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Automatic REM Sleep Detection Associated with Idiopathic REM Sleep Behavior Disorder

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***Abstract*— Rapid eye movement sleep Behavior Disorder (RBD) is a strong early marker of later development of Parkinsonism. Currently there are no objective methods to identify and discriminate abnormal from normal motor activity during REM sleep. Therefore, a REM sleep detection without the use of chin electromyography (EMG) is useful. This is addressed by analyzing the classification performance when implementing two automatic REM sleep detectors. The first detector uses the electroencephalography (EEG), electrooculography (EOG) and EMG to detect REM sleep, while the second detector only uses the EEG and EOG. *Method*: Ten normal controls and ten age matched patients diagnosed with RBD were enrolled. All subjects underwent one polysomnographic (PSG) recording, which was manual scored according to the new sleep-scoring standard from the American Academy of Sleep Medicine. Based on the manual scoring, an automatic computerized REM detection algorithm has been implemented, using wavelet packet combined with artificial neural network. *Results*: When using the EEG, EOG and EMG modalities, it was possible to correctly classify REM sleep with an average Area Under Curve (AUC) equal to 0.90 ± 0.03 for normal subjects and AUC = 0.81 ± 0.05 for RBD subjects. The performance difference between the two groups was significant ($p < 0.01$). No significant drop ($p > 0.05$) in performance was observed when only using the EEG and EOG in neither of the groups. *Conclusion*: The overall result indicates that the EMG does not play an important role when classifying REM sleep.**

I. INTRODUCTION

REM behavior Disorder, dream enacting behavior and abnormal muscle activity during REM sleep, may be early markers for neurodegenerative diseases, such as Parkinsons disease (PD) and atypical PD. More than 50% of the subjects diagnosed with RBD will develop PD within a time span of 5-10 years [1] [2] [3]. Detection of RBD is therefore highly important, provided that neuroprotective treatment becomes available. No accepted full automatic RBD detector exists. The few proposed computerized methods [4] [5] [6] [7] [8] [9], all assume the presence of a manual scored hypnogram. This study will attempt to automatic score the Rapid Eye Movement (REM) sleep stage according to the new international sleep-scoring standard from the American Academy of Sleep Medicine (AASM). According to the AASM a sleep stage epoch of 30 seconds must be scored as REM when the electroencephalography (EEG) has low amplitude with mixed frequencies (i.e. 4-7 Hz) in the frontal, central and occipital electrodes. Furthermore, there should also be relatively low electromyographic (EMG) tone in the chin. If there is no indication of another sleep stage between the rapid eye movement bursts, it is assumed to be REM [10]. However, according to the International Classification of Sleep Disorders (ICSD), RBD is characterized by the intermittent loss of REM sleep electromyographic atonia, and by the appearance of elaborate motor activity associated with dream mentation [11]. This contradicts with the AASM definition of REM sleep where there should be a relatively low EMG tone.

This problem was addressed in [12] where a full computerized implementation attempt of the AASM was proposed, and the developed algorithm was capable to accurately score normal sleep, but failed in scoring abnormal sleep as encountered in neurodegenerative patients. The hypothesis is that the EMG improves the classification performance in normal subjects only. In this study, two REM sleep detectors will be proposed. The first one uses the EEG, electrooculography (EOG) and EMG to detect REM, while the second one uses the EEG and EOG. Both detectors are tested on control and RBD subjects.

II. METHODOLOGY

A. Subject Selection

A total of twenty subjects, from the Danish Centre for Sleep Medicine, Department of Clinical Neurophysiology, Glostrup University Hospital, Denmark, were involved in this study. Ten out of the twenty subjects (2 females, 8 males, age: 57.4 ± 10.6 years) were diagnosed RBD, while the last ten subjects (7 females, 3 males, age: 53.6 ± 11.8 years) were normal controls. Specialized neurologists conducted the diagnoses of all candidates, and subjects with any abnormalities that could have affected the sleep recording were excluded. None of the involved subjects were taking any medication, which was known to affect sleep. The presented data did not allow us to balance the two groups in age and gender without allowing a gender-skewed distribution in the groups.

