phi(x)||^2 = k(x,x)$, $(c \cdot \phi(x)) = \sum_{i=1}^{l} \alpha_i k(x_i, x)$, and $||a||^2 = \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j k(x_i, x_j)$. The description can then be represented by the decision function as shown in equation 4, and any sample point 'x' will be classified as outlier if $f(x) > 0$.

$$f(x) = k(x,x) - \sum_{i=1}^{l} \alpha_i k(x_i, x) + ||a||^2 - R \tag{4}$$

E. Model Selection and Testing Methodology

The model estimation and validation has been performed by using a leave-one-out patient approach. Their are two parameters to be optimized. The SVDD parameter ν and the kernel parameter. We have used a radially symmetric Gaussian kernel function as it can be explained using a single variance parameter σ as shown in equation 5.

$$k(x_i, x) = exp(\frac{-||x - x_i||^2}{\sigma}) \quad \forall \quad \sigma > 0 \tag{5}$$

Let P_n represents the total number of patients and P_l be the left-out patient. Then, $P_n - P_l$ represent the patients corresponding to training sample. The training sample is again divided into two sets comprising train samples and validation samples. SVDD parameters are tuned on the train data and tested on validation data. This process is repeated in 10 randomization to train the classifier explicitly on the data using a model cost function as shown in equation 6. The best SVDD parameters corresponding to the model with the least cost are then used to test the performance on the left-out patient.

$$cost(\nu, \sigma) = w \times sensitivity(\nu, \sigma) - ppv(\nu, \sigma) \quad w = -2 \tag{6}$$

III. Results and Discussion

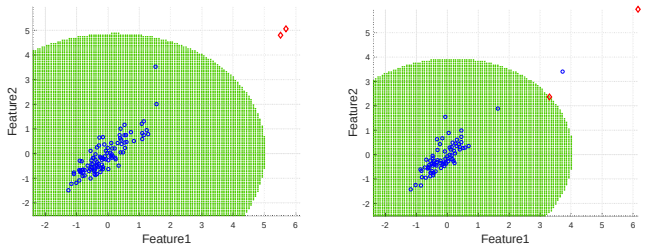
In this study we have evaluated the performance of accelerometer based seizure detection system using data from only one wrist-worn sensor with a seizure duration of $\geq 10s$. The advantage of using a short seizure duration is that we can detect all convulsive seizures with duration $\geq 10s$. However, a disadvantage associated with a short seizure duration is that the FAR of the system might be increased as we are now considering all movement epoch's that are $\geq 10s$. The increase in the number of movement epoch's is mostly due to the non-seizure moves which, further contributes towards skewing or increasing the degree of class imbalance in the data. Movement data recorded using a accelerometer device will have a large amount of non-seizure moves in comparison to seizures. Therefore, algorithms more appropriate to handling imbalanced data are more suitable to seizure detection problem. Therefore, in this study we have employed an algorithm based on SVDD which is more suitable for imbalanced dataset.

A total of 12 patients with 21 GTCS events were included in the study. The optimal SVDD parameters were selected by leave-one-patient-out validation approach. The parameters ν and σ were determined on data from 11 patients and tested on the left-out patient to calculate the performance measures (sensitivity and FAR). Fig. 1 shows the validation results, the number of detected seizures (Fig. 1a) and the FAR (Fig. 1b) shown as histogram plots. The proposed algorithm could correctly detect $20/21$ GTCS events with a sensitivity of 95.23% with a mean FAR of $0.72/24h$ over 12 patients. The algorithm could also correctly classify $1504/1534$ non-seizure moves with a specificity of 98.04%. The overall confusion matrix for the validation results is shown in Table I.

TABLE I: Overall confusion matrix.

Class	Non-Seizure (Predicted)	GTCS (Predicted)
Non-Seizure (Target)	1504	30
GTCS (Target)	1	20

For all the patients except patient no. 11 all seizure events are detected by the algorithm as seen from Fig. 1. One GTCS event could not be detected by the algorithm. Fig. 2 shows the decision boundary obtained for patient no. 8 (Fig. 2a) and patient no. 11 (Fig. 2b). The spherical region in green represents the decision boundary that encloses the non-seizure moves ($\circ$ in blue). The decision boundary shown in Fig. 2 is calculated using only two features for visualization purposes. The two features were mean and standard deviation of the resultant signal. All GTCS events are correctly detected for patient no. 8, while one event is missed for patient no. 11 as seen from Fig. 2a and Fig. 2b respectively.



