Sleep-awake Classification using EEG Band-power-ratios and Complexity Measures

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***Abstract*—Single-channel sleep EEG data from eight subjects have been analyzed using Lempel-Ziv complexity measure and alpha-delta and gamma-delta power ratios. Complexity values are consistently high during the waking state for all the subjects and low during the sleep state. Similarly, both the power ratios are high when the subjects are awake and become low during sleep. We have obtained an accuracy of 93.9% in classifying EEG epochs into data corresponding to sleep or awake states. The misclassification is mainly arising from the fact that both the complexity values and the power ratios during the REM sleep state are sometimes comparable to the waking state. By adding another signal such as electromyogram or electrooculogram, one maybe able to minimize the misclassification. The uniqueness of our work is that we have been able to achieve a good accuracy using only one EEG channel, two carefully chosen simple features and a linear classifier.**

***Index Terms*—sleep, waking state, coma, MCS, complexity, power ratio, EEG, alpha, gamma, delta, LDA.**

I. Motivation

Not much is known about the integrity of the circadian rhythm of sleep-wake cycle for the patients with disorders of consciousness (DOC). Physicians specializing in neurorehabilitation have observed that presenting sensory stimuli of special interest to such patients result in faster recovery of coma patients. In such cases, it is crucial that the stimuli are delivered when the patient is in a waking state. Unlike the normal people, it is not easy to determine whether a coma patient is sleeping or awake. So, it is very useful to investigate as to whether it is possible to identify the sleep-awake state of such DOC patients using electroencephalogram (EEG), electromyogram (EMG), etc. This study is a prelude to such an attempt. We use readily available sleep EEG data of normal people and subjects with mild difficulty falling asleep and perform a binary classification of sleep-awake states using a single EEG channel.

Disorders of consciousness is a broad term encompassing different states of consciousness including coma, vegetative state, minimally conscious state and locked-in-syndrome [2]. It is extremely difficult to distinguish between these states by relying only on behavioral responses [9]. Unfortunately, till date most of the clinicians rely only on the subjective scale such as Glasgow coma score (GCS) [22] for the diagnosis of DOC patients. Such scoring systems result in a high rate of misdiagnosis (40%) [20]. This calls for an effective and objective measure that can reliably distinguish between these different states of consciousness. It has been reported that sensory stimulation techniques using audio, visual or olfactory stimuli have the potential to improve the diagnostic accuracy as well as prognosis of the patients with DOC [3, 13]. Further, such stimulation techniques can be more effective if these stimuli are delivered when the patient is in waking state. Hence, the information of sleep-awake states of the patient becomes very important for the clinicians. Unlike healthy subjects, there is no consistent pattern reported in the sleep architecture of coma patients [12].

Sleep is generally divided into two broad categories: Non rapid eye movement (NREM) and rapid eye movement (REM) [5]. NREM is further subdivided into four stages representing a continuum of relative depth with stage 4 being the deepest sleep state. REM stage is quite similar to that of wake state in terms of the EEG patterns and therefore sometimes referred to as paradoxical sleep [21]. In case of DOC patients who do not show a consistent sleep-wake cycle, the more important question is to detect whether the brain is in sleep or awake state, rather than the details of different sleep stages. Hence, we have focused our research on the detection of only two broad states i.e. sleep and awake.

Electrical activity of the brain shows highly non-linear and dynamic properties [23]. Hence, non-linear dynamical features such as complexity and entropy of the EEG signal can provide crucial information about the different brain states, particularly sleeping and awake brain. We expect that the level of complexity would vary between the sleep and awake states of the brain. In this paper, we have used Lempel-Ziv complexity (LZC) measure as a primary feature for the binary classification of sleep/awake states of brain along with the ratios of spectral power in the

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alpha to delta and gamma to delta band frequencies as the secondary feature. LZC provides the spatio-temporal information, while the frequency information is captured by the spectral powers of alpha, delta and gamma frequency bands. Thus, the primary and secondary features combined together provide a rich information to distinguish between the sleep and awake states of the human brain. The proposed method utilizes the non-linear dynamics as well as conventional power spectral techniques for feature selection and linear discriminant analysis (LDA) for classification of each epoch into sleep/wake state using a single channel EEG signal.

