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Analysis of the Electromyogram of Rapid Eye Movement Sleep using Wavelet Techniques

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Abstract—**Quantitative electromyographic (EMG) signal analysis in the frequency domain using classical power spectrum analysis techniques has been well documented over the past decade. Yet due to the nature of EMG, frequency analysis cannot be used to approximate a signal whose properties change over time. To address this problem a time varying feature representation has to be analyzed to extract useful information from the signal. In this paper, Wavelet analysis technique has been used to extract features from EMG, and Linear Discriminant Analysis have been used to classify the signal into two classes, normal or abnormal, which reflects the loss of rapid eye movement sleep atonia commonly seen in Parkinson disease (PD). An overall classification accuracy of 94.3% was achieved.**

I. INTRODUCTION

SLEEP is a universal biological phenomenon and in humans accounts for the way in which one spends a third of his/her life. Sleep is not only an eventless process, but rather many events occur in the body during this state: blood pressure falls, heart rate slows down, muscles relax, and the body's metabolic rate decreases. Some autonomic functions fluctuate dramatically in rapid eye movement sleep however. During polysomnography (a sleep study), multiple physiological variables are tracked over time. During sleep, the brain in humans undergoes a characteristic cycle (approximately 90 minutes) of physiological activity that includes intervals of dreaming. Physiological activities have been used to divide sleep into different states: Rapid Eye Movement sleep (REM, or dreaming sleep) and Non-Rapid Eye Movement (NREM) sleep. Each type has a distinct set of associated neurological characteristics. REM sleep is characterized by: rapid eye movements, minimal EMG tone (sleep paralysis), and a desynchronized Electroencephalogram (EEG). Neurotransmitter levels and brain connectivity are modulated in sleep and this leads to the normal paralysis of REM sleep.

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Many sleep disorders not only diminish daytime performance, increase sleepiness and affect mood, but can also lead to serious consequences such as high blood pressure, and cardiovascular diseases. Other motor disorders of sleep can predict neurodegenerative diseases such as PD. Rapid eye movement Sleep Behavior Disorder (RBD) is a sleep abnormality in which, patients lose their normal muscle atonia and in turn enact their dreams. This can result in serious injury [1]. RBD can also be an early warning for the emergence of Parkinsonism and other neurodegenerative conditions antedating the illness by many years [2]. RBD is characterized by increased axial submental (under the chin) muscle tone in REM sleep. Therefore, chin EMG, which is routinely collected in sleep studies, can be used as a valuable signal in detecting early forms of neurodegenerative conditions. This may also provide a useful measure for assessing response to neuroprotective drugs.

II. METHOD

A. Data Acquisition

A traditional scoring system for sleep has been established [3], with the electrophysiological parameters of EEG, EOG and EMG. The system used for recording chin EMG signals during sleep includes 3 relatively midline electrodes, one above the jaw line, one below the jaw line and one back-up electrode. The two electrodes are typically subtracted from another to eliminate artifacts shared by both electrodes. The EMG signal is freely triggered and band-pass filtered at 10 - 100 Hz. The impedance of each electrode is less than 10KΩ with a minimum digital resolution of 12 bits per sample. The sampling rate is 256 Hz. Similar electrodes are used to record EEG and EOG amongst other physiological parameters. The properties of EEG, EOG and EMG signals help the sleep technologists score the various stages of sleep and develop a hypnogram- a graph of the sleep stages over time. Each sleep staging decision is based on a 30 second window of the physiological signals called an epoch. The hypnogram reveals the macro architecture of sleep by characterizing the alternation of NREM and REM sleep phases. Data collection from human in this study was facilitated through a protocol approved by the local research ethics board.

B. Wavelet Analysis Technique

It has been shown in the literature that biomedical signals such as EMG, and EEG are nonstationary, therefore a nonstationary analysis tool must be identified to extract useful information from the signal. To address this problem, a time-frequency representation is required [4]. Short Time Fourier Transform (STFT) is an intuitive modification of the Fourier transform to analyze nonstationary signals. The basic idea behind the STFT is that of segmentation of the signal by time-localized windowing and performing Fourier transformation to each segment one at a time. The STFT maps a signal into a two dimensional time-frequency representation which achieves some degree of compromise between time and frequency representation of a signal. The imprecision drawback comes from the fixed length time window used to analyze the entire signal regardless of the frequency content of each segment [5]. To analyze the signal flexibly, a variable size window is needed to access accurate view either in time or frequency. The wavelet transform has this property. The wavelet transform uses multi-resolution technique by which different frequencies are analyzed with different resolutions. Wavelet analysis techniques were independently researched and developed in the fields of mathematics, quantum physics, electrical engineering and seismic geology [6]. These serve as strong analysis tools for transient events in time varying signals such as EMG. The wavelet Transform (WT) specifically permits to distinguish between nonstationary signals with different frequency features [7].

