Harmonic Parameters with HHT and Wavelet Transform for Automatic Sleep Stages Scoring

Wei-Chih Tang, Shih-Wei Lu, Chih-Mong Tsai, Cheng-Yan Kao, and Hsiu-Hui Lee

***Abstract*—**Previously, harmonic parameters (HPs) have been selected as features extracted from EEG signals for automatic sleep scoring. However, in previous studies, only one HP parameter was used, which were directly extracted from the whole epoch of EEG signal.

In this study, two different transformations were applied to extract HPs from EEG signals: Hilbert-Huang transform (HHT) and wavelet transform (WT). EEG signals are decomposed by the two transformations; and features were extracted from different components. Twelve parameters (four sets of HPs) were extracted. Some of the parameters are highly diverse among different stages.

Afterward, HPs from two transformations were used to building a rough sleep stages scoring model using the classifier SVM. The performance of this model is about 78% using the features obtained by our proposed extractions. Our results suggest that these features may be useful for automatic sleep stages scoring.

***Keywords*—**EEG, harmonic parameter, Hilbert-Huang transform, sleep stages, wavelet transform.

I. Introduction

CURRENTLY, quality of sleep plays important role in quality of life. Sleep stages scoring is a multi-class classification problem, and provides useful information for the diagnosis of sleep state. Previously, many different systems were developed for automatic sleep stages scoring. They not only include features extracted from EEG, but also include those from EOG and ECG. Neural network, Fourier transformation, and wavelet transformation are the approaches used in most of these systems.

The standard criteria of sleep stages scoring are based on Rechtschanffen and Kales (R&K standard criteria). [1] R&K standard criteria based on four main rhythms and some patterns of EEG, EOG and EMG. The four main EEG rhythms are: Delta waves: 0 to 4 Hz, slow wave with highest amplitude; Theta waves: 4 to 8 Hz, amplitude smaller than delta waves; Alpha waves: 8 to 13Hz, amplitude smaller then theta waves; and Beta waves: 13 to 30Hz or higher, low amplitude and highest frequency waves.

'Awake' stage is characterized by EEG alpha activities that occur in more than 50% of the epoch. Beta waves also appear in the 'awake' stage. Beta waves imply arousal if observed in other stages.

Stage 1: EEG signals mixing low-amplitude and high-frequency waves, such as alpha and theta waves.

Stage 2: it can be manifested by the low voltage waves with sleep spindles and k-complex, or beta waves less than 20%. According to R&K standard criteria, many epochs may have no stage 2 characteristics, like spindles and k-complex, but those are scored as stage 2 not stage 1.

Stage 3 and 4: they can be characterized by delta waves. If delta waves occupying 20-50% of one epoch, the epoch is scored as stage 3. If delta waves occupying more than 50% of one epoch, this epoch is scored as stage 4.

'REM' Stage: in this stage, brain activity is similar to stage 1 or 'awake' stage. EEG signals of REM stage are composed of low-amplitude waves and little theta waves.

HHT and WT are suitable for the processing of non-stationary signals. Therefore, we can extract features from the signals been processed by these transformations. In this paper, two sets of features, HPs with HHT and HPs with WT, extracted from the electroencephalogram (EEG), are applied to the automatic sleep stage scoring, respectively.

II. Materials and Methods

A. Materials

The training data were acquired from 5 subjects with putative sleep apnea and were referred to the sleeping center (Taipei Medical University Hospital, Taipei, Taiwan Republic of China). Data from two subjects are not the complete recordings in the whole night; only three to four hours of the EEG activities were recorded. The total number of the training data is 3257 epochs.

EEG was recorded by standard PSG. An experienced sleep specialist blind to the objective of this study, scored all 30-second epochs based on R&K standard criteria. Table 1 is distribution of each stage in training data. The EEG recorded

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between C3 and A1 position was used for this study. The EEG channel was sampled at 128Hz.

