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EOG and EMG: Two Important Switches in Automatic Sleep Stage Classification

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Abstract — **Sleep is a natural periodic state of rest for the body, in which the eyes are usually closed and consciousness is completely or partially lost. In this investigation we used the EOG and EMG signals acquired from 10 patients undergoing overnight polysomnography with their sleep stages determined by expert sleep specialists based on RK rules. Differentiation between Stage 1, Awake and REM stages challenged a well trained neural network classifier to distinguish between classes when only EEG-derived signal features were used. To meet this challenge and improve the classification rate, extra features extracted from EOG and EMG signals were fed to the classifier. In this study, two simple feature extraction algorithms were applied to EOG and EMG signals. The statistics of the results were calculated and displayed in an easy to visualize fashion to observe tendencies for each sleep stage. Inclusion of these features show a great promise to improve the classification rate towards the target rate of 100%.**

I. INTRODUCTION

Sleep is an essential part of human life. We spend a third of our lives sleeping. Sleep is not an eventless process. On the contrary, many events occur in the body during this state: blood pressure falls, heartbeat slows down, muscles relax, and the body's metabolic rate decreases.

Nocturnal polysomnography (NPSG) is a diagnostic test in which a number of physiologic variables are measured and recorded during sleep. Theses recordings or full night sleep data, are then analyzed by a qualified physician or sleep specialist to determine whether or not a person has a sleep disorder.

Different stages of sleep are determined by predefined patterns or waves of electrical activity observed in EEG, EOG and EMG signals and by the variety of behavioral and physiological states. Sleep states are comprised of two general stages: rapid eye movement (REM) and non-rapid eye movement (NREM). NREM is in turn subdivided into four stages: 1, 2, 3, and 4 according to Rechtschaffen and Kales (RK) sleep scoring standard [1]. In one of our most recent investigations, we applied a number of feature extraction methods to EEG signals with promising results. In these studies a well designed artificial neural network (ANN) classifier attained accuracies up to 80% with an overall sensitivity of 80% and specificity of 96.67%. The ANN, used for this experiment was a 9-input, 30-hidden node, 3-output feed-forward network implemented with a bipolar sigmoid activation function. The bipolar sigmoid function was designed using a steepness of 2.5. Back propagation algorithm was used in implementing, training, and evaluating this neural network. For training, each input feature vector comprised of 240 elements (40 samples of each sleep stage, 40 features derived from the EEG signal during the Awake stage, 40 features derived from the EEG during sleep Stage 1, and others). Testing data used feature vectors with 60 elements (10 samples of each sleep stage, 10 features derived from EEG during Awake stage, 10 features derived from the EEG during sleep Stage 1 and so on) [2-3].

These results, even though promising were not acceptable for this application. The ANN could not clearly differentiate between the feature sets representing Awake, REM and Stage 1 stages. In order to improve the accuracy of automated sleep classification developed in this research, some EOG and EMG signal features were added to the EEG signal features. EOG is the switch among REM stage (also Awake stage) and NREM stages. Moreover, EMG distinguishes between Awake stage and the rest of the stages. Table I summarizes the RK rules and the roles of EEG, EMG and EOG in sleep stage classification.

A. Electrooculogram (EOG)

The EOG is frequently the method of choice for recording eye movements in sleep research. During wakefulness, rapid eye movements may be very frequent or rare, depending on the extent to which vision is being used. Eye movement is absent during NREM, although some brain activity may be picked up by the testing equipment and be recorded incorrectly as eye activity.

B. Rapid Eye Movements (REM's) and Slow Eye Movements (SEM's)

The EOG signal is composed of basically 2 rhythms, Slow Eye Movements (SEMs) and Rapid Eye Movements (REMs). During REM stage, there are bursts of rapid eye movements in the recording, sometimes between REMs there are periods of no eye movements (Fig. 1). Slow rolling eye movements are one of the first indicators of sleep onset, they are present during stage 1. Fig. 2 shows this kind of EOG signal activity.

