Phasic Electromyographic Metric detection based on wavelet analysis

Jacqueline A. Fairley, George Georgoulas, Chryostomos Stylios, George Vachtsevanos, David B. Rye and Donald L. Bliwise

Abstract—The Phasic Electromyographic Metric (PEM) has been recently introduced as a sensitive indicator to differentiate Parkinson’s Disease (PD) patients from controls, non-PD patients with a history of RBD from controls, and PD patients with early and late stage disease. However, PEM assessment through visual inspection is a cumbersome and time consuming process. Therefore, a reliable automated approach is required so as to increase the utilization of PEM as a reliable and efficient clinical tool to track PD progression. In this study an automated method for the detection of PEM is presented, based on the use of signal analysis and pattern recognition techniques. The results are promising indicating that an automatic PEM identification procedure is feasible.

I. INTRODUCTION

Rapid Eye Movement Behavior Disorder (RBD) refers to a neurodegenerative condition in which patients act out their dreams and engage in potentially disruptive, injurious and even dangerous behavior while asleep [1]-[3]. Clinical reports of RBD have been shown to anticipate the development of neurodegenerative conditions like Parkinson’s Disease (PD) by 20 years or more [4]-[6]. Despite this potential prognostic significance for human disease, the field of Sleep Medicine lacks an accepted computerized approach to quantify muscle activity in sleep. This study focuses on the detection of the phasic electromyographic metric (PEM), a measure of muscle activity. Bliwise et al. has provided evidence based on traditional visual analyses from “expert” scorers that PEM recorded during sleep is a sensitive indicator: a) to differentiate PD patients from controls [7]; b) to distinguish non-PD patients with a history of RBD from controls [8]; and c) to differentiate PD patients with early and late stage disease [9]. These outcomes suggest that computer-aided PEM detection is promising for clinicians to determine prognosis, track disease course, and, potentially, monitor treatment of RBD and PD patients.

Traditionally computer-aided methods in the field of biomedical engineering apply signal processing techniques to raw signals in order to de-noise them and more importantly to “condense” the contained information. The wavelet transform is a signal processing method that is particularly useful for such medical applications [10],[11]. Wavelet transform analysis performs a decomposition of the original signal into a number of user-defined scales, each scale representing a particular “coarseness” of the signal under study [12]. Moreover, the localized nature of the wavelet transform makes it an ideal signal processing technique to handle non-stationary signals and to isolate aperiodic events, which are commonly found within biological data sets.

The remainder of this paper is structured as follows. Section II presents the data collection procedures and a step by step description of the PEM detection methodology. Section III summarizes the results obtained from our approach and finally Section IV concludes the paper and provides information regarding future works.

II. MATERIALS AND METHODS

A. Data Collection

This study adhered to U.S. Department of Health and Human Services experimentation guidelines and received Institutional Review Board approval from Emory University. The study sample included de-identified polysomnogram ( PSG ) data from one male, 72 years of age, with a history of sleep complaints. The data set consisted of a single overnight PSG of approximately seven hours in duration.

B. Polysomnographic Techniques

Psg data was collected at the Emory Clinic Sleep Disorders Center (ECSDC) located in Atlanta, Georgia. Using calibrated sleep monitoring equipment sleep technicians at ECSDC attached surface electrodes to the right and left anterior tibialis, legs, to extract the limb muscle activity at a sampling rate of 200Hz.

The psg data record was obtained using an Embla (Flaga Medcare) Model N-7000 digital polysomnographic/EEG system, in real time, in conjunction with a personal computer using the sleep data collection software program Somnologica ® 2.0 [13]. Psg data were converted from Somnologica .edf format, for EEG power analysis, via the MATLAB software (version 7.8 R2009a) using the biosig toolbox [14]. A Dell Optiplex 745 desktop computer with an Intel Core 2 Duo processor and a Toshiba Satellite A100 laptop with an Intel Core Duo processor were used to conduct all data analysis.

