Classification of Convulsive Psychogenic Non-epileptic Seizures Using Histogram of Oriented Motion of Accelerometry Signals

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***Abstract*— A seizure is caused due to sudden surge of electrical activity within the brain. There is another class of seizures called psychogenic non-epileptic seizure (PNES) that mimics epilepsy, but is caused due to underlying psychology. The diagnosis of PNES is done using video-electroencephalography monitoring (VEM), which is a resource intensive process. Recently, accelerometers have been shown to be effective in classification of epileptic and non-epileptic seizures. In this work, we propose a novel feature called histogram of oriented motion (HOOM) extracted from accelerometer signals for classification of convulsive PNES. An automated algorithm based on HOOM is proposed. The algorithm showed a high sensitivity of (93.33%) and an overall accuracy of (80%) in classifying convulsive PNES.**

I. INTRODUCTION

The current method to diagnose epilepsy is to use electroencephalography (EEG). However, there are certain seizure types that do not show typical seizure related activity on EEG and are classified as psychogenic non-epileptic seizures (PNES). Jones *et. al.* [1] have shown that correct and early diagnosis of PNES is a critical problem. 10% to 40% patients referred to hospitals as having ES are found to be having PNES. Moreover, correct diagnosis of PNES is often delayed by (μ 5.6 & σ 7.7 years) and patients having PNES are continuously treated with anti epileptic drugs, which have serious teratogenic effects.

The gold standard to diagnose PNES is video electroencephalography monitoring (VEM). One of the vital parameters observed during VEM is the stereotypical movement of the limbs during seizure. Thus, making limb movement analysis an imperative step in the diagnosis of convulsive PNES. VEM being a resource intensive process, triggers the need for an alternative method of PNES diagnosis.

Nisjen *et. al.* [2] has demonstrated the use of $3D$ accelerometer for detection of motor seizures with good accuracy. They performed time-frequency analysis of accelerometry data for detection and classification of myoclonic seizures using data recorded from the limbs and chest of the patient. Becq *et. al.* [3] showed that different patterns corresponding to seizures are present on the accelerometer data. They have shown the use of entropy based features extracted from the norm of accelerometer data, in automated detection and classification of Tonic-Clonic seizures. Cuppens *et. al.* [4] showed the use of accelerometer based device for detection and classification of nocturnal hyper-motor seizures from normal moves, using an algorithm based on novelty detection. Beniczky *et. al.* [5] have shown that PNES and ES can be differentiated using sEMG data by features based on amplitude, frequency, coherence and duration of the silent periods.

In this work, we have considered only convulsive seizures. The classification and detection of convulsive PNES are mentioned rarely in the literature. Recently Bayly *et. al.* [6] has demonstrated that convulsive PNES can be differentiated from convulsive ES using short time Fourier transform (STFT). They showed that the variation of dominant frequency over the course of an event is more stable during convulsive PNES whereas the dominant frequency continuously evolves during an ES. In this paper, an approach for classification of convulsive PNES using a novel feature called histogram of oriented motion (HOOM) is presented. This approach is one step in the development of a wearable ambulatory monitoring system for diagnosis of PNES.

II. METHODS

A. Experimental Design

Two hand held devices with MEMS accelerometer sensor were used for data collection. The devices were time synchronized with VEM setup in order to ensure exact comparison and analysis. The devices were strapped on the wrist of patients. A total of 34 convulsive events were recorded, which included 19 PNES and 15 ES events. All the events were annotated by expert neurologists and their classification is considered as the ground truth. Table I shows the patient demography and event statistics. Royal Melbourne Hospital ethics committee approval (HREC Project 300.259).

TABLE I: Table shows the demography of the patients.