II. MATERIALS AND METHODS

A. Data Acquisition

The data were acquired from 10 volunteer subjects suffering from sleep apnea. NPSG studies were performed in an accredited sleep laboratory (Sleep Consultants Inc., Fort Worth, Texas). The sleep laboratory provided the 10 pre-recorded and scored NPSG data files. Each data set comprised of EEG, EOG, and EMG recordings. The 10-20 standard electrode placement system was used for EEG recording. Specifically, recordings between C_1 and A_2 positions were used for these patients. These bioelectric signals were amplified using a Nihon Kohden polygraph (Irvine, CA) and the data acquisition was achieved using a Telefactor System (Conshocken, PA) for polysomnography.

EEG and EOG channels were stored using a sampling frequency of 1000 Hz. EMG channel was then digitized using a sampling frequency of 39 Hz. Finally, the sleep specialists scored all 30-second epochs based on the RK standard method ("gold standard").

B. Feature Extraction

EOG Signal - REMs are of great interest because they provide good markers for this sleep stage. After performing a visual analysis of the EOG epochs and their corresponding power spectrum estimates, it was found that SEMs are waves in the frequency range of 0.1 Hz to 0.3 Hz. On the other hand, REM activity was concentrated between 0.3 and 0.45 Hz [4].

Estimate of the power spectrum P(f) of EOG signals was computed by means of autoregressive modeling [5-6]. This type of estimation provides better results when working with short segments. For this study we used a model order of 10, based on Akaike's final prediction error criteria [7-8].

As previously mentioned, the frequency range between 0.35 and 0.4 Hz was of great interest as REM activity is reflected in that band. In order to detect REM rhythms the energy contained in that range of frequencies was computed using the following integral,

$$ECB = \int_{fl = 0.35\ Hz}^{fh = 0.5\ Hz} P(f)\, df \qquad (1)$$

where ECB is the energy content band and P(f) is the power spectrum of the EOG segments. ECB was approximated by rectangular integration.

EMG Signal - It is established that the Awake stage presents the highest muscular activity in contrast to REM stage which has the lowest EMG activity. It should be noted that muscular activity is strongly linked to the epoch energy. EMG epochs containing high muscular activity also have high energy levels. EMG segments having low levels of energy have low level of muscular activity.

To calculate the energy signal the following formula was used:

$$Energy = \left[\frac{\sum_{n=1}^{N} \left[X(n) - E[X] \right]^2}{N} \right] \qquad (2)$$

where X(n) is and EMG epoch, E[X] is the mean value of the signal and N is the number of samples in the segment and other terms are as defined before (each 30-seconds epoch contained 1170 samples).

III. RESULTS

After running the feature extraction algorithms on sleep data on both signals (EOG and EMG), the feature vectors were split into different groups based on information given in the "gold standard". Statistical measures were then computed to show the tendencies for each stage (mean, standard deviation, maximum value and minimum value). These results are summarized in tables II and Table III. These results can be better visualized by using box plot graphs (as shown in Figs 5 and 6).

IV. CONCLUSIONS

The results demonstrate that the extracted features provide promising possibilities to distinguish between different sleep stages: Awake, N-REM and REM stages. The ECB of the REM stage is a powerful feature for detecting epochs with high ocular activity. It is clear that the Awake stage presents high ocular activity (eye movements and eye blinks). Therefore, the introduction of the EMG epoch energy was necessary. This last feature extraction method served as a switch between Awake and REM stages. It is important to notice that EOG and EMG algorithms could be modified to provide a binary result. In other words, they could search the signals for the presence or absence of certain activity (in this case, REM activity or muscular activity). In our future research, EOG and EMG features will be incorporated into the ANN and fuzzy rules will be integrated to improve on the performance of the ANN and achieve a scoring accuracy close to 100% between the Awake and REM stages.

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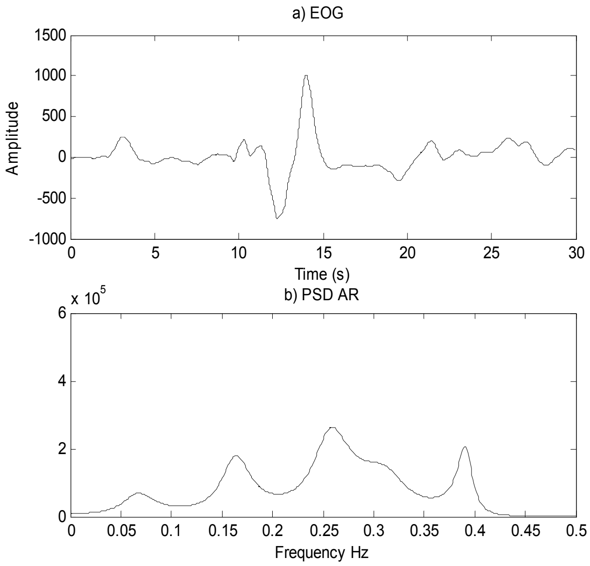

Fig. 1. EOG and REM activity.