C. Assessment and Classification of Phasic Electromyographic Muscle Activity

Manual/visual scoring of PEM activity was based upon guidelines specified by Montplaisir et al. [15], with novel additional guidelines proposed by the authors. PEM activity in the right and left leg electrode channels were defined by
EMG activity of duration greater than 100 milliseconds with signal amplitude being at least four times the pre-sleep baseline. In this research study, the visual identification of PEM utilized a 1.0 second mini epoch analysis window in contrast the 2.0 second mini-epoch window used by Montplaisir et al. [15]. We did not specify an upper limit on PEM duration, therefore multiple burst of PEM activity were allowed within the 1.0 second mini epoch window provided repetitive returns to baseline were detectable between PEM events.

Visual scoring was conducted separately for each leg channel. A total of five PEM Scorers (A, B, C, D, E) were instructed to implement binary labeling, using Somnologica® 2.0, of EMG leg movements meeting previously mentioned criteria as PEM activity (1) and not meeting criteria as non-PEM (0), all based on unanimous expert scoring.

To prevent erroneous results, EMG data segments contaminated by excessive body movements (i.e. patient position change in bed) were excluded from the final data set. In order to focus on expert based visually distinguishable PEM the original seven hour PSG were reduced to 1.4 hours (right leg) and 1.45 hours (left leg) data sets, excluding artifacts. Table I includes a detailed description of the PEM and Non-PEM distribution, 1 epoch equivalent to 1 second, for the right and left leg data sets, unanimous decision. An example of PEM and Non-PEM activity, from the data set, is displayed in Figure 1.

### Table I

<table>
<thead>
<tr>
<th>Leg</th>
<th>PEM Epochs</th>
<th>Non-PEM Epochs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Right</td>
<td>599</td>
<td>6857</td>
</tr>
<tr>
<td>Left</td>
<td>491</td>
<td>7203</td>
</tr>
</tbody>
</table>

Fig. 1: Plot of PEM activity with PEMRL indicating right leg PEM activity (top panel) and PEMLL indicating left leg PEM activity (bottom panel), portions not labeled indicate Non-PEM activity.

#### D. Automatic Detection Procedure

The automatic detection procedure consisted of several stages. During the first stage the raw signal is segmented into one minute epochs with each epoch containing 200 samples. In stage two, feature extraction is applied based on wavelet analysis. As it is generally stated, feature extraction is more of an art than a science; therefore we extracted and tested a number of features, potentially containing redundant information. To deal with redundancy issues, we included a dimensionality reduction stage using Principal Component Analysis (PCA) prior to the final classification stage. The entire procedure is depicted in Figure 2. The remainder of section II describes each one of these stages along with the experimental procedure involved to assess the validity of the proposed approach.

![Diagram](image)

**Fig. 2:** The automatic detection procedure.

#### E. Wavelet Feature extraction

Wavelet analysis has gained great popularity for the analysis of non-stationary signals, specifically as an alternative to short-time Fourier transform analysis. The intrinsic property of the wavelet transform to localize well both in time and frequency domain makes it very appealing
for biological signal analysis. Moreover, even for stationary signals, it can be used to analyze data sets containing a mixture of features at different resolutions [16].

In the case of a continuous signal \( s(t) \), the corresponding continuous wavelet transform (CWT) is produced by taking the inner product of the signal with translated and scaled versions of an (real or complex) analyzing (mother wavelet) function \( \psi \). Translations and dilations of the mother wavelet (Eq. 1) are used to transform the signal into another form (time-scale representation).

\[
\psi_{ab}(t) = \frac{1}{\sqrt{a}} \psi \left( \frac{t-b}{a} \right) 
\]  

(1)

In the case of the discrete parameter wavelet transform (DPWT) [16], the dilation and translation parameters \( a, b \) are restricted only to discrete values leading to the following expression:

\[
\psi_{m,n}(t) = a_0^{-m/2} \psi \left( \frac{t-nb_0a_0^m}{a_0^m} \right) 
\]  

(2)

The choice of \( a_0 = 2 \) and \( b_0 = 2 \) (dyadic grid arrangement) is generally accepted, such that:

\[
\psi_{m,n}(t) = 2^{-m/2} \psi \left( 2^{-m}t-n \right) 
\]  