Demography	ES	PNES
Patients	9	6
Number of events	15	19
Age	29.11 ± 12.04	34.66 ± 15.16
Male:Female	$4:5$	$1:5$
Duration of events (seconds)	110.00 ± 112.78	225.00 ± 191.90

The diagnosis of convulsive PNES is based on the stereotypical movement of limbs during seizure. The movement of the upper limb during a convulsive seizure can be represented

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as movement about a fixed ball and socket joint at the shoulder. Thus, the movement pattern can be represented by a trajectory of varying radial distance from a fixed point (*i.e.* shoulder joint) in a spherical co-ordinate system. The analysis of the pattern of movements is done by obtaining histogram of the points representing the trajectory in spherical co-ordinate system. Therefore, the feature vector derived from the histogram of points in the spherical co-ordinate system is given the name "histogram of oriented motion (HOOM)". Histogram with varying bin resolution in short time windows of 2.56 seconds over the entire seizure duration are calculated and analyzed. We then calculate the variation along every bin of histogram over the entire seizure duration, which is then used as a feature vector for classification of PNES. The proposed methodology is shown in Fig. 1.

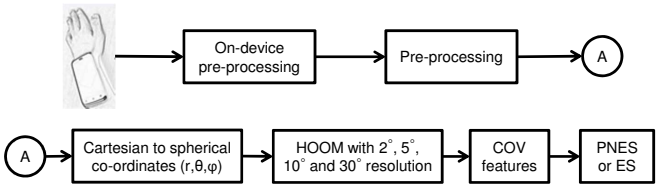


Fig. 1: Flowchart describing the methodology for PNES classification.

B. Pre-Processing

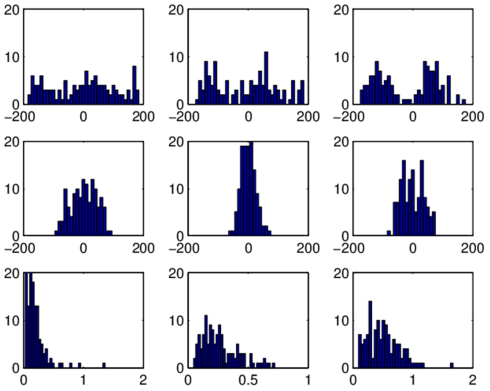
The accelerometer data was collected with a sampling frequency of 50 Hz. The data is analyzed in short time windows of 2.56 seconds epochs with 50% overlap. In every time window, data is first filtered using an activity filter, which filters out any activity below $\pm 0.2g$ as subtle activity. Then, a Butterworth 6^{th} order band-pass filter with $2-25$ Hz as the cut-off frequency is applied [6].

Accelerometer data in every time window is then converted from Cartesian to spherical co-ordinates. Every point in the spherical co-ordinate system is represented by a radial distance r, the polar angle θ representing the inclination from the reference plane and the azimuthal angle φ representing the angle between the reference axis and orthogonal projection of the point on the reference plane. Equations $r = \sqrt{x^2+y^2+z^2}$, $\varphi = \tan^{-1}\frac{y}{x}$ and $\theta = \cos^{-1}\frac{z}{r}$ are used for converting Cartesian to spherical co-ordinates. Fig. 2 shows the accelerometer data in spherical co-ordinate system.

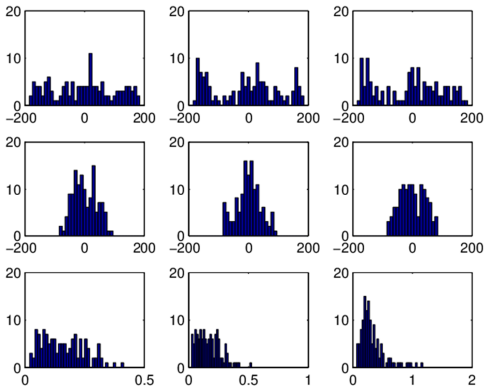
C. Feature Extraction

Histogram of Oriented Motion (HOOM): The motivation behind the work comes from the use of the histogram of oriented optical flow (HOOF) and histogram of oriented gradient (HOG) in detection of humans in image processing [7]. The challenging task in automated classification of convulsive events lies in detecting features which can capture the movement pattern of the limbs. Several features in time, frequency and wavelet domain have been proposed earlier to identify ES [4]. However, to discriminate between two seizure types a feature set which can capture the movement patterns in PNES and ES will be a differentiating feature. Histogram of spherical co-ordinates was used to capture the variation in movement pattern.