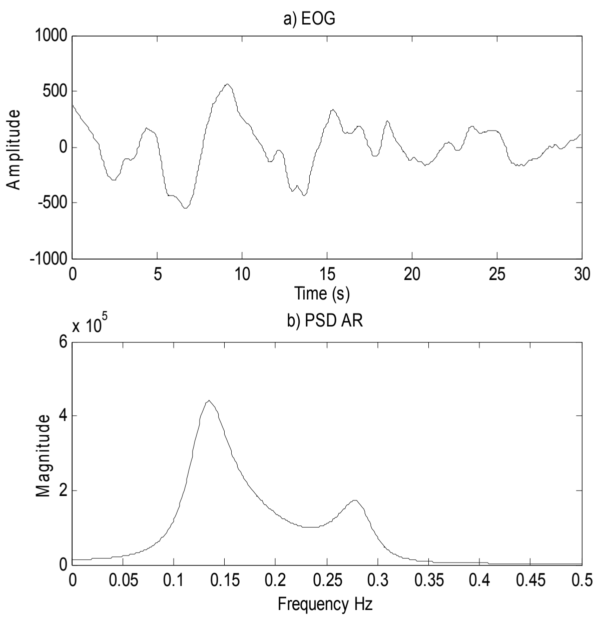

Fig. 2. EOG and SEM activity.

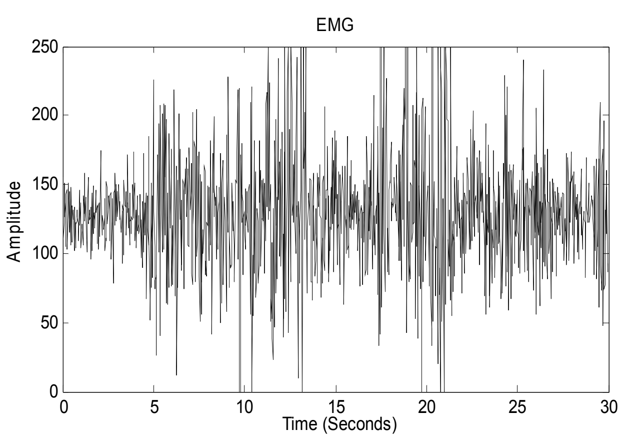

Fig. 3. EMG activity in Awake Stage.

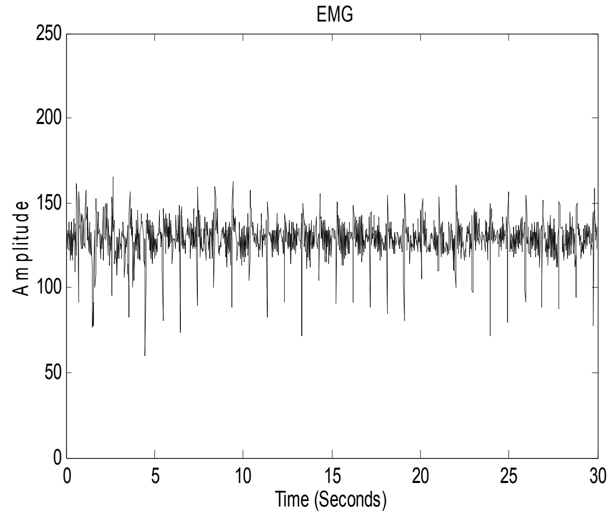

Fig. 4. EMG activity in REM Stage.

