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

Shitanshu Kusmakar1, Jayavardhana Gubbi1, Aravinda S. Rao1, Bernard Yan2, Terence J.O’Brien2 and Marimuthu Palaniswami1

Abstract— 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). Benbadis et. al. [1] have stated in their work, that the correct and early diagnosis of PNES is a critical problem, as the treatment is dependent on the type of the neurological disorder. The authors showed that nearly 30% of the patients treated for epilepsy are found to be having PNES. PNES is a significant neurological disorder with a prevalence of 1 to 33 per 100,000. Reuber et. al. [2] stated that correct diagnosis of PNES is often delayed upto 7.2 years, and patients with PNES are treated for epilepsy 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. Further, Nisjen et. al. [3] reported that during a seizure, arm movements are dominant over other limb movements. Thus, movement analysis of arms will be a good method to monitor seizures. VEM being a resource intensive process, triggers the need for an alternative method of PNES diagnosis.

Nisjen et. al. [4] has demonstrated the use of 3D accelerometer for detection of motor seizures with good accuracy. Nisjen et. al. [5] further extended their work to automatic detection of convulsive epileptic seizures using data recorded from accelerometer sensors placed at four limbs and chest of the patient using time frequency analysis. Becq et. al. [6] 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. [7] showed the use of accelerometer based device for detection of nocturnal hyper-motor seizures using algorithm based on novelty detection. Conradsen et. al. [8] reported high sensitivity in detection of general tonic clonic seizures (GTCS) using sEMG data collected from deltoid and anterior tibial muscles. Beniczky et. al. [9] have shown that PNES and GTCS can be differentiated using sEMG data by features based on amplitude, frequency, coherence and duration of the accelerometer signals.

All the approaches discussed above are used for the classification and detection of seizures which evolve as motor manifestations called as “convulsive seizures”. In this work, we have considered only convulsive seizures. The classification and detection of convulsive PNES is mentioned rarely in literature. Recently Bayly et. al. [10] has demonstrated that convulsive PNES can be differentiated from convulsive ES using short time fourier transform (STFT). They showed that the variation of frequency over the course of event is more stable during convulsive PNES and evolves during 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 automated system that can detect and classify convulsive PNES and perform unobtrusive ambulatory monitoring of epileptic patients.

II. METHODS

A. Experimental Design

Two hand held devices with MEMS accelerometer sensor and on-device processing capabilities were used for data collection. The devices were strapped on the wrist of patients. A total of 34 convulsive events were recorded, which included both PNES and 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.
The diagnosis of convulsive PNES is based on stereotypical movement of limbs during seizure. During convulsive seizures, involuntary contraction of the muscles occur, which leads to complex and rhythmic movement patterns of limbs. The movement of the upper limb during a convulsive seizure can be represented 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 histogram of points in 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 analysed. 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.

**B. Pre-Processing**

The data was collected with a sampling frequency of 50 Hz. Every packet of data has movement data recorded from three co-ordinate axes corresponding to x, y and z directions of the MEMS device with a time stamp. The data is analysed in short time windows of 2.56 seconds epochs with 50% overlap. In every time window, 3-D accelerometer data is first filtered using an activity filter, which filters out any activity below ±0.2g as subtle activity. Then, a Butterworth 6th order band-pass filter with 2 – 25 Hz as the cutoff frequency is applied [10].

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

<table>
<thead>
<tr>
<th>Demography</th>
<th>ES</th>
<th>PNES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patients</td>
<td>9</td>
<td>6</td>
</tr>
<tr>
<td>Number of events</td>
<td>15</td>
<td>19</td>
</tr>
<tr>
<td>Age</td>
<td>29.11 ± 12.04</td>
<td>34.66 ± 15.16</td>
</tr>
<tr>
<td>Male-Female</td>
<td>4 : 5</td>
<td>1 : 5</td>
</tr>
<tr>
<td>Duration of events (seconds)</td>
<td>110.00 ± 112.78</td>
<td>225.00 ± 191.90</td>
</tr>
</tbody>
</table>

**C. Feature Extraction**

**Histogram of Oriented Motion (HOOM):** Motivation behind the work comes from the use of histogram of oriented gradient (HOG) and histogram of oriented optical flow (HOOF) in detection of humans in image processing [11]. The challenging task in automated classification of convulsive events lie in detecting features which can capture the movement pattern of limbs. A feature set which captures the movement patterns in PNES and ES will be a differentiating feature for the two types of seizures. Histogram of spherical co-ordinates was used to capture the variation in movement pattern.

Seizure events in every 2.56 seconds window are divided into bins of $2^\circ$, $5^\circ$, $10^\circ$, and $30^\circ$ resolution from $-180^\circ$ respectively for $\theta$ and $\varphi$. 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 $\theta$, $\varphi$ and radial distance with time is obtained as shown in Fig. 3.