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B. Polysomnography Montage and Data Extraction

All twenty subjects underwent a full night polysomnography (PSG), involving the EEG ($F_4 - A_1$, $C_4 - A_1$ and $O_2 - A_1$), EMG (CHIN), EOG_{LEFT}, EOG_{RIGHT}, electrocardiogram (ECG) and respiration (nasal flow, respiration belts and pulse oxymetry), which is necessary for the standard physiological recording of human sleep. The impedance was kept less than 5kΩ, and all modalities had a sampling frequency of 256 Hz [10]. Visual inspection of all the recordings was conducted by a specialist, and corrupted recordings, where the analysed channels were flat, not connected or continuously contaminated by artifacts were rejected. A total of 19,725 30-seconds epochs were recorded, where 3,799 epochs were labeled as REM. The recordings were scored according to the new standard from the AASM by experienced sleep specialists. The difficulty of scoring the REM sleep stage in subjects with increased motor activity (i.e RBD) were solved by ignoring the presence of any motor activity, and only relaying on the EEG and EOG. The raw sleep data and the manual scored hypnograms were extracted from the recording software, Nervus *(V5.5, Cephalon DK, Norresundby, Denmark)*, using the build-in export data tool, and saved on a harddisk in the widely used European Data Format (EDF) [13]. The exported data was analysed in MATLAB *(R2010b, 64 bit, The MathWorks, Natick, MA., USA)*.

C. Biomedical Signal Processing

A block diagram of the proposed REM detector is illustrated in fig. 1. The electrophysiological signals of

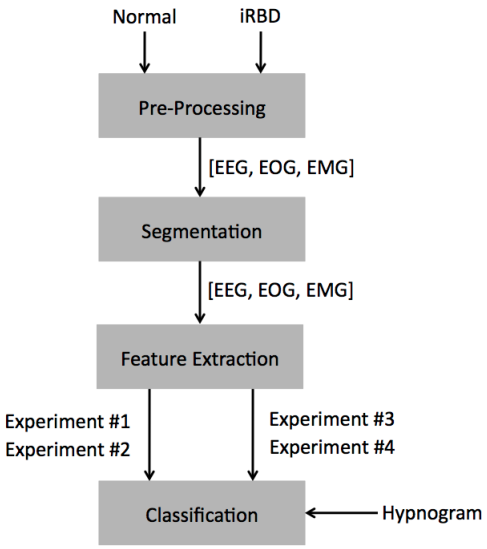

Fig. 1. Block diagram of the REM detector.

the two groups (normal, iRBD) are fed to the algorithm separately. After removing noise in the preprocessing stage, the EEG, EOG and EMG are segmented into 30-second epochs. Wavelet and correlation based features are then extracted from each epoch before they are fed to a neural network for classification, using supervised learning. The four experiments are described in Table I.

1) Discrete Wavelet Packet Transformation: Discrete Wavelet Packet Transformation (DWPT) is an effective method for detecting and characterizing specific events in time and frequency, and is widely used in EEG and EMG analysis. This is obtained by splitting the original signal into two bands, a high frequency band and a low frequency band, using a series of quadrature mirror filters. The high frequency band is called detail coefficients, while the low-pass band is called approximation coefficients. A further decomposition can be obtained by splitting both of the newly found coefficients into another high and low frequency band [14].

2) Preprocessing and Segmentation: The signals are often affected by noise from slow movement, instability of the electrode-skin interface and power-line noise. To reduce these interferences, all three EEG channels, two EOG channels and one EMG channel were preprocessed before extracting the features, using three FIR band-pass filters. The EEG was band-pass filtered with cutoff (6dB) frequencies 0.3-35 Hz. The EOG and EMG were filtered in a similar way, but for frequencies 0.3-10 Hz and 30-96 Hz respectively. Normally the EMG is not filtered from 30 Hz but from 10 Hz. However, to reduce the presence of ECG artifacts this was increased to 30 Hz [15]. The three electrophysiological signals were segmented into 30 seconds epochs (7680 samples) for further processing.

