HISTOGRAM BASED QUANTIFICATION OF SUBMENTAL EMG

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Abstract: For a better understanding of the mechanisms regulating the events that disrupt sleep continuity there is need for automatic analysis of spontaneous motor patterns which occur in submental EMG (Electromyogram). This could be helpful in the diagnosis and treatment of sleep disturbances.

Peak amplitude histogram-based thresholding was used for the quantification of events (phasic bursts, muscle twitches, artifacts and Movement Time) in the submental electromyographic signal, without pre-knowledge of the sleep stages of the signals under analysis.

The method was applied to 19 all-night sleep recordings of human different subjects, and three performance criteria (Sensitivity, Positive Predictive Accuracy and Percentage of Detected Activity in the signal) were computed. A sensitivity of 86 per cent and a Positive Predictive Accuracy of 89 per cent were reached while the average percentage of detected phasic activity was 16.77.

The algorithm proposed in this paper does not need knowledge on the hypnograms of the signal and could be used as a step towards its automatic generation.

Introduction

Submental sleep EMG (Electromyogram) is a nonstationary signal, with characteristics that differ both between subjects and recordings of the same subject.

The sampling rate of the signal ranges in the literature from 200 to 5000 Hz [1]. Band pass filtering between 20 and 100 Hz is sometimes performed [2]. In this frequency range the individual action potentials of EMG cannot be recognized. Because an analysis in frequency domain results in the loss of time information, time domain quantification of EMG activity is needed.

According to the usually applied sleep stage scoring manual of Rechtschaffen and Kales [3], sleep is quantified into stages W(wake), REM(Rapid Eye Movement), S1(light sleep), S2, S3, S4 (deep sleep), in epochs of 20 or 30 seconds based on the waveforms in the signals. Low EMG tonus is an indicator of REM sleep stage, when characteristic EEG (Electroencephalogram) and EOG (Electrooculogram) patterns are also present. Sudden, short but clear elevations of EMG amplitude, so called phasic events are often indicators of arousals from sleep (Fig. 1).

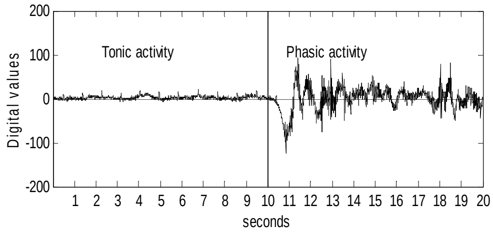

Figure 1: Example of tonic and phasic activity in submental surface EMG

This paper presents a way to quantify phasic and tonic activity in submental surface EMG without pre-knowledge of the sleep stages of the signals under analysis.

Materials and Methods

Recordings and visual scoring

Data was pooled from the SIESTA database of polygraphic recordings [4]. As an initial study we focused on 19 submental signals collected during 8 hours of sleep. The sampling rate of the data was 200-256 Hz. The signals have a 16 bit resolution with physical values ranging between -250 mV and 250 mV.

For each recording we had either two or three hypnograms scored by human experts using 30 seconds consecutive epochs of the signal to stages Wake, Stages 1 to 4, Stage REM and Movement Time. Two different experts scored the first two, and the third (in case we had one) represented the consensus hypnogram between the first two.

The EMG events were classified as tonic and phasic in 15 second epochs. An epoch was scored phasic if it contained at least one clear elevation of the signal amplitude lasting at least 0.1 seconds.

Method

We preprocessed the signal by high pass filtering it at 20 Hz and subsequently taking measures of envelope for consecutive epochs. The epoch length was varied between 5 and 20 seconds. 15 s turned out to produce

ISSN: 1727-1983

the best results, so we chose this value for further experiments. As a measure of envelope the value of the sample to give the maximum absolute value was taken.

A histogram was then calculated out of the vector of measures of envelope. We assumed the bins in the histogram with centers close to zero and large numbers of elements represent the tonic level within the signal, and therefore a signal dependant threshold for the tonic level can be obtained by isolating these bins from the rest. This way the problem of separating the phasic events from the tonic activity is simplified.

Several variations in the calculation parameters were considered for isolating the bins of phasic activity from the background tonic EMG. For example, the length of the bins was varied between 5 and 10 sample values. The length 5 produced the best results and was chosen for further studies.

The analysis was performed on the positive and the negative measures of envelope parts separately, since this method proved to outperform the simpler analysis of absolute values only. If the difference between the maximum number of elements within the positive and respectively the negative measures of envelope parts was found to be significant, only the bins neighboring the bin corresponding to the greatest peak were considered to be tonic related bins.