Seizure events in every 2.56 second window are divided into bins of 2°, 5°, 10°, and 30° resolution from $-180°$ to 180° respectively for θ and φ. The radial distance is also divided into bins of length 180, 72, 36, and 12 respectively. Thus, in every window of 2.56 seconds the variation or the evolution of θ, φ and radial distance with time is obtained as shown in Fig. 3. As stated earlier the temporal evolution



(a) ES event



(b) PNES event

Fig. 3: Histograms for (a) ES and (b) PNES shown for three windows of 2.56 seconds epoch (Left-Right):for both (a) & (b) (Row 1) φ with 10° resolution (Row 2) θ with 10° resolution (Row 3) radial distance r.

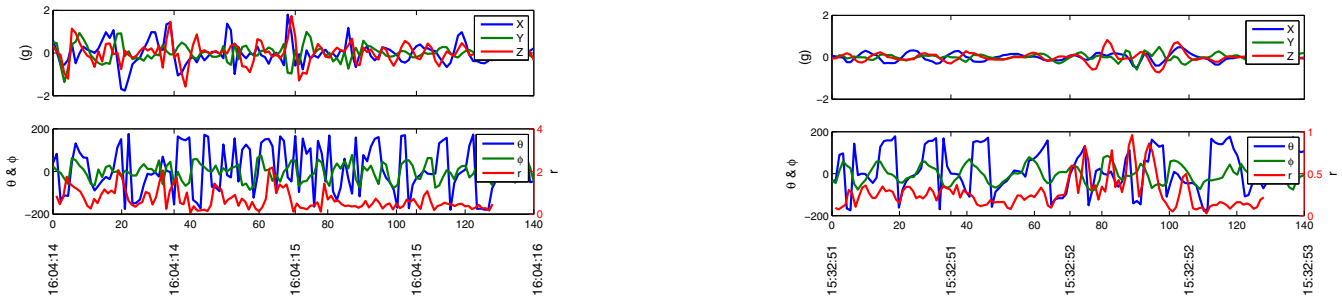
of PNES events is more stable in time (*i.e.* the coefficient of variation is less) when compared to ES events. Thus, the coefficient of variation is an important parameter to capture the typical characteristic of the PNES and ES events. Coefficient of variation of θ, φ and the radial distance r in every time window is calculated for the entire event duration. Equations 1, 2 and 3 show the input feature set.

$$M_\theta = \left(COV_{\theta_1} COV_{\theta_2} \ldots COV_{\theta_j}\right) \quad (1)$$

$$M_\varphi = \left(COV_{\varphi_1} COV_{\varphi_2} \ldots COV_{\varphi_j}\right) \quad (2)$$

$$M_r = \left(COV_{r_1} COV_{r_2} \ldots COV_{r_j}\right) \quad (3)$$

where, M_θ, M_φ and M_r represents feature vectors of length j, $\forall j \in 180, 72, 36, 12$ for bin resolution of 2°, 5°, 10°, and 30° respectively. COV_{θ_i}, COV_{φ_i} and COV_{r_i} represents



(a) (b)

Fig. 2: Figure shows the cartesian (x, y, z) and spherical co-ordinate (r, θ, φ) in 2.56 seconds window: (a) typical convulsive ES event (b) typical convulsive PNES event as depicted in a window of 2.56 seconds.

the mean value of coefficient of variation for θ, φ, and the radial distance r in the i^{th} bin of histogram. Features are then normalized such that each attribute is centered to have a zero mean and scaled to have a standard deviation of 1. The features are then fed as an input to classification algorithm.