(3)

However, most biological signal processing applications involve discrete time signals. In this case the discrete time wavelet transform (DTWT) [16] is given by:

\[
\psi_{m,n}(t) = 2^{-m/2} \sum_k \chi(t) \psi \left( 2^{-m}k-n \right) 
\]  

(4)

Different mother wavelets have been proposed and methods exist for the development of customized wavelets [17]. However, many merits produced by the use of custom made wavelets are insignificant compared to the use of existing wavelets [18]. In this work, we have experimented using Daubechies and symmlet families with different values of vanishing moments. All the aforementioned wavelets were developed by Daubechies [17] and they demonstrate the appealing property of having compact support such that the wavelet transform can be computed with finite impulse response conjugate mirror filters using a fast filter bank algorithm.

In this work, we performed wavelet decomposition up to level four and using as inputs the wavelet coefficients, we calculated the following quantities at each level:

- Standard deviation,
- Mean absolute deviation,
- Skewness,
- Kurtosis,
- Curve length and
- Shannon’s entropy (using as inputs the normalized squared detailed coefficients).

Therefore in total, we calculated 24 features for each epoch. Figure 3 depicts the histograms (crude approximation of the underlying probability density functions (pdfs)) of the Mean Absolute Deviation of the wavelet coefficients produced by the application of the wavelet transform using a symmlet mother wavelet with 5 vanishing moments for the left leg data set. Figure 3 indicates that the two classes are characterized by distinct ranges of values. Also, different levels of overlapping are observed depending on the decomposition level.

![Fig. 3: Crude “pdf” of the Mean Absolute Deviation of the wavelet coefficients (using symmlet with five vanishing moments) at level 1 and 2.](image)

**F. Dimensionality Reduction**

As previously stated, for real world applications we tend to extract more features than necessary in an effort to include all possible information. On the other hand the inclusion of redundant information may negatively affect the performance of the classifier. Therefore, typically following the feature extraction stage some dimensionality reduction method is applied.

There are two major families of dimensionality reduction techniques. The first one attempts to select a subset of the original features whereas the second one maps the original space into a lower dimension space through a mathematical transformation. Among the latter approaches the most widely used technique is PCA or the Karhunen-Loeve transformation. PCA linearly transforms the original space [19],[20] by projecting the \( N \)-dimensional data onto the \( M \)
(M≤N) eigenvectors of their covariance matrix corresponding to the M larger eigenvalues. Even if the entire set of the eigenvectors is to be retained this may also lead to an improvement of classification performance due to the uncorrelated nature of the new set of features.

G. Classification

As stated earlier in the introduction we are proposing a classification approach to discriminate between PEM and non-PEM segment. During the last three decades many novel and powerful methods have been proposed in the field of pattern recognition. However in most cases simpler more traditional classifiers actually perform in a similar manner to novel classifiers when utilized in real world applications [21]. Therefore, in this work we used a simple minimum distance linear classifier [19],[20] to detect PEM and non-PEM segments.

H. Experimental procedure

We have conducted four different sets of experiments. More specifically we have examined separately the recordings coming from the left leg and right leg using: a) only those segments that were labeled unanimously by all five experts and b) using all segments applying the majority vote scheme for labeling. We have varied the number of retained principal components from one to 24 and the number of vanishing moments from one to 15 for the symmlet and daubechies wavelet families.

In order to test our approach in a manner with minimum bias we applied an “inner” and an “outer” loop validation scheme. The outer loop was included in order to asses the performance of our approach while the inner scheme was applied in order to tune our procedure (number of retained principal components and selection of the number of vanishing moments). With the “outer” scheme we divided the data set into training and testing sets (80% for training and 25% for testing) using a similar reshuffle scheme. The inner loop was repeated 10 times and the best configuration (number of principal components and number of vanishing moments), in terms of average classification performance was selected and the model was retrained using both the training and testing sets of the inner loop and tested using the testing set of the outer loop. This method decoupled the parameter selection stage from the estimation of the performance [22] thus avoiding our reaching overly optimistic conclusions about the capabilities of our approach. Lastly, the outer loop procedure was repeated 20 times and the results are presented in the following section.