The threshold to delimitate the highest bins from the rest was set as the bin center where the corresponding number of elements reached a quarter of the height of the highest bin. The measure of envelope of each epoch was compared to the threshold and all epochs with measures of envelope exceeding the threshold, in absolute value, were marked as phasic events. Fig. 2 illustrates the location of the thresholds.

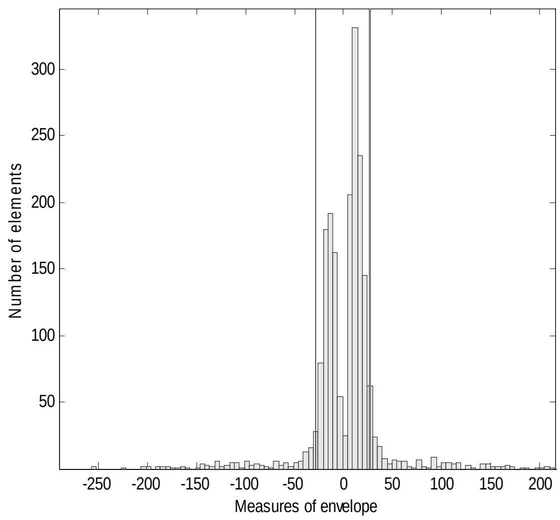

Figure 2: Setting the threshold for the events in the signal. A bin length of the histograms of 5 corresponds to 0.03mV.

Performance tests

We compared the performance of the above mentioned method's output and Brunner et al.'s [5] algorithm's output to the visually scored signals. We chose, as performance indicators the following:

- *Sensitivity (S) :*

$$S = \frac{\text{Number of True Phasic Events Detected by the Algorithm}}{\text{Total Number of True Phasic Events, scored visually}} \quad (1)$$

- *Positive Predictive Accuracy (PPA) :*

$$PPA = \frac{\text{Number of True Phasic Events Detected by the Algorithm}}{\text{Total Number of Phasic Events Detected by the Algorithm}} \quad (2)$$

- *Percentage of Detected Activity within the signal (P):*

$$P = \frac{\text{Total Length of Phasic Events Detected by the Algorithm}}{\text{Length of the Signal}} \quad (3)$$

Since we had several hypnograms for the same signal, we took as valid performance criteria values the ones that gave the best overall PPA and its corresponding S.

Results

The values for S, PPA and P computed for both methods are illustrated in Table 1. A more illustrative comparison is shown in Figure 3.

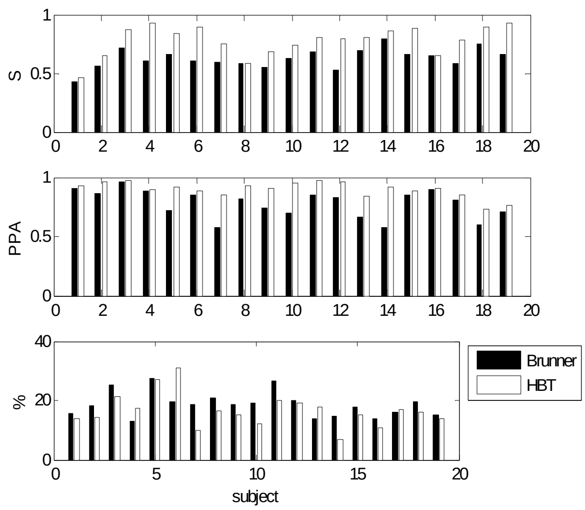

Figure 3: Results of the comparison between Brunner et al's algorithm and the method proposed in this paper (HBT), with respect to Sensitivity, Positive Predictive Accuracy and Percentage of Detected Activity in the signal

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Table 1: Sensitivity, Positive Predictive Accuracy and Percentage of Detected Activity values for the proposed method, compared to Brunner et al.'s algorithm's output for each of the 19 subjects