II. Related Literature

Sleep analysis is usually performed by the experts based on the polysomnographic (PSG) recordings acquired during sleep which includes multiple bio-signals such as EEG, chin electromyogram (EMG), electrooculogram (EOG), respiration and oxygen saturation (SpO_2). Scoring is generally done according to the standard Rechtschaffen and Kales (R& K) rules [18]. Such manual scoring procedure is extremely time-consuming and suffer from subjectivity as well as inter-rater variability. To overcome this issue, many studies have attempted to develop an automated sleep scoring method that can replace the manual scoring system. The performance of these automated sleep identification methods mainly depend on the choice of the features and classifier. Most of the studies have used features based on frequency content of the EEG signals; such as dominant spectral frequency in EEG epochs or spectral power of different frequency sub-bands [6, 7, 11]. Few studies also utilized the temporal or time-frequency information embedded in the sleep EEG signals [8, 16]. Recent studies have further explored the nonlinear features such as entropy, complexity and fractal dimensions to improve the accuracy of the sleep stage classification [8, 17]. The most commonly used classifiers are fuzzy-logic and neural networks [1, 15, 19]. Many studies have utilized multi-channel PSG signals for sleep stage detection, but using more number of channels during sleep becomes inconvenient, resulting in sleep disturbance. Therefore, single channel EEG based system is more suitable for sleep studies. The reported overall agreements of single-channel EEG based sleep scoring methods are still less than 83% and accuracy could further be improved.

III. Materials and Method

A. Dataset used for the Study

We have used PhysioNet sleep-EDF database that provides sleep recordings and corresponding hypnograms in European data format [10]. It contains EEG recordings of two channels, namely FPz-Cz and Pz-Oz along with horizontal EOG and submental EMG, each sampled at 100 Hz, from 4 ambulatory healthy volunteers and 4 subjects who had mild difficulty falling asleep, but otherwise healthy

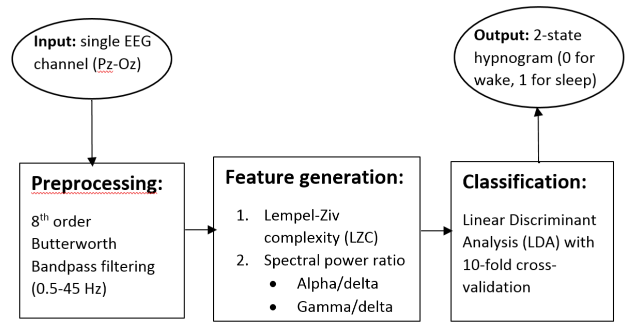

Fig. 1. Flowchart of the proposed method for sleep-awake classification.

during a night in the hospital. We have used only Pz-Oz EEG channel in our study.

B. Proposed Method

A flowchart of the proposed method is presented in Figure 1. The method comprises of three major steps: 1) preprocessing; 2) feature generation and; 3) classification.

Step1: Preprocessing: The Pz-Oz EEG signal is first passed through an 8th order Butterworth bandpass filter with 0.5-45 Hz passband. This filtered signal is then used for extracting features.

Step2: Feature generation: The continuous filtered signal is then segmented into 30 sec long epochs. Two feature sets are generated for each epoch, namely Lempel-Ziv complexity and spectral power ratios.

1) Lempel-Ziv Complexity Measure: LZC is based on the coarse-graining of the measurements, which means that the raw signal is transformed into a new time-series with very few symbols as the elements of the series [24]. LZC measures the number of distinct patterns in the given sequence. Here, we have converted the time-series into a binary sequence and then evaluated the number of distinct patterns contained in it . It is also normalized to make it independent of the sequence length. This EEG complexity measure has already shown its capability to measure the depth of anaesthesia and its online implementation feasibility [24]. Hence, it can be a good feature candidate for characterizing the different states of brain, especially a sleeping and awake brain.

2) Spectral power ratios: From the magnitudes of the discrete Fourier transform of each epoch, the power in each of delta, alpha and gamma frequency bands is obtained. The extracted features are the ratios of the powers in alpha and gamma bands to the power in the delta band. Since in sleep state, the signals of higher frequency such as alpha and gamma bands reduce while the low frequency signal such as delta dominates, we expect that the ratio of gamma to delta and alpha to delta would increase in waking state and fall sharply during sleep state of the brain. Hence, the power ratios of high-frequency to low-frequency

TABLE I
NUMBER OF 30-SEC EPOCHS FROM ALL EIGHT SUBJECTS USED IN THIS STUDY

Subject No.	Number of Wake epochs	Number of Sleep epochs
S1	1824	1024
S2	1885	944
S3	2104	676
S4	1909	948
S5	75	870
S6	128	923
S7	70	956
S8	60	792
Total	7133	8055

EEG signal carry potential information that can be used to perform sleep/wake classification.

