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Wavelet analysis for detection of phasic electromyographic activity in sleep: Influence of mother wavelet and dimensionality reduction

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ABSTRACT

Phasic electromyographic (EMG) activity during sleep is characterized by brief muscle twitches (duration 100–500 ms, amplitude four times background activity). High rates of such activity may have clinical relevance. This paper presents wavelet (WT) analyses to detect phasic EMG, examining both Symlet and Daubechies approaches. Feature extraction included 1 s epoch processing with 24 WT-based features and dimensionality reduction involved comparing two techniques: principal component analysis and a feature/variable selection algorithm. Classification was conducted using a linear classifier. Valid automated detection was obtained in comparison to expert human judgment with high ($>90\%$) classification performance for 11/12 datasets.

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1. Introduction

Labor-intensive, visual analysis of surface electromyographic (EMG) activity during human sleep studies (i.e., polysomnography, PSG) has provided a quantitative, physiologic research metric to potentially track development of some neurodegenerative conditions [1]. High rates of EMG activity during rapid eye movement (REM) sleep occur in patients with idiopathic REM behaviour disorder (RBD), a dramatic condition in which patients act out their dreams and engage in potentially disruptive, injurious and even dangerous behaviors (e.g., walking through glass doors) while asleep [2]. RBD appears, in some cases, to be the earliest sign of impending Parkinson's Disease (PD), which may occur decades later [3]. The elevated phasic muscle activity is subtle but can be a potentially stable and objective physiological marker of disease process [4] even on nights without dream enactment. This makes it a potentially attractive metric as a diagnostic tool for widespread use in sleep medicine. However, visual analyses of such activity are extremely labor intensive (approximately 6 to 8 h of visual scoring time per sleep recording [1]) and hinder immediate application in the clinical setting of overnight diagnostic PSG. The work that we present here expedites detection of phasic muscle activity by introducing a computerized identification scheme. This work builds upon our previous investigation of *unsupervised*, feature-based phasic EMG activity identification [5] by evaluating the performance of a *supervised* phasic EMG activity detector, based on the discrete wavelet (WT) transform [6]. We describe use of WT analysis to decompose the EMG signal to discriminate between phasic and non-phasic EMG activity. In this work we use the WT transform to improve such discrimination, which contrasts to the approach shown in [5], which considered time and frequency components of the EMG signal separately. We excluded several features used previously [5] because of redundancy.

Few computerized methods for quantification of surface EMG signals recorded during human sleep to track neurodegenerative disease have been attempted to date [7,8]. Apart from a small range of features analyzed, such prior attempts all relied prematurely on case identification to derive estimates of case sensitivity and case specificity, a strategy which ultimately confounds the two separate issues of signal identification performance and patient (case) versus control identification [5]. Such confusion can greatly exaggerate performance estimates of a computerized system by essentially "stacking the deck," against the presence or absence of time-based signals that occur stochastically in both patients and controls over seconds to minutes during the course of a night of sleep. Before evaluating the performance of any case-based

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Table 1
Sleep duration and relative distribution of sleep stages (% sleep in min) for epochs selected for EMG analysis.

Subject	Duration of Sleep (min)	NREM (% of sleep [duration])	REM (% of sleep [duration])
001	134	64.08	35.92
002	191	74.61	25.39
003	184	64.34	35.66
004	187	67.03	32.97
005	197	74.96	25.04
006	196	76.67	23.34

identifying computerized system in a clinical or epidemiologic setting, its accuracy regarding signal identification and validity must be demonstrated in real time.

2. Materials and methods

2.1. Polysomnographic (PSG) data collection

We analyzed twelve overnight de-identified PSG data sets (each consisting of separate left and right leg recordings from six individuals) derived from the sleep laboratory at Emory University School of Medicine in Atlanta, Georgia under an Institutional Review Board approved protocol. Sleep durations for selected epochs of PSG data for the six individuals are shown in Table 1. Extraction of real time leg muscle activity was obtained from bipolar (i.e., two active sites on each leg) surface electrodes with impedances below 10,000 Ω placed above the right and left anterior tibialis. Data acquisition was accomplished using the Embla (MedCare, Bloomfield, CO) sleep monitoring model N-7000 digital PSG system, with the software program Somnologica ® 2.0 at sampling rates of at least 200 Hz, which ensures sufficient sampling to capture phasic EMG activity occurring within the 0.1 s range specified within classical visual scoring guidelines. EMG data was converted from Somnologica Embla format to.edf format, using the MATLAB (version 7.8 R2009a) toolbox BioSig (Schloegl A-Graz University of Technology, Graz, Austria). WT analysis and classification routines were run using MATLAB (MathWorks®; Natick, MA) software programs.

