Semi-Automated Annotation of Phasic Electromyographic Activity

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Abstract. Recent research on manual/visual identification of phasic muscle activity utilizing the phasic electromyographic metric (PEM) in human polysomnograms (PSGs) cites evidence that PEM is a potentially reliable quantitative metric to assist in distinguishing between neurodegenerative disorder populations and age-matched controls. However, visual scoring of PEM activity is time consuming-preventing feasible implementation within a clinical setting. Therefore, here we propose an assistive/semi-supervised software platform designed and tested to automatically identify and characterize PEM events in a clinical setting that will be extremely useful for sleep physicians and technicians. The proposed semi-automated approach consists of four levels: A) Signal Parsing, B) Calculation of quantitative features on candidate PEM events, C) Classification of PEM and non-PEM events using a linear classifier, and D) Post-processing/Expert feedback to correct/remove automated misclassifications of PEM and Non-PEM events. Performance evaluation of the designed software compared to manual labeling is provided for electromyographic (EMG) activity from the PSG of a control subject. Results indicate that the semi-automated approach provides an excellent benchmark that could be embedded into a clinical decision support system to detect PEM events that would be used in neurological disorder identification and treatment.

Keywords: Phasic Electromyographic Metric, PEM, EMG, Clinical Decision Support Systems, Graphical User Interfaces, GUIs.

1 Introduction

The movement disorders literature in sleep medicine contains a plethora of schemes (visual [1-4] and computerized [5-10]) to characterize electromyographic (EMG) activity during sleep, providing evidence differentiating between healthy and neurodegenerative patient populations. Notwithstanding the relevant clinical benefit of early diagnosis of neurodegenerative conditions from implementation of these schemes a standardized EMG processing methodology has yet to be adopted in clinical practice [11].

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Impediments to the adaptation of a standardized methodology to measure EMG activity during sleep for clinical assessment have been outlined by Neikrug and Ancoli-Israel [12], with concerns relevant to our study summarized below:

a. Consistency in scoring and defining pertinent EMG activity metrics are lacking, preventing valid comparisons between studies across different labs.
b. Major drawbacks in visual scoring methods (laborious time consumption and mislabeling) and absence of rigorous validation of computerized approaches with prevalence values of patient populations equal to that encountered clinically.
c. Delineation of amount, duration, and level of phasic EMG activity required for pathological classification.

Addressing the concerns posed by Neikrug and Ancoli-Isreal are crucial in order to efficiently translate research findings regarding EMG activity in sleep for clinical benefit. Therefore we present a quantitative methodology, within a user friendly computerized approach,that will establish standards required tackle the issues mentioned in a) and b). The proposed system builds upon our previous work [9] to define quantitative features which efficiently compare to validated visual scoring techniques for phasic EMG metric (PEM) identification, established by Bliwise *et al.* [4]. We utilize the validated quantitative features to develop an assistive/semi-supervised graphical user interface (GUI) that reduces scoring time in labeling phasic EMG events. The major aim of this work is the design and development of a user friendly GUI for automatic phasic EMG identification that will be used in both healthy and neurodegenerative patient populations, so there is not included any classification of pathological cases that will be future work. Therefore, the evaluation of the proposed approach is obtained by comparing elapsed times of expert scoring using our GUI for manual and semi-supervised labeling of phasic EMG leg events from a human control data set. Our work represents an excellent benchmark for the development of a clinical decision support system to detect PEM events for future use in neurological disorder identification and treatment within a clinical setting.

2 Methods

2.1 Data Collection

All data collected in this study followed Institutional Review Board guidelines outlined by Emory University (Atlanta, Georgia, USA) under the approved protocol IRB00024934. Overnight polysomnogram (PSG) data were recorded from one 72 year old male subject (S001), not meeting ICSD criteria for neurodegenerative disease diagnoses, using the Embla Model N7000 data acquisition unit and the proprietary software program RemLogic^{TM}. Electromyogram (EMG) data was recorded, digitized at a sampling rate of 200Hz with impedance values<10,000 Ohms, from bilateral electrodes located on the left anterior tibialis (left leg). EMG signals were exported

from RemLogic using the European Data Format (.edf). The proprietary numerical computing software program MATLAB® (version 8.2 R2013b) and the open source software library for biomedical signal processing BioSig Toolbox (http://biosig.sourceforge.net/), MATLAB® compatible, version 2.88 (Schloegl A-Graz University of Technology, Graz, Austria) were utilized to convert .edf files into a .mat format for quantitative processing and GUI scoring. Data segments containing artifacts were manually excluded from the final data set, which consisted of ~4.5 hours of EMG data from Rapid Eye Movement (REM) and Non-REM sleep, approximately distributed equally.