Step3: Classification: To classify the EEG signal epoch-wise into two classes namely awake and sleep states, the linear classifier LDA is used. The set of features obtained in the previous step for each epoch and each subject is fed to the LDA which fits a linear discriminant function to the training set. After the model is trained, it is used to predict the labels for the unseen test data so as to find the generalization ability of the classifier. Here since we had limited data, we used cross-validation technique with 10 folds of partition for generating training and test datasets.

Next, in order to assess the performance of the model, we generate confusion matrices between the predicted class labels and true class labels epoch-wise for each feature individually and then combination of both the features. To further evaluate the agreement between the proposed method and the manual score, Cohen's kappa coefficient [4] is calculated using the generated confusion matrix. The kappa coefficient κ takes into account the agreements that occur by chance and therefore considered as a more robust measure than conventional percent agreements.

The kappa coefficient can be calculated as follows:

$$\kappa = \frac{P_o - P_c}{1 - P_c} \tag{1}$$

where P_o is the proportion of observed agreements given by:

$$P_o = \frac{\sum_{i=1}^{2} C_{ii}}{N} \tag{2}$$

where N is the total number of epochs which is the sum of all the entries in the confusion matrix and C_{ij} is the (i, j) element of the matrix. P_c is the proportion of agreements by chance, given by:

$$P_c = \frac{\sum_{i=1}^{2}(\sum_{j=1}^{2} C_{ij} \sum_{j=1}^{2} C_{ji})}{N^2} \tag{3}$$

IV. RESULTS

Table I shows the number of epochs in the sleep and awake states for all the eight subjects used in this study.

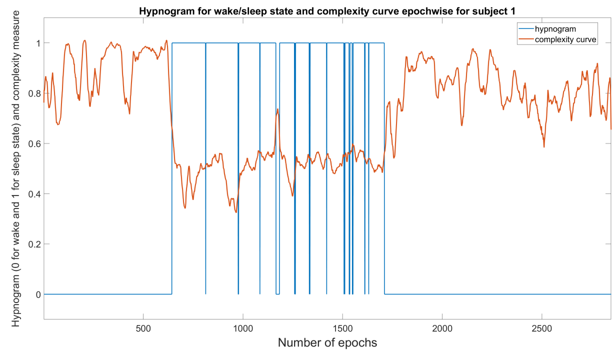

Fig. 2. Epoch-wise LZC values derived from the EEG of subject 1, along with the hypnogram. red: LZC values; blue: two-state hypnogram.

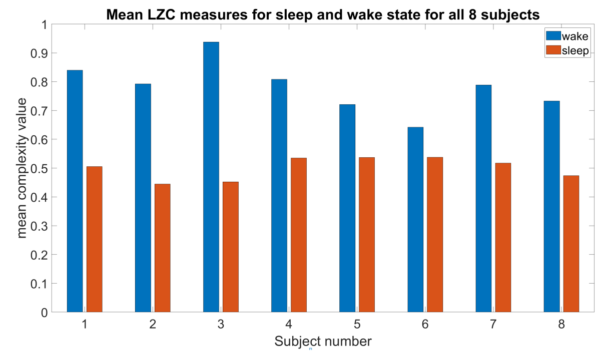

Fig. 3. Means of the LZC values of EEG for all the eight subjects. blue: wake state EEG; red: sleep EEG.

A. Role of complexity measure in sleep/awake classification

It can be seen that the LZC is working extremely well in determining the sleep/awake state of the brain. Figure 2 shows the epoch-wise LZC values along with the corresponding hypnogram of sleep/wake state for one of the subjects. As expected, the value of complexity is high in awake state and decreases during sleep. In the awake state, the brain is active and so the complexity of EEG signal is higher, while in sleep state, these activities get reduced and thereby the complexity of the EEG signal drops. It is evident from Figure 3 that the mean complexity values are consistently higher for the awake state than for the sleep state for all the eight subjects.

B. Role of spectral power ratios in sleep/awake classification

Figure 4 shows that gamma band is dominant when the brain is in awake state, while the sleep state is predominantly governed by the slow moving delta frequency. Also, the mean power ratio of alpha to delta frequency bands is much higher in the awake state than sleep state across all the eight subjects, as evident from Figure 5. This value is even higher in case of gamma to delta power ratio as shown by Figure 6 and 7. The consistently