3) Feature Extraction: The spectral aspect of each EEG epoch were analyzed using the DWPT. The EEG epochs were attempted decomposed into the five clinical EEG bands δ(0-4Hz) θ(4-8Hz), α(8-13Hz), β(13-30Hz) and γ(>30Hz) using the db4 motherwavelet at level 5. The closest approximation to the clinical bands correspond to the bands δ(0-4Hz), θ(4-8Hz), α(8-16Hz), β(16-32Hz) and γ(32-96Hz). The relative wavelet energies of the bands were used as normalization scheme [14]. If the wavelet coefficients are denoted $W_j(k)$, where j corresponds to the band, and k is the time index. Then the energy of each band, in one epoch, is given by:

$$E_j = \sum_k |W_j(k)|^2 \tag{1}$$

The total energy is then:

$$E_{total} = \sum_j E_j \tag{2}$$

Then the relative wavelet energy of the epochs is defined as:

$$p_j(n) = \frac{E_j(n)}{E_{total}(n)} \tag{3}$$

In (3) $p_j(n)$ corresponds to the percentage of the total energy of band j in epoch n. The name rapid-eye-movement indicates a rapid change in the EOG signal, as opposed to slow-eye-movement seen in sleep stage non-REM-1 and

reading-eyes in wake. The AASM definition of slow-eye-movement is very vague, and reading eyes depends entirely on how quickly the patient can read. To reduce the presence of high frequency noise the EOG has been band-pass filtered (0.3-10 Hz), and instead of computing the relative energy, the normalized correlation coefficient between the two EOG channels was calculated. If the EOG_{LEFT} is denoted $x_n(k)$, and EOG_{RIGHT} $y_n(k)$, where k corresponds to the time index and n corresponds to the epoch number, then the normalized correlation coefficient is given by:

$$R_n = \frac{COV(x_n(k), y_n(k))}{\sigma_{x_n(k)}\sigma_{y_n(k)}} \tag{4}$$

The correlation coefficients were calculated by the covariance matrix for each epoch. To measure the motor activity during sleep, the chin EMG was calculated by using the widely accepted root-mean-square (RMS) approach. If the chin EMG is denoted $z_n(k)$, where k corresponds to the time index and n corresponds to epoch. Then the RMS can be calculated as:

$$RMS_n = \sqrt{\frac{1}{M}\sum_{k=0}^{M-1} z_n^2(k)} \tag{5}$$

In (5) the M corresponds to the total number of samples in one epoch $(M = 256 \cdot 30 = 7{,}680)$. The EEG, EOG and EMG feature vectors were then stacked into one feature matrix. The two classes, i.e. REM versus everything else, were then attempted classified by using an artificial neural network.

4) Classification and Evaluation: In this study the REM sleep dependency of the EMG was analyzed. This was obtained by conducting four experiments as defined in Table I, where '-' denotes an unused modality, while '+' denotes an used modality. REM sleep was first modelled by using

TABLE I
EXPERIMENTS

Exp #	EEG	EOG	EMG	Data
1	+	+	+	Normal Controls
2	+	+	-	Normal Controls
3	+	+	+	iRBD
4	+	+	-	iRBD

the normal subjects, with and without the EMG (#1 and #2). Subsequent, REM sleep was then modelled using the RBD subjects, with and without the EMG (#3 and #4), followed by a statistical significant analysis (t-test, $\alpha = 0.05$, two-tailed). A classifier model for each of the four experiments was created, using supervised learning and the 5-fold-cross-validation scheme. In the 5-fold-cross-validation, the data is randomly divided into 5 subject specific subsets. Iterative a different fold is held out for testing, while the remaining 4 folds, which were linear normalized to unit variance and zero mean, are used for training. This was done 5 times so each fold was used for testing. The above process was repeated three times to reshuffle the fold combination. The number of neurons was varied from 1 to 25, and the model with the best average test performance was selected which proved to be 5 neurons. The artificial neural network was implemented as a two layer feed-forward neural network with a hypebolic tangent function for the hidden layer and a logistic sigmoidal function for the output layer. The logistic function makes it possible to interpreted the output as probabilities [16][17][18][19]. The area under the receiver operating characteristic (ROC) curve, also called AUC, for each test-fold, was separately computed, and used as a performance measure [20]. Furthermore, for visualization of the ROC, the individual test-fold probabilities were merged into a single ROC curve.