(a) Patinet no.8 (b) Patinet no.11

Fig. 2: The decision region for (a) Patient no. 8 and (b) Patient no. 11. The $\diamond$ in red shows the GTCS event and $\circ$ in blue shows the non-seizure moves. The spherical region in green represents the spherical decision boundary. Events lying outside the spherical region are classified as seizure events. All GTCS events are classified as seizures for Patient no. 8 while one is missed for patient no. 11.

The reason attributed to missing a GTCS event for patient no. 11 can be explained by the manifestation of these events. GTCS events are characterized by vigorous activity on the accelerometer data. The patterns show a block like pattern representing tonic phase followed by repetitive jerk like movements representative of clonic phase. These patterns embedded in the accelerometer data can be extracted using time domain features. However, for the GTCS event corresponding to patient no. 11 it was observed that the GTCS events were rather subtle in comparison to other GTCS events. The missed event characterized more of a continuous repetitive non-seizure move, which was not representative of a seizure move. We could not establish the exact reasons attributed to the varied semiology of this event, which may require studying patients medical history.

Detection of seizures as outliers is well suited to cases where only few events are observed. Algorithms like SVDD can handle the class imbalance in the data and hence, modeling strategies based on SVDD is more suited to movement data collected using continuous monitoring devices like accelerometers. Most of the studies on the validation of accelerometer data for detection of seizures are based in a hospital setting. In a typical hospital setting the movement of the patient might be restricted and thus the data might be representative of a moderate class imbalance. However, in home setting the patient is likely to get involved in many activities of daily living and a model learned using a classifier not suited to the class skews in the data might result in too many false alarms or might fail in detecting seizures.

The performance of the algorithm can be further improved by improving the detection of seizures that are classified as non-seizure move as is the case with seizures from patient no. 11. The detection of seizure events that are more visually representative of non-seizure moves may be improved with features having higher time resolution or using features in frequency domain. We restricted ourself to only time domain features as features with low computational complexity would be more advantageous to ambulatory monitoring seizure detection system.

The results shown here are preliminary results of the algorithm based on SVDD incorporating new time domain features, single sensor and a short seizure duration. The proposed algorithm needs to be tested on a larger set of patient. Also, as a future work we would try to address the detection of different seizure types. GTCS have a higher associated risk of SUDEP however, there are other seizure types that can manifest as convulsions and may cause injury to the patient in case of unnoticed seizure.

IV. Conclusion

We proposed a seizure detection system based on a single wrist-worn accelerometer sensor capable of detecting seizures with short duration. The proposed system represents the ideal design-form of an ambulatory monitoring seizure detection system. The system is trained using an algorithm more suited to seizure data. Support vector data description is used to model the seizure activity. The proposed algorithm showed an overall GTCS detection sensitivity of 95.23% with a mean FAR of $0.72/24h$ on data from 12 GTCS patients.

References

[1] R. Surges, R. D. Thijs, H. L. Tan, and J. W. Sander, "Sudden unexpected death in epilepsy: risk factors and potential pathomechanisms," *Nature Reviews Neurology*, vol. 5, no. 9, pp. 492–504, 2009.

[2] C. Jory, R. Shankar, D. Coker, B. McLean, J. Hanna, and C. Newman, "Safe and sound? a systematic literature review of seizure detection methods for personal use," *Seizure*, vol. 36, pp. 4–15, 2016.

[3] A. Schulze-Bonhage, F. Sales, K. Wagner, R. Teotonio, A. Carius, A. Schelle, and M. Ihle, "Views of patients with epilepsy on seizure prediction devices," *Epilepsy & behavior*, vol. 18, no. 4, pp. 388–396, 2010.

[4] U. Kramer, S. Kipervasser, A. Shlitner, and R. Kuzniecky, "A novel portable seizure detection alarm system: preliminary results," *Journal of Clinical Neurophysiology*, vol. 28, no. 1, pp. 36–38, 2011.

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

[8] K. Cuppens, P. Karsmakers, A. Van de Vel, B. Bonroy, M. Milosevic, S. Luca, T. Croonenborghs, B. Ceulemans, L. Lagae, S. Huffel *et al.*, "Accelerometry-based home monitoring for detection of nocturnal hypermotor seizures based on novelty detection," 2014.