No	*Sensitivity*	S Brunner	*PPA*	PPA Brunner	*percentage*	percentage Brunner
1	*0.4606*	0.4243	*0.9286*	0.9023	*13.7*	15.7
2	*0.6508*	0.5582	*0.9620*	0.8645	*14.4*	18.2
3	*0.8722*	0.7222	*0.9675*	0.9608	*21.4*	25.2
4	*0.9312*	0.6085	*0.8913*	0.8818	*17.5*	12.8
5	*0.8402*	0.6588	*0.9223*	0.7212	*27.2*	27.5
6	*0.8989*	0.6044	*0.8877*	0.8528	*30.8*	19.3
7	*0.7514*	0.5954	*0.8519*	0.5741	*9.6*	18.4
8	*0.5827*	0.5827	*0.9243*	0.8150	*16.6*	20.7
9	*0.6807*	0.5462	*0.9083*	0.7438	*15.2*	18.6
10	*0.7436*	0.6325	*0.9533*	0.6994	*11.9*	18.9
11	*0.8076*	0.6861	*0.9711*	0.8553	*19.9*	26.4
12	*0.7966*	0.5282	*0.9589*	0.8297	*19.2*	19.8
13	*0.8098*	0.6976	*0.8407*	0.6639	*17.8*	13.8
14	*0.8660*	0.7938	*0.9125*	0.5750	*6.8*	14.5
15	*0.8870*	0.6652	*0.8817*	0.8497	*14.9*	17.6
16	*0.6520*	0.6471	*0.9083*	0.8908	*10.5*	13.8
17	*0.7817*	0.5845	*0.8475*	0.8074	*16.9*	16.0
18	*0.8989*	0.7528	*0.7361*	0.6013	*16.0*	19.4
19	*0.9273*	0.6606	*0.7586*	0.7073	*14.0*	15.2

6.8 to 30.8% of the epochs contained phasic activity during sleep, depending on whether the recordings came from healthy subjects or patients with various disorders.

An analysis of the dependence of the overall performance to the length of the epoch of the measures of envelope vector and/or the length of the bins used to compute the histogram leads to the following conclusions:

1) Positive Predictive Accuracy decreases with the length of the epoch used to take the measures of envelope. This tendency can be seen with respect to Sensitivity too in most cases. This is illustrated in Figure 4.

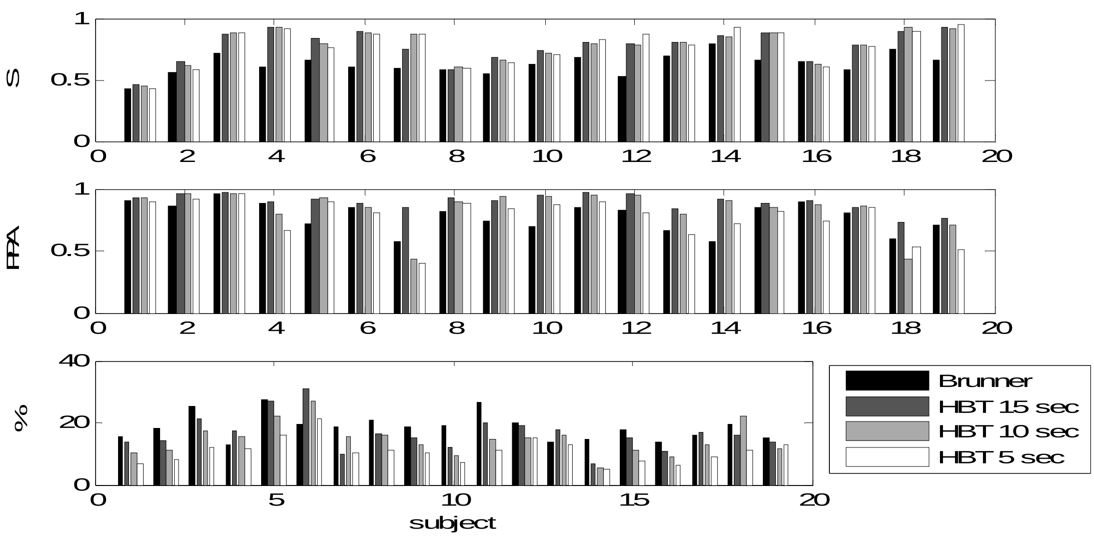

Figure 4: Comparison between S and PPA values obtained after applying HBT method to vectors of measures of envelope of length 15, 10 and respectively 5. The length of the bins of the histogram is set to 5.

2) Sensitivity is inversely proportional to the length of the bins used to compute the histogram, while the PPA increases in most cases with the length of the bins (Fig. 5):