D. Classification using 2-norm soft-margin SVM

Support vector machine (SVM) is a binary classification method, that shows good performance in pattern recognition problems with excellent ability to prevent overfitting. SVM maps the input features from R^d dimension to R^{d_h} dimension using a linear or non linear kernel function $\phi(\cdot) : R^d \rightarrow R^{d_h}$. The decision boundary separating the two classes is learned in the form of a hyperplane. The optimization problem in SVM is formulated as the maximization of the distance separating the hyperplanes to maximize the buffer region and minimize the training error. However, in real life, applications perfect separation of the data is rarely possible. When data is not linearly separable, SVM algorithm is modified by introducing an error margin called the slack term (ξ). Thus, the conditions for the hyperplane separating the data is relaxed and the optimization problem for SVM is as shown in equation 4.

$$\min_{\omega,b,\xi} \frac{1}{2}\|\omega\|^2 + \frac{C}{n}\sum_{i=1}^{n} l(\xi^k) \tag{4}$$

subject to $y_i(\omega \cdot x_i + b) \geq 1 - \xi_i, \forall \quad i \in 1, \ldots, n$. Where C is a positive regularization constant and ξ is the slack term, we used $C = 1$ and dot product as the kernel function. When $k = 2$ the SVM is called the 2-norm soft-margin SVM.

SVM algorithm is well suited for classification of seizures as it can handle moderately imbalanced data. Convulsive ES are found to evolve with varying dominant frequency, thus most of the ES events are detected as outliers in the data. However, in SVM algorithm the hyperplane separating the two classes is learned using the instances that are close to the boundary. Thus, SVM algorithm is not affected by outliers in the data even if they are large in number.

III. Results and Discussion

New feature vector called Histogram of Oriented Motion (HOOM) is proposed and the classification results with different bin resolution are summarized in Table II. Five fold cross-validation was used to validate and tune the training model. The data was randomly divided into five folds, with approximately equal class proportion in every fold. The bin size in construction of HOOM features is an unknown parameter. Hence, a detailed study was conducted with different bin resolution as shown in Table II.

TABLE II: Classification performance of algorithm with different bin sizes

Bin resolution	Sensitivity	Specificity	Accuracy	f-score
2-degree	73.33%	73.33%	73.33%	0.71
5-degree	66.67%	76.67%	72.86%	0.67
10-degree	93.33%	70.00%	80.00%	0.83
30-degree	73.33%	61.67%	67.62%	0.65

The optimum bin resolution for HOOM is selected as 10°, as it shows a high classification accuracy. Table III shows the five fold cross-validation results with 10° as bin resolution. Our results showed that algorithm based on the proposed feature - HOOM, can classify PNES from ES.

TABLE III: Five fold cross-validation results with bin size as 10°

Cross-validation	Sensitivity	Specificity	Accuracy	f-score
1^{st} fold	100.00%	100.00%	100%	1
2^{nd} fold	100.00%	100.00%	100%	1
3^{rd} fold	66.67%	25.00%	42.86%	0.50
4^{th} fold	100.00%	100.00%	100%	1
5^{th} fold	100.00%	25.00%	57.14%	0.67
Overall	93.33%	70.00%	80.00%	0.83

A direct comparison of the results was not possible. As, no algorithm addressing automated classification of PNES and ES using accelerometry signals is reported in literature. However, E. Pippa *et. al.* [8] in their recent work have shown a similar classification of ES and PNES using EEG signal. Since, in PNES there are no specific changes in the EEG, these methods rely upon detecting the bradycardia and hypotension associated characteristics of EEG signals for classifying an event into PNES. However, our method is based on the visual clues observed in limb movement during

VEM, which is used as one of the parameters to differentiate PNES from ES by clinical experts [6]. Moreover, our algorithm is based on accelerometry data recorded from wrist of patients. Thus, having a potential to be implemented on a wearable device. Table IV shows the comparison of the classification model based on HOOM with those proposed by E. Pippa *et. al.*

TABLE IV: Comparison of proposed classification model with models using EEG signals as proposed by Pippa *et. al.* [8].