TABLE I
EEG DATA STAGE DISTRIBUTION

stage	Epochs	Percentage
awake	299	9.2%
Stage 1	425	13%
Stage 2	1580	48.5%
Stage 3	470	14.4%
Stage 4	118	3.6%
REM	365	8.6%

B. EEG Processing

Two transformations of the EEG data are used in this study. If Hilbert Huang Transformation was used, the complete EEG data vector was processed using a 7th-order Butterworth band-pass filter with cut-off frequency of 0.5~30Hz. If wavelet transformation was used, the EEG signals are decomposed into several components. Last approximate coefficients were filtered by 5th-order Butterworth high-pass filter with a cut-off frequency beyond 0.5Hz.

C. Feature Extraction

As in [2]-[3], HPs extracted from EEG signals were used for automatic sleep stage scoring. HPs are based on autoregressive (AR) model. Using AR model to compute power spectral density, selecting the order 'p' for AR model is a problem. This selection could be based on a priori knowledge or different criteria [2]. The AR model equations are more suitable for the processing of stationary signals. Therefore, HHT and WT were used to obtain stationary data from EEG. HPs were extracted from the stationary data afterward.

HPs include the center frequency, the bandwidth and the value at center frequency [2]-[4]. These parameters are defined as follows:

$$f_c = \sum_{f_L}^{f_H} f P_{xx}(f) / \sum_{f_L}^{f_H} p_{xx}(f) \tag{1}$$

$$f_\sigma = \sqrt{\sum_{f_L}^{f_H} (f - f_c)^2 P_{xx}(f) / \sum_{f_L}^{f_H} P_{xx}(f)} \tag{2}$$

$$S_{f_c} = P_{xx}(\hat{f}_c) \tag{3}$$

These parameters are calculated using power spectral density function between f_H and f_L thus allow investigating a specific frequency band in the signal. The spectral density function $P_{xx}(f)$ is estimated using the Yule-Walker method [4]-[5].

HHT uses empirical mode decomposition (EMD) to decompose the EEG signals into many IMFs (Intrinsic Mode Functions). Each of the IMFs can be used to calculate three HPs. The HPs of IMFs from four highest frequencies are extracted using the above formulas. The other IMFs with low frequencies are usually treated as noises and are discarded. For each of the IMFs, f indices may span from different lowest frequency to highest frequency.

In the extraction of HPs using WT, the EEG channel is sampled at 128Hz, 4 level Symlets8 (sym8) wavelets function was applied to decomposed the EEG signals [6]. The frequency band of approximate coefficients process thought high-pass filter is 0.5-4Hz (a4), and the frequency bands of detail coefficients are 16-32Hz (d2); 8-16Hz (d3); 4-8Hz (d4) respectively. The detail coefficients d1 (32-64Hz) is regarded as noise. HPs were calculated from different components: a4, d2, d3 and d4.

The computation of spectral density was in discrete form, the value at center frequency was calculated by $\hat{f}_c$, means the closest f index of the f_c.

III. RESULTS

The means and standard deviations of the HPs extracted from the training data using HHT and WT in different stages were calculated. The figures Fig. 1- Fig. 6 show the results for some of HPs, which reveal clearly different distributions in every stage.