III. RESULTS

Tables II through IX comprise the results for the four different sets of experiments described in the previous section for the two wavelet families presented in the form of average confusion matrices. Table X presents the respective sensitivity (proportion of actual PEM epochs which are correctly identified) and specificity (proportion of actual non-PEM epochs which are correctly identified) for each of the eight aforementioned configurations.
TABLE IX
AVERAGE CONFUSION MATRIX – MAJORITY LABELING, RIGHT LEG, SYMMLET FAMILY

<table>
<thead>
<tr>
<th>Predicted Class</th>
<th>Actual class</th>
<th>Non-PEM</th>
<th>PEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-PEM</td>
<td>1413.25</td>
<td>21.1</td>
<td></td>
</tr>
<tr>
<td>PEM</td>
<td>43.75</td>
<td>141.9</td>
<td></td>
</tr>
</tbody>
</table>

TABLE X
SENSITIVITY AND SPECIFICITY

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>D - U - L</td>
<td>93.16</td>
<td>98.79</td>
</tr>
<tr>
<td>D - U - R</td>
<td>92.79</td>
<td>98.54</td>
</tr>
<tr>
<td>D - M - L</td>
<td>90.56</td>
<td>97.08</td>
</tr>
<tr>
<td>D - M - R</td>
<td>87.79</td>
<td>96.83</td>
</tr>
<tr>
<td>S - U - L</td>
<td>92.76</td>
<td>98.81</td>
</tr>
<tr>
<td>S - U - R</td>
<td>91.71</td>
<td>98.55</td>
</tr>
<tr>
<td>S - M - L</td>
<td>90.70</td>
<td>97.33</td>
</tr>
<tr>
<td>S - M - R</td>
<td>87.06</td>
<td>97.00</td>
</tr>
</tbody>
</table>

L = Left Leg, R = Right Leg, U = Unanimous voting, M = Majority voting, S = Symmlet mother wavelet, D = Daubechies mother wavelet.

IV. CONCLUSION

In this study, we investigated the development of an automated method for the detection of PEM activity. Presence of excessive PEM activity is closely linked to a number of neurodegenerative disorders, which include Parkinson’s Disease (PD) and Rapid Eye Movement Behavior Disorder (RBD). Therefore, the automated detection of PEM is a favorable method for clinical use in the tracking of PD and RBD.

The proposed approach is based on the application of the wavelet transform on the EMG signal and extraction of features in the wavelet domain. The experimental results indicate that PEM and Non-PEM activity can be efficiently identified using quantitative methods. More specifically for the unanimous voting scheme the sensitivity is approximately 92% for both legs also with very high specificity (above 98.5% in all four cases). In case of majority voting labeling there is a drop in algorithm performance which can be justified by the fact that we included cases that expert PEM scorers found problematic to classify.

In terms of the best PEM detection configuration the use of the Daubechies family appears to be the optimal choice. However, no clear choice for the selection of the number of vanishing moments and the number retained principal components were found. In general configurations with 9 to 14 vanishing moments and more than 15 principal components produced comparable results (only in the case of the right leg and with majority voting labeling, a smaller number of principal components was more appropriate). More data are needed before we reach a safe conclusion about the optimal selection of the aforementioned parameters.

In order to extend this work toward a computer-aided clinician tool further analysis will be required to adapt the current methodology to automatically compensate for artifact segments, which were manually excluded for this study.

Moreover, further investigations will be conducted to address automated PEM detection methods across various subject populations (controls, RBD patients and PD patients).

Finally we suggest the investigation of a method to quantify PEM activity without the restriction of the one second epochs. Being that this artificial segmentation might be responsible for the disagreement among experts since most of the dubious cases involved epochs with PEM events crossing segmentation boarders. Therefore in future work we will refine our approach to tackle these borderline cases.

ACKNOWLEDGMENT

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REFERENCES