2.2 Graphical User Interface (GUI)

The proposed semi-automated approach consists of four levels: A) Signal parsing to segment the signal into 1 sec windows, B) Calculation of quantitative features on candidate PEM events, C) Classification of PEM and non-PEM events using a linear classifier, and D) Post-processing/Expert feedback to correct/remove automated misclassifications of PEM and Non-PEM events. Details regarding pertinent aspects of each level of our semi-automated PEM annotator are delineated below:

2.3 Level A: Signal Parsing

Unlike our previous work [9,14] in order to detect candidate PEMs we parse the signal using a non-overlapping sliding window. The size of the window is chosen as 1 sec.

2.4 Level B: Calculation of Quantitative Features on Candidate PEM Events

Expanding upon our previous work we automated, within the GUI, the calculation of 15 features on the candidate PEM and Non-PEM events obtained from Stage A using a 1 sec non-overlapping moving window. Feature descriptions and corresponding mathematical equations were described in detail in our previous work [9] and are reprinted below, for the reader's convenience:

1. Relative EMG Frequency Power (Prel): a frequency domain feature that provides a sub-band analysis of the high frequency EMG signal components (frequency band [12.5 to 32 Hz]) [15] (sampled at 200 Hz) with the power spectra density ($P(f)$) extracted using the Fast Fourier Transform (FFT) [16,17]

   i. $$\text{Prel}=\frac{P([12.5-32Hz])}{P([8-32Hz])}=\frac{\int_{12.5}^{32} P(f)\,df}{\int_{8}^{32} P(f)\,df} \quad . \tag{1}$$

2. Spectral Edge Frequency 95th Percentile (SEF 95): the frequency up to which 95 percent of the total signal power is accumulated [18].

$$\int_{0}^{SEF95} P(f)df = 0.95 \int_{0}^{f_s/2} P(f)df \ , \tag{2}$$

where f_s , is the sampling frequency.

3. Skewness (*Skew*): a time domain feature that measures the asymmetry of the probability distribution of the EMG signal amplitude [19].

$$Skew = \frac{1/M \sum_{i=1}^{M} (x(i) - \bar{x})^3}{\left(1/M \sum_{i=1}^{M} (x(i) - \bar{x})^2\right)^3} , \tag{3}$$

with *M* representing the number of data samples contained in the processing window and $\bar{x}$ symbolizing the sample mean $\bar{x} = \frac{1}{M} \sum_{i=1}^{M} x_i$ within that interval.

4. Variance (s^2) [19]:

$$s^2 = \frac{1}{M-1} \sum_{i=1}^{M} (x(i) - \bar{x})^2 \ . \tag{4}$$

5. Kurtosis (Kurt): a measure of the peakedness or flatness of the probability distribution of the signal amplitude [20]

$$Kurt = \frac{1/M \sum_{i=1}^{M} (x(i) - \bar{x})^4}{\left(1/M \sum_{i=1}^{M} (x(i) - \bar{x})^2\right)^2} . \tag{5}$$

6. Entropy (Ent): an information domain feature that calculates the amount of uncertainty or unpredictability of the EMG signal amplitude

$$Ent = -\sum_{i=1}^{n} \frac{bin_i}{M} \log\left(\frac{bin_i}{M}\right) , \tag{6}$$

with *M* symbolizing the length of the data signal, *n* representing the number of bins, with the optimal number of bins obtained using the Freedman–Diaconis rule [21], to estimate the histogram of the data signal with bin_i indicating the number of data samples from EMG signal contained in the i^{th} histogram bin [22].

7. Mobility (*Mobi*): a time domain feature that measures the relative average slope of the EMG signal. It is expressed as the standard deviation (*std*) of the slope (signal's first derivative dx/dt) with reference to the *std* of the signal amplitude [22].

$$Mobi = \frac{std\left(\frac{d(x)}{dt}\right)}{std(x)}, \tag{7}$$

where, the EMG signal is symbolized by the discrete variable x for $std(x) = s$ (See equation 4) and a first order approximation is used to calculate the derivative such that,

$$std\left(\frac{d(x)}{dt}\right) = sqrt\left(\frac{1}{M-2}\sum_{i=1}^{M-1}\left(f_{sampl}(x(i+1)-x(i)) - \frac{1}{M-1}\sum_{i=1}^{M-1} f_{sampl}(x(i+1)-x(i))\right)^2\right). \tag{8}$$

8. 75th Amplitude Percentile (75_Amp): the amplitude value below which 75% of the total EMG signal amplitude resides [22]. So, the value separates lowest 75% and highest 25% of the data. It is also called upper quartile or third quartile.

$$card\{x(i) \mid x(i) < 75\_Amp\} = \frac{75 \cdot M}{100}, \tag{9}$$

where M is the number of samples $x(i)$ of the EMG signal in one epoch and card represents the number of elements within the sample set (set's cardinality).