WT of a time domain signal $x(t)$is as follows

$$X_{WT}(\tau, s) = \int x(t).\Psi^{*}_{\tau.s}(t)dt \quad (1)$$

The Ψ is called a mother wavelet which is scaled by parameter s and translated by τ. This results in a series of coefficients representing the instantaneous frequency of the signal in time [7] [8].

The scaled mother wavelet which is called the *baby wavelet* is defined as follows

$$\Psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\Psi(\frac{t-\tau}{s}) \quad (2)$$

Combining the two Equations of (1) and (2), the wavelet transform of the signal is defined as [9]

$$X_{WT}(\tau, s) = \frac{1}{\sqrt{|s|}}\int x(t).\Psi^{*}\left(\frac{t-\tau}{s}\right)dt \quad (3)$$

This is called Continuous Wavelet Transform (CWT). CWT is more immune to time-shifts in the input signal, which makes it very suitable for this feature analysis application. Therefore CWT will be the feature extraction technique of choice in this paper. The CWT is provided by Equation 3, where $x(t)$ is the chin EMG signal recorded on 8 hour sleep basis, and $\Psi(t)$ is the mother wavelet or the basis function. When WT is computed restrictively in dyadic (power of two) scale and positions of the data series, the method is denominated as Discrete Wavelet Transform (DWT) in which it is applied on the discrete sequence of input $x[n]$ [8][9].

$$\{(s_k, \tau_j)\} = \{(2^j, k2^j): j, k \in \mathbb{Z}\} \quad (4)$$

In the case of DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cutoff frequencies at different scales. First the samples are passed through a half band digital low pass filter with impulse response g resulting in a convolution of the two:

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k] \quad (5)$$

A half band low pass filter removes all frequencies above half of the highest frequency in the signal. The signal is also decomposed simultaneously using a high pass filter h. The outputs will give the detail coefficients (from the high pass filter) and approximation coefficients (from the low pass). Figure (1) shows the one level decomposition of the original signal [10].

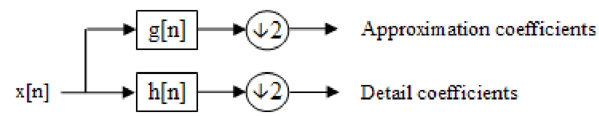

Fig. 1. The one level Decomposition diagram

A suitable mother wavelet selection is the kernel of feature extraction [6]. It must be well adapted to the events to be classified. Multiresolutional Analysis (MRA) assures that once a scaling function is specified, the associate function $\Psi(t)$ can be generated. The properties of mother wavelet, such as orthogonality, regularity, support width and symmetry are discriminative properties that are important to keep in mind when choosing the mother wavelet. The basic requirement for mother wavelet for DWT is orthogonality since it avoids redundancy in decomposition of the signal and ensures the unique reconstruction for energy finite signals. Daubechies wavelets (db) along with Symlet (sym) and Coiflets are among the family of wavelets that have these properties. For this reason we have used the Daubechies in this paper [11].

The second step of the signal processing is the actual processing or signal manipulation and evaluation. The feature extraction stage implements techniques which are chosen based on the practices, and judgments for assumptions that are considered relevant to the case. In this step DWT and CWT are implemented to extract relevant information from the signal.