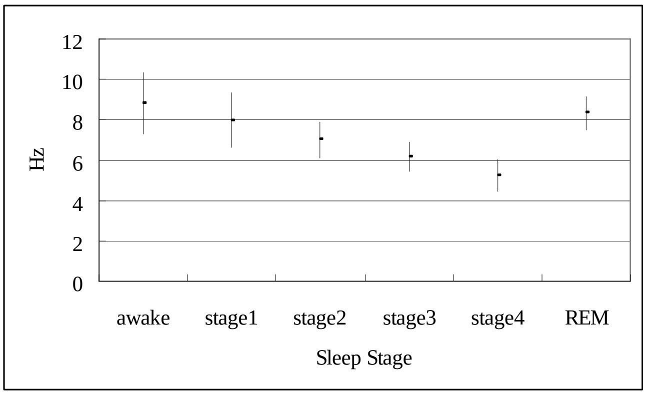

Fig. 1 The center frequency of IMF2

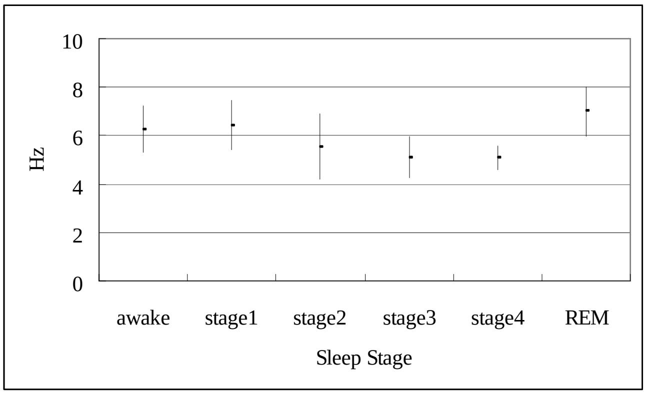

Fig. 2 The bandwidth of IMF1

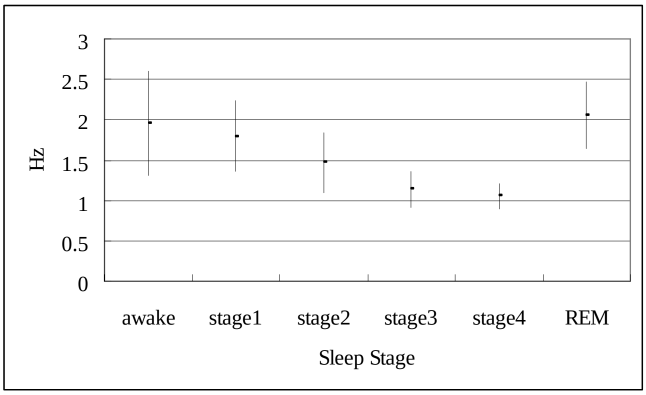

Fig. 3 The center frequency of IMF4

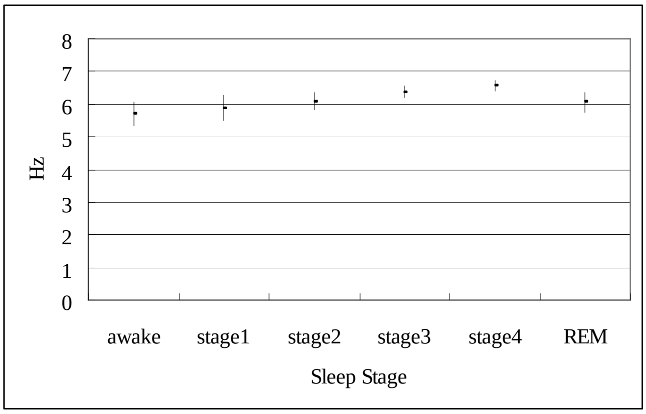

Fig. 4 The center frequency of d4 (4-8Hz)

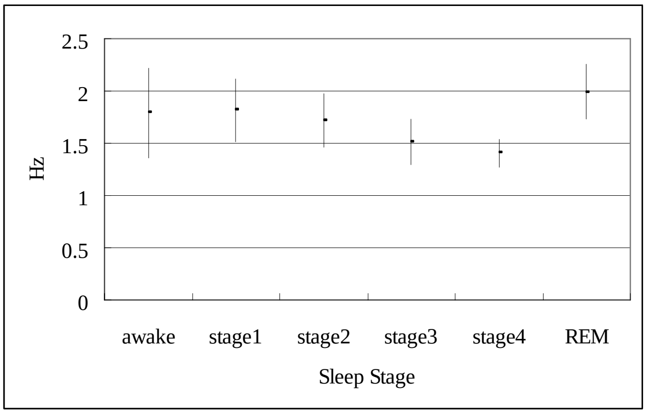

Fig. 5 The bandwidth of a4 (0.5-4Hz)

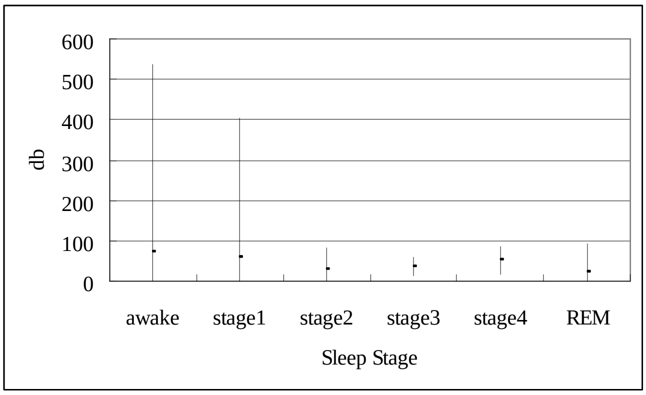

Fig. 6 The value at center frequency of d4 (4-8Hz)

