Electrophysiological Signals Segmentation for EEG Frequency Bands and Heart Rate Variability Analysis

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Abstract— **Biological signals like Electroencephalography (EEG) and Electrocardiography (ECG) provide very useful information related to brain and heart condition. Spectral analysis of EEG frequency bands and analysis of Heart Rate Variability (HRV) of ECG signal are largely used as a biomarker in studying various pathological conditions. However, the studies on EEG and HRV frequency bands analysis have shown inconsistency in the size of segment length used to extract the features. In the power spectral analysis, the trade-off between time and frequency resolution remain unsolved issue. To increase a frequency resolution and reduced a spectral leakage, a long segment of input data is necessary. However, for a stationary consideration a short segment data is needed. Therefore, in this study we examine the effect of segmentation time window and overlapping in spectral analysis of EEG frequency bands and HRV. The EEG and ECG signals used in this study are collected from the healthy and sleep apnea patients. Five features (delta, theta, alpha, sigma and beta) are extracted from EEG frequency bands and three (LFnu,HFnu, LF/HF) from the HRV by using spectral analysis at various window size and overlapping percentage. The results show the optimum window size for EEG is achieved at 10 sec and 120 sec for HRV analysis.**

Keywords— **EEG, ECG, frequency bands, Heart Rate Variability**

I. INTRODUCTION

Electroencephalography (EEG) is a biological signal of brain activity. Frequency bands analysis of EEG consist of five bands defined as delta, theta, alpha, sigma and beta which marked different sleep stages and could detect changes in brain activity. Studies have reported that brain and heart are the two physiological parameters interact during sleep [1-6]. Heart activity which can be monitored through Electrocardiography (ECG) signal has become an important noninvasive method in assessing cardiac state and the status of Autonomic Nervous System (ANS) which control the heart rate in human. Through a spectral analysis of Heart Rate Variability (HRV), the Low Frequency (LF) and High Frequency (HF) bands are used to define the subsystem of ANS: Sympathetic and Parasympathetic activities respectively. The Very Low Frequency (VLF) band is believed to reflect the thermoregulation mechanism and the LF/HF ratio is used as a marker of sympathovagal balances [7].

Previous studies on EEG and HRV frequency bands analysis have shown inconsistency in the size of segment length used to extract the features. Some studies have used 2, 5 and 20 seconds time segments to calculate EEG frequency bands [2, 8-9]. In the ECG spectral power analysis, a window size of 2, 4 and 5 minutes have been used to calculate frequency components of HRV [1, 10-13]. In one study, a 64 s time segment window with 50 % overlapping were used to compute a power in delta bands of EEG and HRV parameters [14]. Recent study has suggested that a new standards and specification for computer based analysis of electrophysiological signals is needed including an optimal sampling rate and segmentation size [15]. In the power spectral analysis, the trade-off between time and frequency resolution remain unsolved issue. To increase a frequency resolution and reduced a spectral leakage, a long segment of input data is necessary. However, for a stationary consideration a short segment data is needed. Therefore, in this study we examine the effect of segmentation size used for extracting features from EEG and ECG signals and further classify these feature content using Feedforward Neural Network (FNN).

II. METHODOLOGY

A. Data

Eight healthy subjects (5 men and 3 women) and eleven sleep apnoea subjects (9 men and 2 women) were recruited for an overnight study at St. Lukes Hospital (Sydney, NSW, Australia). An eight-hour PSG was recorded with sampling frequency of 256 Hz using Bio-Logic System and Adults Sleepscan Vision Analysis (Bio-Logic Corp, USA). The PSG recordings were consisted of three EEG channels (C3-A2, C4-A1 and O2-A1), one ECG (lead II), two electrooculograpy (EOG) channels to record eye movements, electromyography (EMG) electrodes positioned on the chin, nasal

J. Goh (ed.), *The 15th International Conference on Biomedical Engineering*, IFMBE Proceedings 43,
DOI: 10.1007/978-3-319-02913-9_177,

airflow, snoring sound, respiratory effort (measured at the chest and abdomen), oxymetry to measure oxygen saturation and actigraphy to record body positioning and leg movements. The sleep stages were visually scored by the sleep technician at 30-s interval and the respiratory signals of apnoea and hypopnoea index (AHI) were evaluated accordingly [16]. Tables 1 summarizes the descriptive clinical demographic.

Table 1 Subjects demographic

	Healthy	Sleep apnoea
Number of subjects (n)	8	11
Age (years)	48.13± 10.52	50.64± 11.39
BMI (kg/m^2)	27.01 ± 2.94	32.92 ± 5.30
AHI	2.75 ± 1.22	48.97± 27.52

B. Feature Extraction

Fig. 1 illustrates the schematic diagram of proposed system in this study. It consists of three stages, the pre-process of the EEG and ECG signals which consist of signal segmentation followed by the feature extraction which serve as an input to the classifier. Finally, the classification of the features into two classes, the healthy or sleep apnoea which also includes the evaluation of the classifier performance.