2.2. Visual labeling of phasic EMG activity

Performance of the automated scheme was evaluated with respect to guidelines for manual assessment of phasic muscle activity found in our previous work [1]. The twelve overnight PSGs were first visually labeled for phasic and non-phasic muscle activity by the same trained visual scorer. Individual 1 s epochs containing visually identifiable artifacts were excluded. The left and right leg EMG recordings were separately marked at 1 s intervals (epochs) as either non-phasic (0), or phasic muscle activity (1). Data epochs that contained signal amplitudes of four times the surrounding background activity, visually estimated for that epoch, with duration ranges of 100 to 500 ms were marked as phasic muscle activity [1,5]. Epochs that did not meet the criteria for phasic muscle activity (e.g., activity >500 ms) were marked as non-phasic muscle activity. Scoring was conducted within the Somnologica software platform with a screen resolution display of 10 s per viewing window and a screen size of 15″ (see Fig. 1). Table 2 contains a summary of the frequency of these visual scoring binary classifications for each data set. EMG epochs with artifacts that included gross movements, ballistocardiographic interference and other spurious information were manually removed prior to formulation of the final data sets and are not included in Table 2.

2.3. Computerized detection algorithm

2.3.1. General approach

In order to discriminate between phasic and non-phasic EMG data segments, we implemented a pattern classification approach (see Fig. 2), which involved data collection, feature extraction (WT decomposition), dimensionality reduction (feature/variable selection [FVS] and principal components analysis [PCA]), and linear classification. We consider feature extraction to be the most essential component of classification system development, because the selection of a "good" set of features are required to fully characterize EMG data for successful automated phasic and non-phasic EMG activity discrimination. To compensate for potentially redundant or irrelevant features, the feature extraction stage was followed by a dimensionality reduction stage which further condensed relevant information in order to reduce classifier training time and increase generalizability of the classifier. Generalizability would be expected to be important if the classification approach was to be readily exported to PSG recordings not included in this initial validation.

We tested both: (a) a linear transformation technique, PCA and (b) a FVS algorithm represented by Forward Floating Search (FFS) using a filter approach [9,10]. Lastly, for automated phasic and non-phasic EMG activity discrimination we employed a linear classifier since it has been cited to provide comparable results to more advanced non-linear classifiers when applied to real data sets [11], resembling the time and frequency components of human muscle activity recorded with surface EMG.

2.3.2. Feature extraction

Classical approaches in signal processing typically have incorporated short-time Fourier transform (STFT) analysis, however, WT analysis has advantages for non-stationary time series, which typically characterize biopotentials [12]. WT analysis differs from traditional STFT by its approach to information in time and frequency domains. More specifically, WTs trade one type of resolution (time vs. frequency) for the other, making them robust for the analysis of non-stationary signals [6]. WTs decompose a signal into scales, each representing a particular "coarseness" of the signal. Data sets containing a mixture of features residing at different time and frequency resolutions are well-suited for WT analysis relative to STFT [13]. The presumed benefits of WT (vs. STFT) to track phasic EMG activity, which appears in varying high frequency bands (see Fig. 1), was a major factor underlying our testing in order to determine whether WT analysis offered unique EMG signal analysis advantages, as was the conventionality of this technique. Other advantages included the lower computational cost of the WT approach.

A WT $\psi(t)$ is a localized waveform (a short-term duration wave), which characterizes waveforms by vanishing moments (VMs) of varying complexity [13]. Two basic manipulations can be performed on the WT, stretching or squeezing (dilation) and moving (translation). Dilation is governed by the scale parameter a, whereas translation is governed by the parameter b. Smaller scales correspond to higher frequency components and higher scales correspond to lower frequency components. Dilated and translated versions of the original mother WT comprise a family of WTs defined by (with the original *mother* WT defined by parameters values $a=1$ and $b=0$):

$$\psi_{a,b}(t)=\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad (1)$$

In our analysis we employed the discrete time WT transform (DTWT), also known as the pyramid algorithm, which is