Classification Model	Sensitivity	Specificity	Accuracy
BayesNet	92.00%	78.00%	86.00%
RandomCommitte	88.00%	77.00%	83.00%
RandomForest	77.00%	70.00%	74.00%
HOOM	93.33%	70.00%	80.00%

The proposed algorithm resulted in an overall sensitivity of 93.33% and an accuracy of 80%. A high classification sensitivity and accuracy shows that HOOM features are able to capture the typical characteristics of convulsive PNES and ES. The results validate the hypothesis by Bayly *et. al.* [6], that convulsive PNES and ES can be differentiated based on their differing patterns of evolution with time. Bayly *et. al.* used short time Fourier transform (STFT) in windows of 2.56 seconds duration. In this work, an easy to compute approach has been adopted. The Fourier transform has an implicit assumption of signal stationarity and thus may not be able to capture and differentiate convulsive PNES for seizures of very short duration. However, HOOM features capturing variations in the movement trajectory of the arm during seizure are able to differentiate convulsive PNES for seizures of very short duration as well. Which is reflected by the high classification sensitivity of the proposed algorithm. Thus, HOOM features are also able to embed the information captured using Fourier transform as reported by Bayly *et. al.* [6].

HOOM is a differentiating feature for classification of PNES and ES. Fig. 2 shows the Cartesian and spherical co-ordinates for a typical convulsive ES and PNES event in a 2.56 second window. It is visually clear from the movement pattern represented by spherical co-ordinates in Fig. 2 that the coefficient of variation will be very low for PNES in comparison to ES. The maximum variation is captured by θ as seen from Fig. 2. The patterns of evolution of θ for PNES over time is shown in Fig. 2(b). It appears periodic thus resulting in a low coefficient of variation for a PNES event. θ for ES is shown in Fig. 2(a), where it evolves unevenly and will have a high coefficient of variation. PNES shows a stable evolution of motor manifestations over time resulting in low coefficient of variation, whereas convulsive ES evolves continuously over time and hence results in higher coefficient of variation. This can also be observed from the histogram of PNES and ES as shown in Fig. 3. Spherical co-ordinate θ is the inclination of the resultant from the z-axis or the sagittal plane of the patient. A higher θ represents any movement away and forth from the sagittal plane. This represents the combination of abduction and adduction movements. The primary muscles in these types of movements are affected by deltoid fibres, latissimus dorsi and pectoralis major. These findings also correlate with Beniczky *et. al.* [5], who have shown that PNES can be distinguished from ES based on activation patterns of the deltoid muscles. Our results suggest, that HOOM features are also able to embed the information captured by sEMG to some extent. Thus, the algorithm has the potential to be implemented in a wearable device for early diagnosis of PNES. Future work involves studying the correlation of HOOM with different muscles involved in motion of arms, and implementing the proposed algorithm in motor recovery of post acute stroke patients.

IV. Conclusion

A novel algorithm based on the newly derived histogram of oriented motion (HOOM) feature is presented for diagnosis of pseudo non-epileptic seizure. HOOM is derived by transforming Cartesian co-ordinates to spherical coordinates. The coefficient of variation of histograms with different bin size for (r, θ, φ) is used to derive feature vectors for classification of PNES. The algorithm resulted in a good classification accuracy with a high f-score of 0.83 for the 10° bin resolution. A high f-score suggests good sensitivity and specificity of the proposed algorithm. The HOOM features are also able to encode the seizure information captured using methods like STFT and sEMG. The encouraging results demonstrates the feasibility of the proposed algorithm in automated classification of convulsive PNES events using a wrist worn accelerometer device.

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