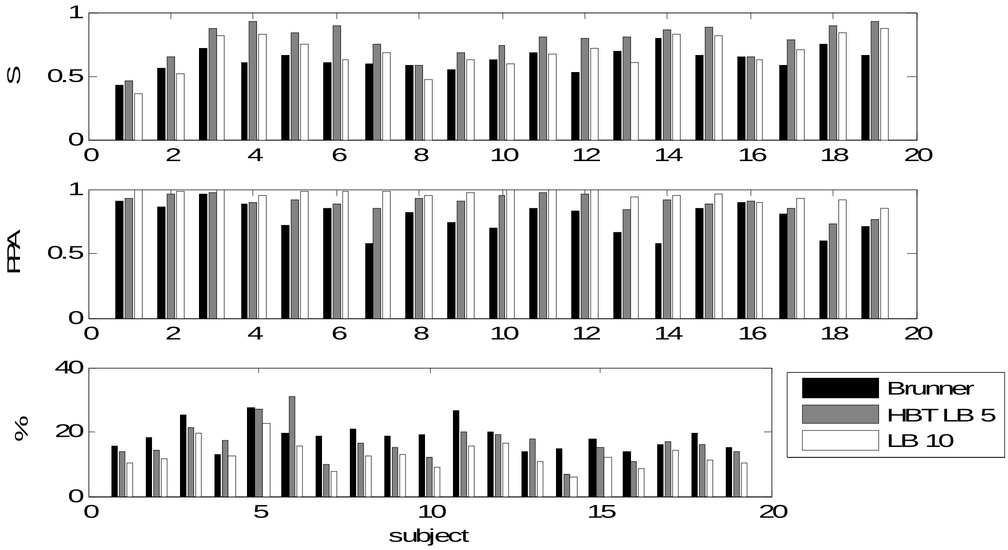

Figure 5: Comparison between S and PPA values obtained after applying HBT using histograms with a bin length of 5 and respectively 10. The epoch for computing the measures of envelope is set to 15.

The proposed method is not computationally intensive but it requires that the EMG signal of the whole recording is available for analysis. It is therefore not suitable for on-line analysis. The setting of the threshold is here automatic. If the user wants to emphasize Sensitivity at the expense of PPA or vice versa, this can be introduced to the method by multiplying the threshold with a constant <1 or >1, respectively.

The method can be applied on EMGs only, but its performance increases in most cases if additional data (ECG (Electrocardiogram) signals recorded from the same subjects) is incorporated into a normalized LMS algorithm after prefiltering [6] so as to remove the ECG artifacts, and then HBT is performed (Table 2).

The average sensitivity and Positive Predictive Accuracy reached were 86 and respectively 89 per cent. The average percentage of detected phasic activity was 16.77.

Table 2: Sensitivity and Positive Predictive Accuracy and Percentage of Detected Activity values for the proposed method with and without ECG artifact removal, for each of the 19 subjects. The number of filter taps and the forgetting factor were chosen 1.05 times the sampling rate and 0.1, respectively

No	Sensitivity (HBT)	S (normalized LMS and HBT)	S Brunner	PPA	PPA (normalized LMS and HBT)	PPA Brunner
1	0.4606	0.4435	0.4243	0.9286	0.9560	0.9023
2	0.6508	0.6508	0.5582	0.9620	0.9506	0.8645
3	0.8722	0.8778	0.7222	0.9675	0.9835	0.9608
4	0.9312	0.9630	0.6085	0.8913	0.7296	0.8818
5	0.8402	0.8481	0.6588	0.9223	0.8977	0.7212
6	0.8989	0.7626	0.6044	0.8877	0.9330	0.8528
7	0.7514	0.7688	0.5954	0.8519	0.8014	0.5741
8	0.5827	0.5962	0.5827	0.9243	0.9333	0.8150
9	0.6807	0.6611	0.5462	0.9083	0.9500	0.7438
10	0.7436	0.7991	0.6325	0.9533	0.9043	0.6994
11	0.8076	0.8557	0.6861	0.9711	0.9251	0.8553
12	0.7966	0.8333	0.5282	0.9589	0.9652	0.8297
13	0.8098	0.8049	0.6976	0.8407	0.8624	0.6639
14	0.8660	0.8969	0.7938	0.9125	0.8736	0.5750
15	0.8870	0.9391	0.6652	0.8817	0.7788	0.8497
16	0.6520	0.7353	0.6471	0.9083	0.8473	0.8908
17	0.7817	0.8592	0.5845	0.8475	0.7767	0.8074
18	0.8989	0.9326	0.7528	0.7361	0.8440	0.6013
19	0.9273	0.9879	0.6606	0.7586	0.7267	0.7073

S increases in 73% of the cases, at the expense of a lowered PPA. PPA improves in 42% of the cases.

Discussion

We proposed an algorithm to quantify events in submental EMG, without pre-knowledge of the sleep stages of signals under analysis. We tested these algorithms' performance on 19 all-night recordings of human sleep. The new method achieves higher Sensitivity and Positive Predictive Accuracy levels than the S and PPA of Brunner et al. However HBT is not suitable for classification of the events, but it is a way of detecting them. The algorithm proposed in this paper does not need information about the sleep stages
of the signal and could be used as a step towards the automatic generation of the hypnograms.

Further development

The present visual scoring of the phasic events was performed by an engineer familiar with EMG. The reliability of the results might improve somewhat if the visual scoring were performed by a neurophysiologist experienced in sleep, or better yet by two of such scoring the signals independently and a third one to perform a consensus scoring.

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