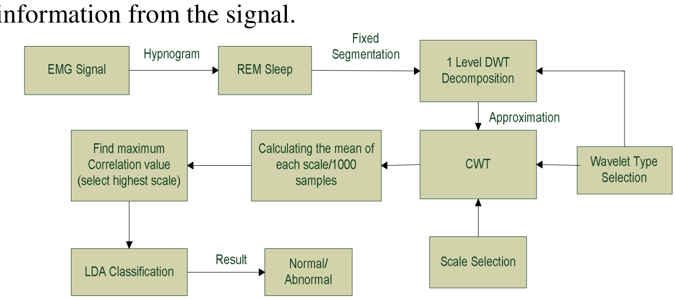

Fig. 2. The algorithm used in this work

III. RESULT

The EMG dataset consists of 4 normal and 4 abnormal (patients with a lack of REM sleep atonia) subjects undergoing overnight polysomnography. Along with the raw data acquired, the hypnogram of each subject was provided as well. Each of these EMG signals was fed to a code that categorizes each stage of sleep with the given hypnogram. Since the focus of this project is on detection of RBD the REM stage was analyzed in detail. As CWT is very computationally intensive and redundant the analysis could not be done on the whole signal and the signal had to be further segmented into smaller portions, i.e. fixed segmentation. The signal was divided into 1000 samples. After segmenting the signal each segment was assumed to be one signal. Therefore the total numbers of segments were calculated to be 2350, which 1641 of them were abnormal and 709 were normal.

The EMG consists of tonic (steady) and phasic (intermittently elevated) bursts in the REM sleep. The phasic REM activity is defined as any burst of EMG activity lasting for 0.1-2s and has amplitude of at least $50\mu V$, while tonic REM constitutes the remainder [12]. For patients with RBD tonic tone is higher than in normal subjects. The increase in tonic EMG activity might reflect disease progression [13], as many have noted that RBD is a precursor to clinically evident PD although medications may also affect this measure [14].

As stated before the sampling rate was 256 Samples/s, accordingly the first level decomposition contains approximation (0~128Hz) and details (128~256 Hz). Since the most EMG tonic movement are in the range of (0~128), approximation coefficients can be a better representation of the decomposed signal than the detailed coefficients. The one level decomposition DWT was used to capture the tonic twitches for each fixed segment and then the CWT was applied to the approximation coefficients of the DWT to extract useful features from the CWT coefficients.

In CWT the scaling function is of importance since when the scale factor, a, is enlarged the effect on frequency is compression as the analysis window is contracted by the amount $1/a$. That means the more stretched the wavelet, the longer the portion of the signal with which it is being compared, and thus the coarser the signal features being measured by the wavelet coefficients. The more compressed the wavelet, the smaller portion of the signal is being compared, and thus the more rapidly changing detailed features being produced and measured.

The scale that was used in this paper was between 15-100 in order for us to measure both the low frequency components (i.e. higher scales) as well as the high frequency components (i.e. lower scales). The CWT coefficients were calculated from approximation of the DWT coefficients using the Daubechies (dB4) family of wavelet and scaling function of 15-100. Fitting of the wavelet CWT to the data results in calculation of a resemblance index between the signal $x(t)$ and the wavelet located at position b and scale a. The higher this value, the more correlated the signal is with the mother wavelet. Since different scales were used, the coefficients are very different from each other for each segment. As a result comparing different scales with each other is not a proper way of analyzing the data. In order to overcome this problem, we compared the mean value of each scale with each other and used the scale that gave us the maximum correlation value. These scales were compared for each segment, and consequently the scale with higher number of counts was chosen as features for the classifier.

Linear Discriminant Analysis (LDA) is a supervised algorithm which searches for those vectors in the underlying space that best discriminate among classes rather than those that best describe the data. LDA has been widely used in many applications involving high dimensional data, such as image and text classification [15]. Table 1 shows the result of the LDA using CWT coefficients for approximation of DWT coefficients using all the segments in the REM stage.

Leave- one-out cross validation is used mainly in the field of machine learning to determine how accurately a learning algorithm will be able to predict data that it was not trained on. When using the leave-one-out method, the learning algorithm is trained multiple times, using all but one of the training set data points. Leave-one-out cross validation is useful because it does not waste data. When training, all but one the points are used, so the resulting regression or classification rules are essentially the same as if they had been trained on all the data points. The main drawback to the leave-one-out method is that it is expensive since the computation must be repeated as many times as there are training set data points. Hence, after the scale was chosen throughout the signals, the parameters of the CWT for the respected scale were used as features to our classifier. Tables I and II shows the result using these features and LDA and LOO techniques using SPSS software [16]. Figure 3 shows three dominant features selected from all the features obtained. As can be seen, this shows a good separation of the two classes.

