Gaussian mixture model for the identification of psychogenic non-epileptic seizures using a wearable accelerometer sensor

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***Abstract*— Any abnormal hypersynchronus activity of neurons can be characterized as an epileptic seizure (ES). A broad class of non-epileptic seizures is comprised of Psychogenic non-epileptic seizures (PNES). PNES are paroxysmal events, which mimics epileptic seizures and pose a diagnostic challenge with epileptic seizures due to their clinical similarities. The diagnosis of PNES is done using video-electroencephalography (VEM) monitoring. VEM being a resource intensive process calls for alternative methods for detection of PNES. There is now an emerging interest in the use of accelerometer based devices for the detection of seizures. In this work, we present an algorithm based on Gaussian mixture model (GMM's) for the identification of PNES, ES and normal movements using a wrist-worn accelerometer device. Features in time, frequency and wavelet domain are extracted from the norm of accelerometry signal. All events are then classified into three classes $i.e$ normal, PNES and ES using a parametric estimate of the multivariate normal probability density function. An algorithm based on GMM's allows us to accurately model the non-epileptic and epileptic movements, thus enhancing the overall predictive accuracy of the system. The new algorithm was tested on data collected from 16 patients and showed an overall detection accuracy of 91% with 25 false alarms.**

I. INTRODUCTION

Treatment of an epileptic disorder is dependent upon the correct identification of the associated aetiology. However, a high proportion of patients are misdiagnosed due to overlaying characteristics of epileptic and non-epileptic seizures. A broad class of non-epileptic seizures is Psychogenic non-epileptic seizures (PNES). Non-epileptic events in our work are termed as PNES. The diagnosis of PNES poses a challenge due to their similarity with epileptic seizures (ES). The gold standard for diagnosis of PNES is in-patient video-electroencephalography monitoring (VEM). There is an emerging interest in alternative methods for diagnosis of PNES, wherein the patient can be monitored in a home environment. In this work, we present a new classification algorithm for detection of PNES and ES events using a wrist-worn accelerometer sensor.

Various approaches have been reported on the detection and classification of different convulsive ES or simple motor seizures (myoclonic, clonic and tonic seizures) [1] [2]. However, not much has been reported in the literature on detection and classification of PNES and ES using an accelerometer sensor. Bayly *et. al.* [3] used an approach based on time-frequency analysis to differentiate PNES from ES using wireless accelerometry. Beniczky *et. al.* [4] reported the use of surface electromyography (sEMG) sensor in the detection of PNES. Pippa *et. al.* [5] and Poulas *et. al.* [6] presented an algorithm based on EEG signals, for classification of PNES. However, the use of EEG or sEMG based ambulatory device might not be a viable solution in terms of cost and comfort for the patient.

In this work, we propose a new classification algorithm based on Gaussian mixture model (GMM) for detection of convulsive PNES and ES using a parametric estimate of the multivariate probability density function of the normal, PNES and ES moves. Seizures are rare events in comparison to normal moves. Thus, modelling the normal movements along with seizure moves will give a better insight into PNES manifestation. This is an extension to our previous work [7], where we had presented a two stage process using k-means and support vector machines (SVM) in comparison to a single step process involving GMM's. Implementation of GMM's increase the overall computational efficiency and predictive accuracy of the algorithm. The algorithm was tested on data collected in a hospital setting from 16 convulsive patients under VEM.

II. METHODS

The correct detection of convulsive seizures is dependent upon correct identification of normal moves. Hence, it is vital for a seizure detection algorithm to classify normal moves correctly. Cuppens *et. al.* [2] in their work proposed an approach where they modelled the normal moves and any event detected as an anomaly or novelty is predicted as a seizure. However, they employed a threshold based method for identification of seizures and approached it as a binary classification problem. In our work, we present a multi-class classification algorithm by modeling the normal and seizure (PNES & ES) moves. The motivation behind this work is derived from the Bayly *et. al.* [3] work, where they have shown that convulsive PNES and ES can be differentiated based on movement patterns. If this is true, then a parametric approach based on modelling the accelerometer data corresponding to normal, PNES and ES events will lead to a better understanding of seizure manifestation. The proposed

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methodology is shown in Fig. 1.

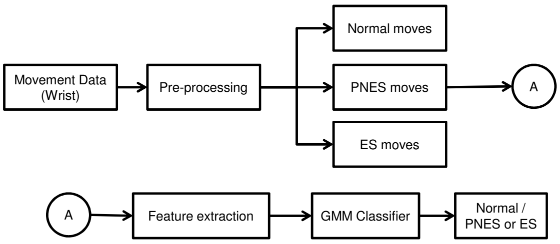


Fig. 1: Flowchart describing the proposed methodology.