III. RESULTS AND DISCUSSION

Each fold in the 5-fold-cross-validation yields one AUC value, and each experiment was repeated three times, which corresponds to 15 AUC values per experiment (5x3). Their mean and standard deviations are reported in Table II.

TABLE II
PERFORMANCE (AUC)

EEG	EOG	EMG	Normal Control (mean $\pm$ std)	iRBD (mean $\pm$ std)
+	+	+	0.90 $\pm$ 0.03	0.81 $\pm$ 0.05
+	+	-	0.89 $\pm$ 0.04	0.81 $\pm$ 0.05

The merged ROC curves of experiment #2 and #4 for each repetition is shown in fig. 2. The three solid lines and the

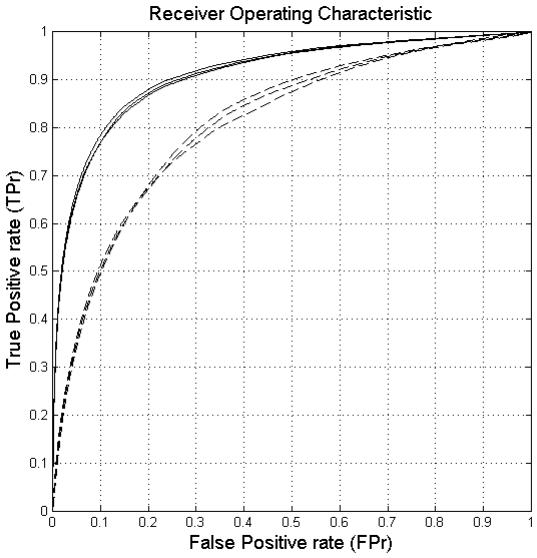

Fig. 2. ROC curves of the two groups when using the EEG and EOG (#2 and #4). The three solid lines and dashed lines correspond to the three repetitions in the normal group and the iRBD group respectively.

three dashed lines correspond to the three repetitions in the normal and RBD group respectively, when not using

the EMG (#2 and #4). A noticeable difference between the groups can be seen. It was possible to correctly classify REM sleep with an average AUC = 0.90 ± 0.03 in normal subjects, when using the chin EMG (#1). The RBD group performed significant $(p < 0.01)$ lower AUC = 0.81 ± 0.05, when using same setup (#3). No significant $(p > 0.05)$ drop in performance was observed within the groups (#1, 2 and #3, 4) when disregarding the chin EMG. To investigate whether the choice of EMG features had an influence, the RMS features were replaced with several other features. Such as kurtosis, log_{10} power and the power ratio of different wavelet bands. However, this did not alter the outcome (data not shown).

According to the results from both groups, the CHIN EMG does not play an important role when attempting to classify REM sleep. Notice, it is not only in REM sleep low chin EMG tone is reported, non-REM-2 and non-REM-3 may also contain low muscle tone. This overlap may explain the low usefulness of the CHIN EMG in the groups. The obvious explanation of the performance difference between the groups could be the scoring problem. It may be that sleep experts have found it difficult to distinguish between REM sleep and awake in the RBD group, and erroneously scored REM as awake and vice versa. However, this may not be the only explanation. Other physiological changes in REM sleep can not be excluded.

IV. Conclusion

In this study two REM sleep detectors were proposed. When using the EEG, EOG and EMG, it was possible to correctly classify REM sleep in normal subjects with a high performance of AUC = 0.90. However, a significant lower, but acceptable performance of AUC = 0.81 was observed in the RBD group. No significant drop in performance was observed when only using EEG and EOG in neither of the groups. The overall result indicates that the EMG does not play an important role when classifying REM sleep.

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