9. Complexity (Comp): the ratio of the mobility (*Mobi*) of the first derivate of the signal to the mobility of the signal amplitude. Complexity expresses the average EMG wave-shape in relation to a pure sine wave [22].

$$Comp = \frac{Mobi(dx/dt)}{Mobi(x)}. \tag{10}$$

10. Mean Absolute Amplitude (*MAA*): a time domain feature that measures the absolute value of the mean EMG amplitude [23].

$$MAA = \frac{1}{M}\sum_{i=1}^{M}\left|x(i)\right|. \tag{11}$$

11. Curve Length (*L*): the sum of the value of the first order differences of the EMG signal amplitude values [24].

$$L = \sum_{i=1}^{M} \left| x(i+1) - x(i) \right| . \tag{12}$$

12. Mean Energy (MnE): a time domain feature that measures the squared EMG signal amplitude [24].

$$MnE = \frac{1}{M} \sum_{i=1}^{M} x(i)^2 . \tag{13}$$

13. Zero Crossings (ZC): defined as the number of crossings of the EMG signal over the ordinate, where the axis equals zero [24].

$$ZC'(i) = \begin{Bmatrix} 1, & x(i) \le 0 \cap x(i+1) > 0 \\ 1, & x(i) \ge 0 \cap x(i+1) < 0 \\ 0, & otherwise \end{Bmatrix},$$

$$ZC(i) = \sum_{i=1}^{M-1} ZC'(i) . \tag{14}$$

14. Average Nonlinear Energy (NE): a non-linear feature that is sensitive to signal fluctuations in the time and frequency domain, with respect to the following non-linear operator (NLO):

$$NLO[i] = x(i)^2 - x(i-1)x(i+1) , \tag{15}$$

the NLO is weighted with a Hanning window and then the NE is calculated as follows:

$$NE = \frac{1}{M} \sum_{i=1}^{M} NLO_w[i] , \tag{16}$$

where, NLO_w is the Hanning windowed version of the nonliner operator, NLO , with M being the data epoch [24].

15. Spectral Entropy (SE): defined as the amount of uncertainty or unpredictability of the EMG signal in the frequency domain [24],

$$SE = -\sum P(f) \log_2 P(f) . \tag{17}$$

2.5 Level C: Classification of PEM and Non-PEM Events Using a Linear Classifier

Supervised classification of one second epochs as PEM versus Non-PEM events were conducted using a linear classifier [25]. The feature vector y obtained from Level B

is represented as $y \in \Re^{15}$, such that the linear discriminant function, $\delta_k(y)$, with respect to the class k is defined by the following:

$$\delta_k(y) = y^T \Sigma^{-1} \mu_k - \frac{1}{2} \mu_k^T \Sigma^{-1} \mu_k + \log \pi_k , \tag{18}$$

where, $k = 1,2$ represents the two classes describing the PEM and Non-PEM events respectively, μ_k is the 15 component mean vector, Σ is the 15×15 feature covariance matrix, Σ^{-1} is the inverse of the feature covariance matrix, and prior probabilities are defined by π_k such that:

$$\pi_k = \frac{N_k}{N_1 + N_2}, \; k = 1,2 , \tag{19}$$

and N_k is the number of samples within the k class training data set.