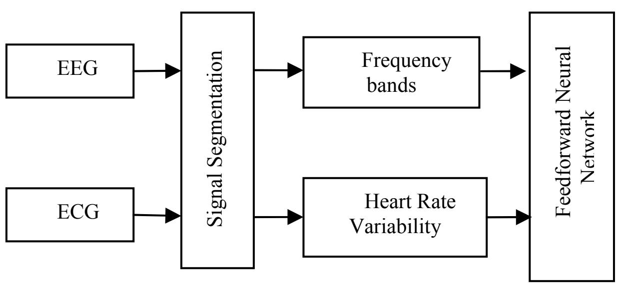

Fig. 1 Schematic diagram of analysis

a) Heart Rate Variability of ECG

Analysis was performed at time windows 5, 10, 30, 60 and 120 seconds with non-overlapping and at 50 % overlapping segment for both signals, ECG and EEG. From an eight hours signal length, a free movement segments were visually selected for calculation of EEG and HRV. R-R intervals (RRI) were calculated and re-sampled at 4 Hz from the identified QRS complex of the ECG [17]. Further non-parametric spectral analysis based on Fast Fourier Transform (FFT) with no windowing function was performed according to Task Force [11]. The power in the VLF (≤ 0.04 Hz), LF (0.04-0.15 Hz) and HF (0.15-0.4 Hz) bands were computed and three features were extracted: LFnu, HFnu and LF/HF. The normalized value was calculated as:

$$LFnu= LF/(Total\ power\text{-}VLF) \tag{1}$$

$$HFnu= HF/(Total\ power\text{-}VLF) \tag{2}$$

b) Frequency Bands Analysis of EEG

Five features were extracted from the spectral analysis of EEG frequency bands. From the corresponding EEG signal in C3-A2 channel, the power spectral was computed using 1024 points FFT with no windowing function for different window size. The estimated absolute powers were grouped into five frequency bands: delta (0.5-4.5 Hz), theta (5-8.5 Hz), alpha (9-12.5 Hz), sigma (13-16.5 Hz) and beta (17-30 Hz). The relative power was derived by dividing the power within each band by the total power (0.5-30 Hz).

C. Classification

The Feedforward Neural Network (FNN) is a supervised classification technique inspired from neuronal function in brain. FNN has been used extensively in data mining and pattern classification. The basic architecture of FNN consists of an input layer, a hidden layer and an output connected in one direction only without having any loops as shown in Fig. 2. Every node in each layer is fully connected with all nodes in the previous layer until it reaches the output. The links between the layers are the modifiable weights calculated at every node [18].

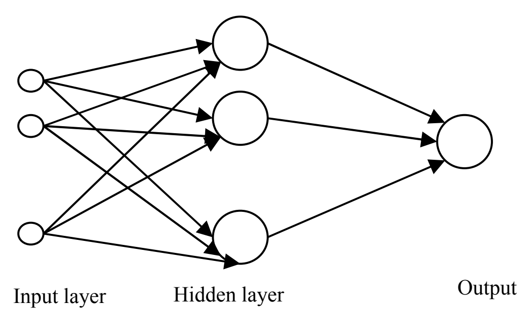

Fig. 2 Feedforward Neural Network Architecture

The training of FNN was conducted by using Levenberg Marquardt backpropagation algorithm. The advantages of this method are its simplicity, easy to understand and computationally efficient.

In our experiment, two hidden layers of FNN were used for classification. Halves of the data set was used for training and the other halves for testing. In the first part of the experiments, a data set for FNN consists of 5-dimensional column vector (d=5) represent EEG frequency bands and 3-dimension column vector (d=3) for HRV was classified separately in order to find an optimum window size. We further combined both features for the classification using the optimal window size values we obtained in the first part of our experiments.

The performance of the classifier was evaluated by calculating the Mean Absolute Error (MAE) as:

$$MAE = \frac{1}{n}\sum_{1}^{n}\left|x_{predicted} - x_{true}\right| \quad (3)$$

where n is the number of test data, $x_{predicted}$ is the estimated class and x_{true} is the true class of the data.

III. RESULTS

Table 1 Mean Absolute Error (%) of FNN

Features	Overlaps N = 0% Y = 50%	Window size (Seconds)				
		5	10	30	60	120
ECG	N	18.32	14.25	15.78	11.54	10.16
	Y	17.45	12.87	15.13	9.52	8.33
EEG	N	10.42	10.33	10.51	11.16	11.32
	Y	9.89	9.00	9.58	10.45	10.12

Table 2 shows the MAE of two hidden layer of FNN in classifying two classes at five window size and two overlapping percentage. The classification performance when both HRV and EEG frequency bands were combined as an input to FNN is shown in Table 3.

Table 3 Mean Absolute Error (%) of FNN for window size = 120 s of ECG and 10 s for EEG

Features	Overlaps percentage	
	0	50
ECG + EEG	8.41	7.55

IV. DISCUSSION

In this paper, we have analyzed the effect of segmentation time window and overlapping in spectral analysis of EEG frequency bands and HRV. It was observed that, a 120 seconds segmentation time window with 50 % overlapping produced an optimum content classification of HRV of ECG. Analysis of EEG frequency bands at window size of 10 seconds with 50% overlapping improved the classification percentage. A FFN with two hidden layers has predicted the two classes at an acceptable result. The accuracy of the system has slightly improved to 93% when features from EEG and HRV were incorporated to the classifier.

V. CONCLUSION

We have examined the effect of segmentation time window and overlapping in spectral analysis of EEG frequency bands and HRV by means of Artificial Neural Network. The classification performance of FNN may vary based on the selection window size used for EEG and HRV analysis.

ACKNOWLEDGMENT

The authors gratefully acknowledge Mr. Gerard Holland from St. Luke's Hospital (Sleep Centre) in Sydney (NSW, Australia), for providing continuous consulting, sleep monitoring and scoring input to our sleep research.

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