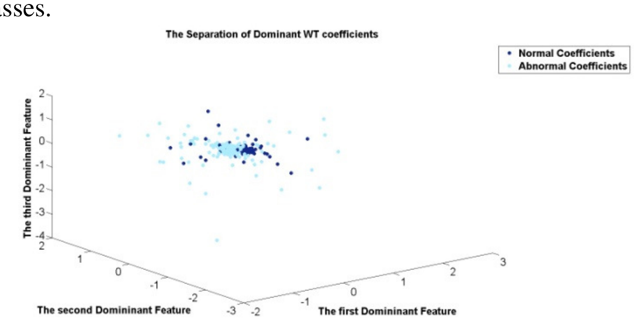

Fig. 3. Dominant CWT Features

TABLE I
LDA CLASSIFICATION OF SEGMENTS OF REM SLEEP USING APPROXIMATION WAVELET COEFFICIENTS

Normal Abnormal	PREDICTED GROUP MEMBERSHIP Normal (%)	Abnormal (%)
Normal	97.5	2.5
Abnormal	8.7	91.3

TABLE II
LEAVE ONE OUT CLASSIFICATION OF SEGMENTS REM USING APPROXIMATION WAVELET COEFFICIENTS

Normal Abnormal	PREDICTED GROUP MEMBERSHIP Normal (%)	Abnormal (%)
Normal	97.5	2.5
Abnormal	8.8	91.2

IV. DISCUSSION

As can be seen from Tables I and II the accuracy of classification of the segments is about 94.3% which makes both the wavelet features very powerful to classify the signal into both normal and abnormal. Figures 4 and 5 show the distribution of normality and abnormality of segments for each subject. This is a good representation of the level of abnormality of subjects with RBD. Aside from distinct classification, the level of abnormality and normality is of importance for neurologists and sleep specialists as this may represent a signal that can be used to follow disease progression or response to therapy.

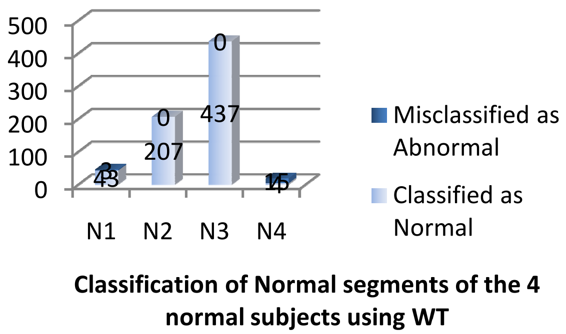

Fig. 4. The Distribution of normality in norma l segments of different subjects; N = Normal

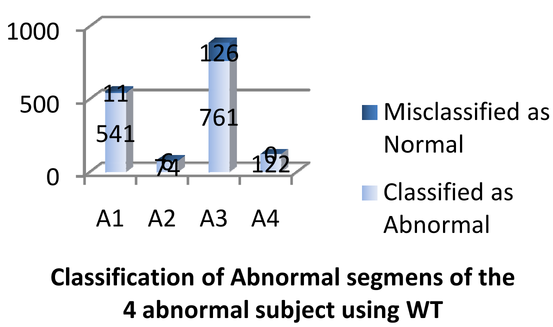

Fig. 5. The Distribution of abnormality in abnormal segments of different subjects with RBD; A= Abnormal

V. CONCLUSION

Since most of the signal processing techniques have to be done on stationary signals and since most of the biomedical signals are nonstationary or cyclo-stationary we have to use techniques that either segments the nonstationary signal into stationary forms such as adaptive signal processing techniques, or use techniques that can be applied to nonstationary signals themselves such as the Wavelet Transform. For this reason CWT and DWT were investigated in this study for the assessment of EMG recorded from normal and abnormal (REM sleep behavior disorder) subjects during sleep. Other choices of mother wavelet as well as other scales for CWT and different decomposition levels of DWT will be examined in future. This work is different from the work reported before such as [9] since the data is collected from a sleeping individual which provides a novel measure where patient cooperation is not required. Furthermore, data analysis can be retrospective to analyze whether or not an individual has abnormalities of motor tone that might predict PD or related disorders from already collected sleep study signals. This approach may provide useful information to clinicians in the form of an easily applicable measure of disease activity sensitive to very early neurodegeneration, and treatment response. The technique is also unique in that we are examining a much different (longer) time scale, with increased computational demands compared to previously described methods.

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