The mean vector and covariance matrix for each class k are estimated during the training phase and are described by the following:

$$\mu_k = \frac{1}{N_k} \sum_{i=1,\, y_i \in k}^{N_k} y_i , \; k = 1,2 , \tag{20}$$

$$\Sigma = \frac{1}{N-2} \sum_{k=1}^{2} \sum_{i=1}^{N} (y_i - \mu_k) \cdot (y_i - \mu_k)^T \; . \tag{21}$$

As for the evaluation of the linear algorithm we used the PEM and Non-PEM events annotated by a phasic EMG expert scorer from the data set of S002. Lastly, to obtain PEM and Non-PEM labeling, the function is maximized using the classification rule k^* where,

$$k^* = \arg\max_{k=1,2} \delta_k(y) . \tag{22}$$

2.6 Level D: Post-processing/Expert Feedback to Correct/Remove Automated Misclassifications of PEM and Non-PEM Events

Level D includes the semi-automated portion of our GUI. This stage permits the user/scorer to provide feedback within the classification scheme by correcting any automated misclassifications, from Level C, of PEM and Non-PEM events. Figure 1 summarizes all the aforementioned levels included within the proposed semi-automated phasic EMG annotator using a flowchart. A screen shot of the visual interface produced by the developed GUI is shown in Figure 2. Lastly Figure 3 displays the output of the GUI following Level C.

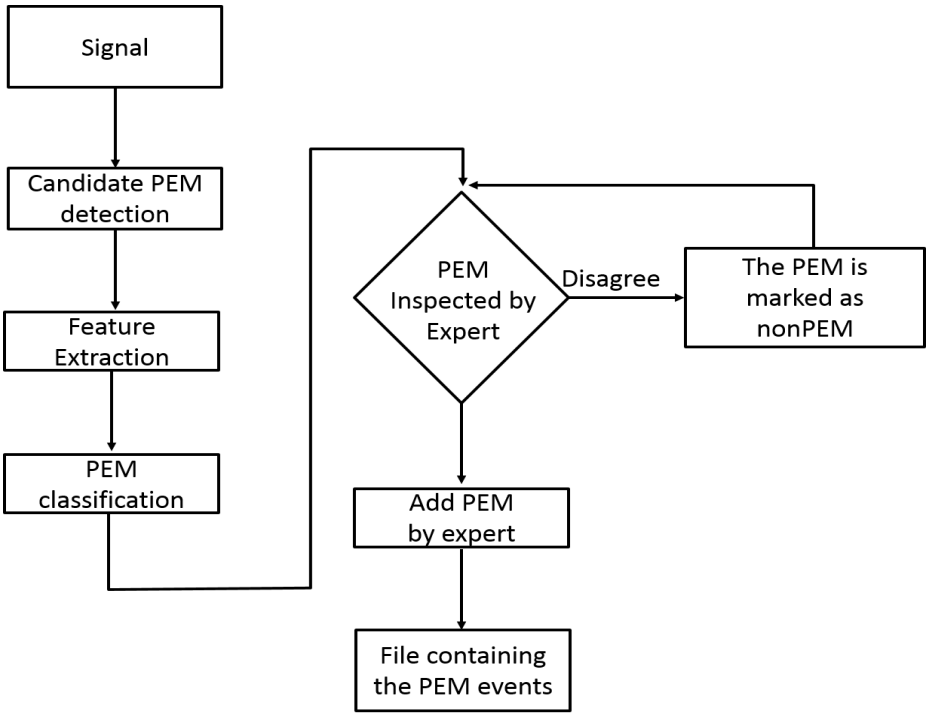

Fig. 1. Flowchart of Semi-Automated PEM Annotator Methodology

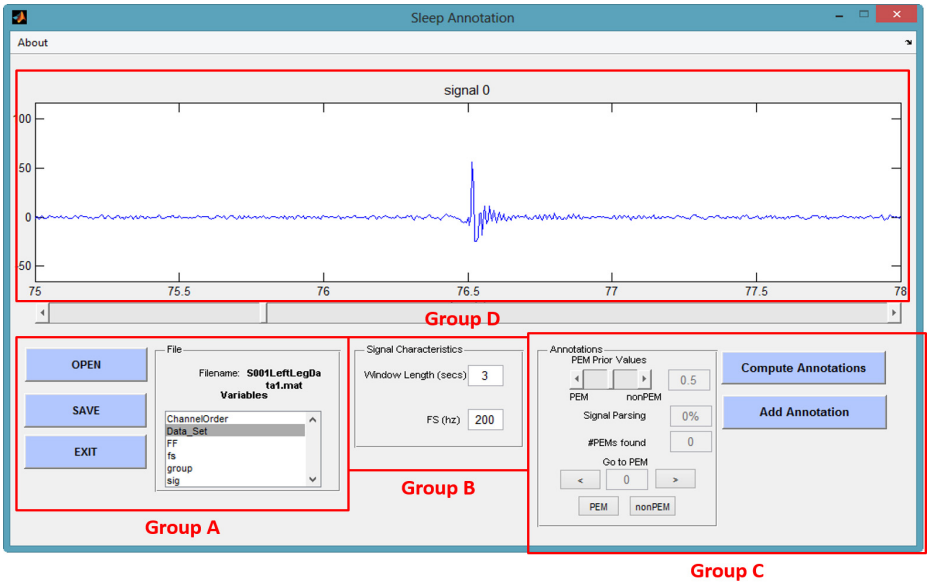

Fig. 2. Screenshot of the left leg EMG data from S001, displayed within our semi-automated phasic EMG activity GUI annotator