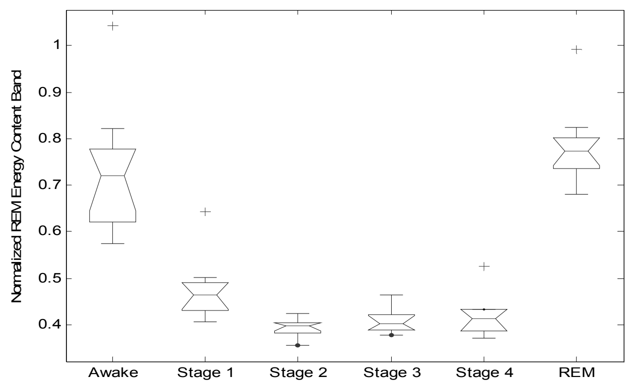

Figure 5. Box plot for table II.

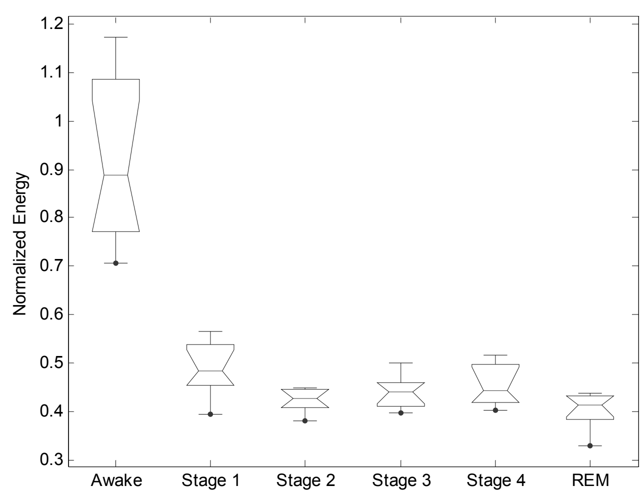

Fig. 6. Box plot for table III.

Table I: RK Rules and Sleep Stages

Pattern		Stage: Awake	Stage 1	Stage 2	Stage 3 and 4	REM
EEG	Slow delta	No	No	No	Yes	No
	Theta	Don't care	Yes	Don't Care	Don't care	Yes
	Sleep spindles	No	No	Yes	Don't care	No
EOG : REM Signal		Yes	No	No	No	Yes
EMG: Muscle Tone		Yes	Don't care	Don't care	Don't care	No

TABLE II Normalized REM ECB Means

Mean	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8	Subject 9	Subject 10
Awake mean	0.6219	1.0426	0.6284	0.5747	0.7402	0.7772	0.7607	0.8227	0.6144	0.7025
Stage1 mean	0.4470	0.6432	0.4827	0.4072	0.4627	0.4304	0.4896	0.4645	0.4226	0.5015
Stage2 mean	0.4043	0.4117	0.3855	0.3676	0.3963	0.4246	0.3833	0.3973	0.3560	0.4017
Stage3 mean	0.4090	0.3929	0.3948	0.4124	0.4644	0.4481	0.4029	0.3798	N/A	0.3790
Stage4 mean	0.4303	0.3870	0.3950	0.4338	0.5270	N/A	N/A	0.3710	N/A	N/A
REM mean	0.8243	0.7742	0.9930	0.7739	0.6795	0.7368	0.7842	0.7280	0.8023	0.7706

*Values beyond the whiskers in the box plot. N/A: Not available (Sleep stage is not present in subject file)

TABLE III Normalized Energy Means

Mean	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8	Subject 9	Subject 10
Awake mean	0.77224	1.0845	0.97738	0.70624	1.1724	1.1517	0.88111	0.89343	0.73277	0.88179
Stage1 mean	0.51215	0.56598	0.45752	0.39469	0.45322	0.42537	0.54105	0.53851	0.45435	0.53504
Stage2 mean	0.42616	0.44866	0.39993	0.38019	0.40843	0.44936	0.44485	0.42682	0.42586	0.42778
Stage3 mean	0.41433	0.44162	0.49467	0.40303	0.44566	0.5	0.39769	0.44763	N/A	0.43419
Stage4 mean	0.41785	0.44438	0.51512	0.40161	0.49747	N/A	N/a	0.43932	N/A	N/A
REM mean	0.38433	0.43147	0.3638	0.32933	0.40936	0.39795	0.43708	0.41668	0.42613	0.43565

*Values beyond the whiskers in the box plot. N/A: Not available (Sleep stage is not present in subject file)

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