A. Data Collection

The study was approved by the human research ethics committee of the Royal Melbourne Hospital in Melbourne, Australia (HREC Project 300.259). Patients admitted to VEM unit of the hospital were recruited in the study. All recruited patients signed an informed consent form. Two ambulatory monitoring hand held device with MEMS accelerometer sensor were firmly wrapped on the patient's wrists. A total of 20 ES and 19 PNES events with one patient having both, PNES (2) and ES (1) events were recorded, making a total of 21 ES and 21 PNES events. Only events with duration greater than 20 seconds are considered in this work, and all events are labelled by expert Neuro-scientist. Table I shows patient demography and event statistics.

TABLE I: Table shows the demography of the patients.

Demography	ES	PNES	ES & PNES
Patients	10	5	1
Seizure events	20	19	3
Normal Movements	358	319	23
Age	30.0 ± 11.5	37.8 ± 17.6	30.0 ± 0.0
Male:Female	5 : 5	1 : 4	0 : 1
Mean event duration (s)	108.0	217.0	113.0

B. Pre-Processing

The data from the accelerometer sensors is acquired from 3 axes with a time stamp. The data acquisition is done at a sampling frequency of $50Hz$. The accelerometer signal is then analyzed in short time windows of 20s duration with 50% overlap. A 20s window is selected as the mean PNES and ES event duration is several times bigger, and a 20s window will be able to capture all such events. The time series signal is then passed through a 6^{th} order Butterworth band pass filter with 2Hz and 25Hz as cutoff frequencies. The norm of the accelerometer signal is then calculated using $R = \sqrt{x^2 + y^2 + z^2}$. We, then used the activity and time filter as reported in the previous work [7] to segment the time series signal into a) no activity; b) normal arm movements; and c) seizure activity. The time series data corresponding to normal arm movements and seizure moves are then analyzed in epochs of 2.56s duration to extract different time, frequency and wavelet domain features. Fig. 2 shows the raw and filtered accelerometer data for the normal, ES and PNES movements.

C. Feature Extraction

PNES events are observed to have a longer mean event duration in comparison to ES. Time domain features can thus be used to differentiate PNES events. The time domain features such as measures of central tendency (mean, median, mode), and measures of dispersion (inter-quartile range, standard deviation, amplitude) have been reported by Cuppens *et. al.* [2] in the detection of seizures using accelerometer signals. The wavelet domain features have been extracted using 'db5' as the mother wavelet in agreement with Nisjen *et. al.* [1]. The first four detail and the approximate coefficient were used for analysis. Sub-band power, entropy (Shannon), and coefficient of variation of kurtosis and skewness were used as features. In, frequency domain features such as mean spectral power and energy of the norm of the accelerometer signal were used as features. Rhythmic movement patterns are the critical differentiator between PNES and ES [3]. Features, in frequency and wavelet domain are likely to capture the difference in evolutionary pattern of convulsive PNES and ES.

D. Gaussian Mixture Model

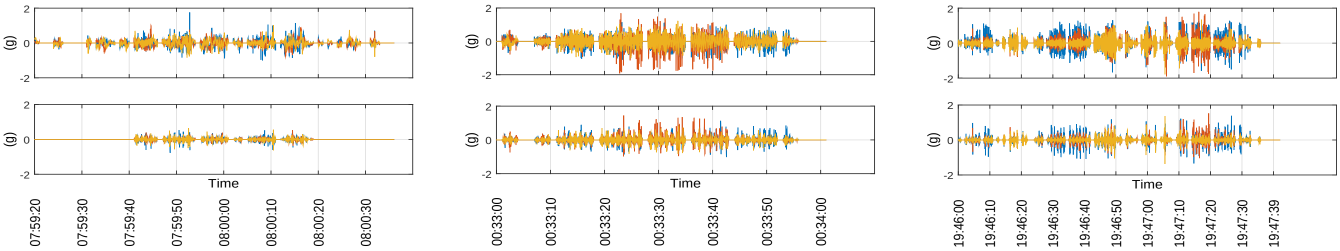
Mixture models are a class of pattern recognition systems. A Gaussian mixture, models the probability density function of the given data using a mixture of density functions. GMM can be viewed as a linear superposition of k Gaussian components as shown in equation (1). GMM provides a better estimation of the density model of the observed variables in comparison to a single Gaussian.