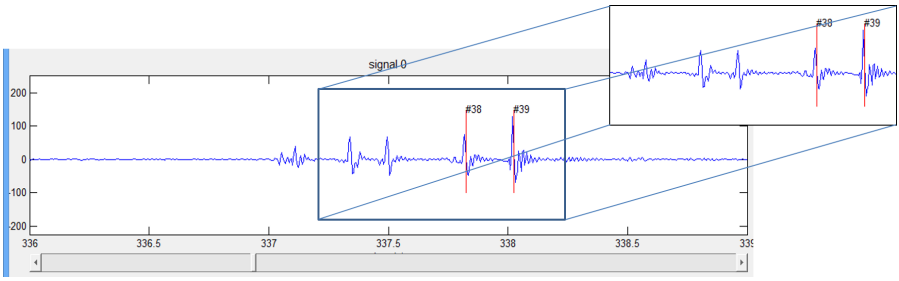

Fig. 3. Four PEM events two are correctly classified and annotated and two are classified as non- PEM events (PEM events demarcated by vertical read lines and #38 and #39)

3 Results

3.1 Classification and Speedup

In this study one expert PEM scorer using the proposed semi-automated phasic EMG activity GUI annotated the left leg EMG PSG data from a single patient, S001. Tables 1 through 3 comprise the classification performance results and time elapsed from the latter. Classification results for all PEM and Non-PEM events using the linear discriminant algorithm are provided in a confusion matrix in Table 1. Results from the linear algorithm "predicted" were compared to the "actual" labels of PEM and Non-PEM events obtained from the expert EMG activity scorer.

Table 1. Confusion matrix of our classification scheme

	PEM (predicted)	**Non-PEM (predicted)**
PEM (actual)	622	50
Non – PEM (actual)	126	7289

Detection rates for PEM and Non-PEM events are displayed in Table 2. The detection rates for PEM and Non-PEM were calculated as follows:

$$Detection\ Rate = \frac{number\ of\ correct\ detections}{number\ of\ correct\ detections\ +\ number\ incorrect\ detections} \quad (20)$$

Table 2. Detection rates for PEM and Non-PEM events for patient S001

PEM (%)	**Non-PEM (%)**
92.56	98.3

Lastly, the time elapsed while the expert labels PEM and Non-PEM events with/without use of our semi-automated phasic EMG activity scheme are shown in Table 3.

Table 3. Time spent by an expert annotating data from a single subject, S001 with or without use of our semi-automated phasic EMG activity annotator

	Time in secs
Annotation time without semi-automated labeling	4hr 26min 2sec
Annotation time with semi-automated labeling	58min 30sec

4 Conclusions

Here we developed and describe a software tool for semi-automated classification of phasic EMG events recorded from surface electrodes in an overnight human PSG. The semi- automated software tool provides to the user the opportunity to add PEM events that are not detected or to remove PEM events that the software incorrectly detected, easily and quickly using a simple point and click operation. Accurate and timely computerized PEM annotation will aid in addressing all the concerns posed by Neikrug and Ancoli-Israel [12] and assist in establishing standardized EMG processing methodologies for future use in neurological disorder identification and treatment.

Future work will incorporate more sophisticated classifiers which provide confidence intervals on the detected events. Also, since PEM events are less prevalent than Non-PEM events we will concentrate on avoiding false dismissals/false negatives (type II errors). The latter will reduce the need for the user to review excessive incorrectly automated-annotations of PEM segments (False Negatives). This will minimize the time spent by the user/scorer for annotation. Moreover, to determine user-friendliness and clinical relevance of the GUI, we will investigate GUI robustness with respect to training levels of scorers (e.g. beginner, intermediate, and expert) and different data sets/patient populations (e.g. neurodegenerative disorder patients and age matched-controls). Lastly, investigation of the proposed future work will aid in meeting the long-term goal to develop a supportive technology for the efficient annotation of EMG events within a clinical decision support system platform.

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