In the above figures, HPs from different component decomposed by HHT or WT have clearly observable differences. For example, Fig. 1 shows the center frequency decreased form the 'awake' stage to stage 4, and increased during REM. This situation was the same in the Fig. 3. The standard deviations of values at center frequency are greater in Fig. 6, but the mean from each was different.

In order to verify the effect of the HPs for automatic sleep stages scoring, we designed a rough sleep stages scoring model using support vector machine (SVM). The SVM tool we used was developed by [8]. The schematic of the model is illustrated in Fig. 7. The ordering in the separation of specific stage form the others was decided empirically.

The model was built using the above training data, and trained by SVM using RBF kernel and default parameters. The testing data include EEG data from another six subjects. Table II shows numbers of epochs of each subject and the prediction accuracies. The accuracies of two types of features are nearly identical. The numbers of HPs with HHT and WT are 12, since there are both four components as described above (HHT: IMF1 to IMF4; WT: a4, d2, d3 and d4). The processing time for the extraction of HPs with HHT is much higher than those of HPs with wavelet transformation. Feature extraction was implemented with MATLAB. HP extraction with HHT takes about one hour for data from one subject. With wavelet transformation, only about 25 seconds are required.

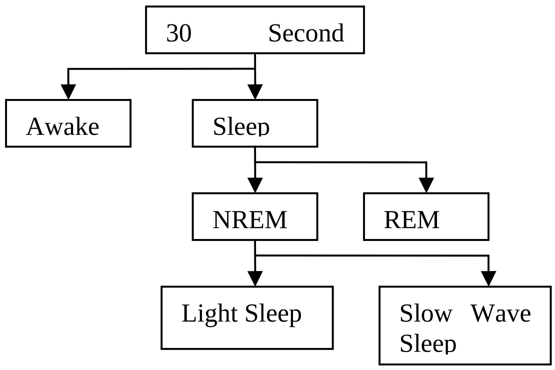

Fig. 7 Diagram of rough automatic sleep stage scoring model

NOTE: Light Sleep means stage1 and stage2 sleep
Slow Wave Sleep means stage3 and stage4 sleep

TABLE II
TESTING BY ROUGH SLEEP STAGES SCORING MODEL

Testing Data	Epochs	Accuracy (HPs with HHT)	Accuracy(HPs with WT)
Subjsct1	812	82.3%	83.4%
Subject2	754	82.4%	82.1%
Subject3	829	82.6%	79.7%
Subject4	805	70.3%	72.4%
Subject5	386	76.5%	73.2%
Subject6	799	70.7%	74.2%
Total / Average Accuracy	4385	77.6%	77.9%

Then performance compare with the normalized relative band energy in many pervious studies [2]-[3], [8] with the same training, testing data and model. The partition of frequency band is in Table III. The accuracy of relative frequency band energy was about 70%.

TABLE III
PARTITION OF THE RELATIVE FREQUENCY BAND

Band	Bandwidth(Hz)
Delta1	0.5 – 2.5
Delta2	2.5 – 4
Theta1	4 – 6
Theta2	6 – 8
Alpha1	8 – 10
Alpha2	10 – 13
Beta1	13 – 20
Beta2	20 – 32
Sleep Spindles	12 – 14

IV. CONCLUSION

HPs with HHT or WT seem to be suitable for the processing of the EEG signals, and have better performance than the relative band energy.

Combining HPs with other features proposed by the previous researches (e.g., wavelet entropy) may achieve higher performance. Using other classifiers or other post processing (e.g., rule-based algorithm or fuzzy reasoning–based classifier [8]) may also improve performance of automatic sleep stages scoring system. These works are in progress and have revealed promising preliminary results.

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