$$p(x) = \Sigma_{k=1}^{K} \pi_k \mathcal{N}(x/\mu_k, \Sigma_k) \qquad (1)$$

where, x is the d-component feature vector, μ is the mean vector with d-components, Σ is the $d \times d$ covariance matrix, and π_k is the mixing parameter. GMM finds wide application in speech recognition, due to their ability to provide a richer class of density models. GMM can be viewed as a soft clustering approach. Owing to this advantage of the GMM's, they were tested in PNES classification problem. A probability density function was estimated for data corresponding to each class (Normal, ES and PNES) using a k-component Gaussian mixture model. The parameters of the mixture model were estimated using expectation maximization (EM) algorithm. The convergence criterion of the algorithm is based on calculating the log likelihood function. Equation (2) to (6) shows the steps of the EM algorithm for GMM.

- Initialization: Initialize the parameters of the GMM (means μ_k, covariance Σ_k and mixing coefficients π_k) using k-means clustering.
- E step: Calculate responsibilities ($\gamma(Z_{nk})$)

$$\gamma(z_{nk}) = \frac{\pi_k \mathcal{N}(x_n/\mu_k, \Sigma_k)}{\sum_{j=1}^{k} \pi_j \mathcal{N}(x_n/\mu_j, \Sigma_j)} \qquad (2)$$



(a) Normal movement (b) ES movement (c) PNES movement

Fig. 2: (Each sub-figure) first raw and second filtered data for a typical (a) Normal (b) ES and (c) PNES movement.

- M step: Re-estimate parameters using the responsibility.

$$\mu_k^{new} = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk}) x_n \tag{3}$$

$$\Sigma_k^{new} = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk})(x_n - \mu_k^{new})(x_n - \mu_k^{new})^T \tag{4}$$

$$\pi_k^{new} = \frac{N_k}{N} \tag{5}$$

$$where \quad N_k = \sum_{n=1}^{N} \gamma(z_{nk})$$

- Calculate log likelihood and check convergence.

$$\ln p(X/\mu, \Sigma, \pi) = \Sigma_{n=1}^{N} ln\{\Sigma_{k=1}^{K} \pi_k \mathcal{N}(x_n/\mu_k, \Sigma_k)\} \tag{6}$$

III. Results and Discussion

A new approach based on GMM's for the detection of PNES is presented. In total 21 ES, 21 PNES, and 700 normal moves were obtained from 16 patients. Owing to the fact that normal moves make majority of movement data, an approach which can accurately model the normal moves along with the seizure moves is presented here. GMM can be viewed as a soft clustering approach. If an event lies on the boundary of the two clusters, then the event will share equal probabilities of association to the two clusters, thereby improving the overall predictive accuracy. Our work is focused upon the identification of PNES events. Therefore, a thorough analysis of the normal and seizure movements can also lead to valuable insights into the seizure semiology of mimics and ES events.

For data corresponding to all the three classes, a feature vector denoted by $v = [v_{1j}, v_{2j}, v_{3j}]$ is calculated for every event. $[v_{1j}, v_{2j}, v_{3j}]$ represent feature vectors corresponding to time, frequency and wavelet space $\forall j \in Normal$, $PNES$, and ES. The data is then randomly partitioned into a training and test set. 60% of the data is used as training, and 40% as testing set for every class. The classification algorithm is framed as a supervised learning task. A k-component Gaussian mixture model was trained and a diagonal covariance matrix (Σ) was used. The parameter k was determined empirically, and it was set to 3. The GMM parameters are then updated using the EM algorithm and log likelihood of the observed data is calculated in every iteration. The convergence criterion of the algorithm is decided based on the log likelihood function. Using the GMM parameters, the posterior probability is calculated for the test set. Class is then assigned based on the highest posterior probability. Table II shows the confusion matrix for the test set.

TABLE II: GMM confusion matrix.

Class	Normal (Predicted)	PNES (Predicted)	ES (Predicted)
Normal (Target)	255	25	0
PNES (Target)	0	7	1
ES (Target)	0	0	8

It can be seen from the confusion matrix in Table II that all ES movements are classified correctly. Whereas, one PNES event is classified as ES. Thus, GMM algorithm shows a good predictive accuracy and strengthens the hypothesis that normal moves can be clearly differentiated from seizure like moves as suggested by Cuppens *et. al.* [2]. Moreover, the algorithm based on GMM can also model PNES and ES events which enables more accurate differentiation of PNES and ES moves. The advantages of soft clustering approach such as GMM can be seen from the comparison with classification algorithms like SVM. SVMs are state of the art classifiers however, the separation of overlapping classes is not as good as GMM. Table III shows that 7 seizure events are not detected by SVMs, indicating that SVMs are not a good choice for imbalanced data (high proportion of normal moves). Moreover, SVM performance is also dependent on chosen parameters ($C = 10$, $\gamma = 0.1$).