As stated earlier the temporal evolution 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 $\theta$, $\varphi$ 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.

$$M_\theta = (COV_\\theta, COV_\\theta_2, \ldots COV_\\theta_j)$$ (1)

$$M_\varphi = (COV_\\varphi, COV_\\varphi_2, \ldots COV_\\varphi_j)$$ (2)

$$M_r = (COV_\\r, COV_\\r_2, \ldots COV_\\r_j)$$ (3)

where, $M_\theta$, $M_\varphi$ and $M_r$ represents feature vectors of length $j$, $\forall j \in 180, 72, 36, 12$ for bin resolution of $2^\circ$, $5^\circ$, $10^\circ$, and $30^\circ$ respectively. $COV_\\theta$, $COV_\\varphi$ and $COV_\\r$ represents the mean value of coefficient of variation for $\theta$, $\varphi$, and the radial distance $r$ in the $i^{th}$ bin of histogram.

Features are then normalized such that each attribute is centered to have mean 0 and scaled to have standard deviation of 1. The normalized features are then fed as 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 $R^{da}$ dimension using a linear or non linear kernel function $\phi(\cdot) : R^d \rightarrow R^{da}$. The decision boundary separating the two classes is learned in the form of a hyperplane. The optimization
Fig. 2: Figure shows the cartesian \((x, y, z)\) and spherical co-ordinate \((r, \theta, \varphi)\) in 2.56 seconds window: (a) typical convulsive ES event (b) typical convulsive PNES event as depicted in a window of 2.56 seconds.

Fig. 3: Histograms for (a) ES and (b) PNES shown for three windows of 2.56 seconds epoch (Left-Right): (Row 1) \(\varphi\) with \(10^\circ\) resolution (Row 2) \(\theta\) with \(10^\circ\) resolution (Row 3) radial distance \(r\)

The data is relaxed and the optimization problem reduces to equation 4.

\[
\min \frac{1}{2} \| \omega \|^2 + C \sum_{i=1}^{n} l(\xi^i) \tag{4}
\]

subject to \(y_i (\omega \cdot x + b) \geq 1 - \xi, \quad \forall \quad i \in 1, \ldots, n\), Where \(C\) is a positive regularization constant and \(\xi\) 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 to 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. A good classification accuracy of 80% is seen with HOOM features extracted with \(10^\circ\) bin resolution.

**TABLE II:** Average results for classification using five fold cross-validation with different bin sizes

<table>
<thead>
<tr>
<th>Bin resolution</th>
<th>Accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>(f)-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-degree</td>
<td>73.33%</td>
<td>73.33%</td>
<td>73.33%</td>
<td>0.71</td>
</tr>
<tr>
<td>5-degree</td>
<td>72.86%</td>
<td>66.67%</td>
<td>76.67%</td>
<td>0.67</td>
</tr>
<tr>
<td>10-degree</td>
<td>80.00%</td>
<td>93.33%</td>
<td>70.00%</td>
<td>0.83</td>
</tr>
<tr>
<td>30-degree</td>
<td>67.62%</td>
<td>75.33%</td>
<td>61.67%</td>
<td>0.65</td>
</tr>
</tbody>
</table>

The optimum bin resolution for HOOM is selected as \(10^\circ\), as it shows a high classification accuracy as shown
in table III. Our results showed that algorithm based on the proposed feature - HOOM results in similar sensitivity in seizure classification as reported by Becq et al. [6] and Cuppens et al. [7]. Jay: Highlight why the proposed method is advantageous

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

<table>
<thead>
<tr>
<th>Cross-validation</th>
<th>Accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>f-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st fold</td>
<td>100%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>1</td>
</tr>
<tr>
<td>2nd fold</td>
<td>100%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>1</td>
</tr>
<tr>
<td>3rd fold</td>
<td>42.86%</td>
<td>66.67%</td>
<td>28.57%</td>
<td>0.50</td>
</tr>
<tr>
<td>4th fold</td>
<td>100%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>1</td>
</tr>
<tr>
<td>5th fold</td>
<td>57.14%</td>
<td>100.00%</td>
<td>25.00%</td>
<td>0.67</td>
</tr>
<tr>
<td>Overall</td>
<td>80.00%</td>
<td>93.33%</td>
<td>70.00%</td>
<td>0.83</td>
</tr>
</tbody>
</table>

These results suggest that HOOM features is able to capture the typical characteristics of convulsive PNES and ES. The results validate the hypothesis by Bayly et al. [2], 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. Features capturing variations in movement trajectory of arm during seizure will be able to differentiate between the two seizure types using the proposed method.

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 events with 2.56 seconds epochs. It is usually 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 sinusoidal with a low coefficient of variation during the 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 for 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 correlate with sEMG based approach of Conradsen et al. [8], where they have shown a high sensitivity in the detection of seizures using sEMG data obtained from deltoid muscles. Our results suggests, that HOOM features are able to embed the information captured by fourier transform [10] and to some extent the information from sEMG [8]. 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.

Jay: Comparison with other methods, is it required??? At least a statement to this effect.

IV. CONCLUSION

A novel algorithm based on 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 on 2.56 seconds windows. The coefficient of variation of histograms with different bin size for (r, θ, φ) are 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. The high f-score suggests the 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. (Jay: This statement should be justified in discussions) The encouraging results demonstrates the feasibility of the proposed algorithm in automated classification of convulsive PNES events using a wrist worn accelerometer device.

REFERENCES