TABLE III: SVM confusion matrix.

Class	Normal (Predicted)	PNES (Predicted)	ES (Predicted)
Normal (Target)	276	4	0
PNES (Target)	5	3	0
ES (Target)	2	1	5

The clear differentiation of PNES and ES events also shows the inherent difference in the evolution of the two seizure types as reported by Bayly *et. al.* [3]. As, seen from the confusion matrix (Table II), the algorithm gave 25 false alarms. However, it can be seen that all the false alarms are normal movements classified as PNES events. As seen from Fig 3, the class overlap in normal and PNES events are of clinical relevance. PNES moves are clearly distinguished from ES moves and are found to have characteristics similar to normal moves. This suggests the underlying psychoses as patient tries to mimic a seizure.

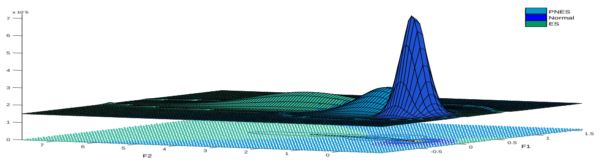


Fig. 3: 3D surface plot of the probability density functions (PDF) and respective contours. The PDF's are calculated using only two features, for visualization purposes.

Fig 3 shows that normal and PNES movement forms a compact distribution in comparison to ES moves. These findings validate the hypothesis that ES manifest as a shock like movement and represents a wider frequency spectrum, whereas PNES events have a lower contribution of energy in the higher frequency bands. This is also true considering PNES events are characterized as physical symptoms triggered due to an underlying psychological disturbance and not triggered by any abnormal hypersynchronus activity in the brain. Table IV shows the performance measures of the proposed algorithm.

TABLE IV: Performance measures of the GMM algorithm.

Measure	Normal moves	PNES moves	ES moves
Sensitivity	0.91	0.87	1.00
Specificity	1.00	0.91	0.98
Precision	1.00	0.21	0.88
F1-score	0.95	0.35	0.94
Overall Accuracy	0.91		

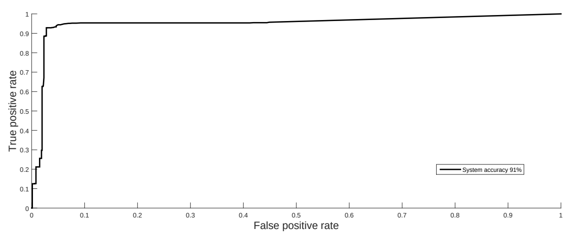


Fig. 4: ROC curve of the proposed PNES classification system.

Based on the encouraging results, we can say that the proposed algorithm can be used in classification of PNES. Fig 4 shows the ROC curve and Table V shows the performance improvement of the proposed PNES classification algorithm. However, the algorithm is developed and tested on data collected in a hospital setting, where typical stimulants of seizures are absent. Moreover, only seizures of duration greater than 20s are considered in this work. So, as a future work, the algorithm can be tested in home surroundings and on seizures of all duration.

IV. Conclusion

A new algorithm based on modeling the multivariate probability density function of the normal and the seizure moves is presented. The probability distribution used is Gaussian and Gaussian mixture models (GMM's) are built. Features in time, frequency and wavelet domain were extracted from the movement data. The algorithm resulted in an overall classification accuracy of 91% with 25 false alarms. The proposed algorithm has a potential to be used on a wrist-worn ambulatory seizure detection system.

TABLE V: Comparison of the proposed approach.

Classification Algorithm		Sensitivity	Specificity	Accuracy
Kusmakar *et. al.* [8]	HOOM	93.33%	70.00%	80.00%
Pippa *et. al.* [5]	Bayes Net	92.00%	78.00%	86.00%
Poulos *et. al.* [6]	Auto cross-correlation	83.00%	90.00%	86.00%
Kusmakar *et. al.* [9]	Muscle Transforms	93.33%	85.00%	88.57%
Proposed	GMM	87.50%	91.00%	91.00%

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