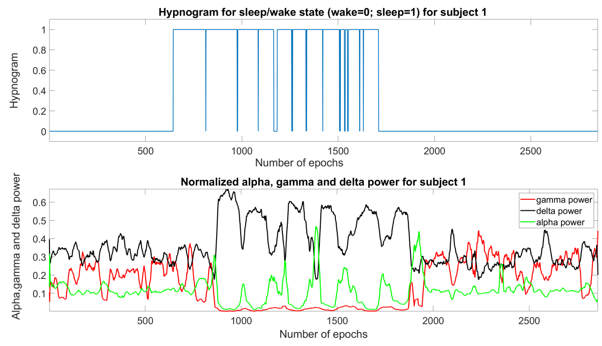

Fig. 4. Normalized gamma, alpha and delta power epoch-wise (lower panel) and the corresponding two-state hypnogram (upper panel) for subject 1. Green: power in the alpha band; black: power in the delta band; red: power in the gamma band;

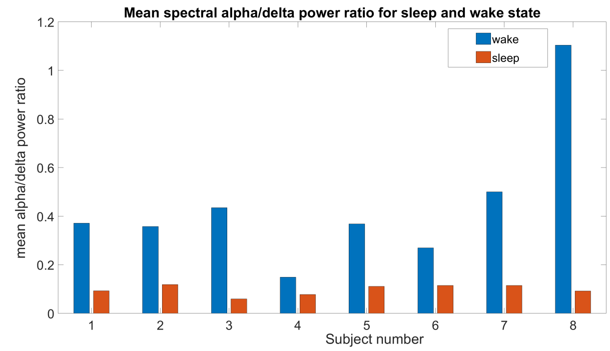

Fig. 5. Ratios of mean powers in the alpha to delta frequency bands for the eight subjects. Blue: from waking state EEG; red: sleep EEG.

large values of gamma/delta power ratio in awake state for all the subjects clearly indicate the dominance of higher frequencies and suppression of low frequency signals in awake state, while the opposite is true for the case of sleep state. Hence the spectral information captured by these two power ratios serves as a complementary feature to improve the classification accuracy.

C. Analysis of classification performance based on the proposed features

1) Performance of complexity measure on sleep/awake detection: For each 30-sec EEG epoch, the primary feature i.e. LZC and the corresponding label (wake/sleep) are used to train the LDA model. Figure 8 shows the confusion matrix of 2-stage classification of EEG epochs between the proposed method and manual scoring. As expected, this feature is able to capture most of the information and provides sensitivity of about 91% for wake state and 96 % for sleep state.

2) Performance of spectral power ratios on sleep/awake detection: It is well established in the literature that sleep state is predominantly occupied by low-frequency signals, especially in deeper stages of sleep such as NREM-4. Considering only power spectral ratios of alpha to delta and gamma to delta frequency bands across all the subjects, classification accuracy of about 78% is achieved. Around 61% of the wake states and 97% of the sleep states are correctly classified using this feature. Figure 9 shows the confusion matrix between the proposed method and manual scoring method using only the secondary feature i.e. power spectral ratios.

3) Performance of the combination of both features on sleep/awake detection: Figure 10 shows the classification performance using confusion matrix obtained by both LZC and spectral power ratio as features. Combining both the features improves the sensitivity to 92.5% for wake state and 95.4% for sleep state, which is higher than the previously reported studies in the literature. Accuracy of greater than 93% could be obtained by LZC alone, which is further improved by combining the power ratio with it. The kappa coefficients and accuracies obtained by using individual features and the combination of both features are presented in Table II. The qualitative interpretations of different ranges of kappa values [14] are mentioned in Table III.

It is evident that the level of agreement between the score generated by experts and that of our method is excellent for LZC and moderate for spectral power-ratios. (Refer Table III). This shows that indeed LZC is a useful feature for sleep/wake state identification.

TABLE II
VALUES OF COHEN'S KAPPA COEFFICIENT AND ACCURACY FOR THE FEATURES USED IN THIS STUDY

	only LZC measure	only spectral power-ratio	both features combined
Kappa coefficient	0.87	0.57	0.88
Accuracy	93.4%	78.1%	93.9%

V. CONCLUSION AND FUTURE WORK

We have demonstrated that the feature vector derived from a single channel EEG consisting of LZC value and the band power ratios is very effective in classifying the awake state from the sleep state of the brain. By utilizing these two simple features, we could achieve an accuracy of 93.9% and kappa coefficient of 0.88. Error analysis indicates that part of the error arises from the fact that the REM sleep epochs are not always correctly classified. The classification accuracy can be improved using features

TABLE III
LEVEL OF AGREEMENT AND KAPPA COEFFICIENT VALUES

Agreement	kappa coefficient
Poor	< 0
Slight	$0 - 0.2$
Fair	$0.21 - 0.40$
Moderate	$0.41 - 0.60$
Substantial	$0.61 - 0.80$
Excellent	> 0.8

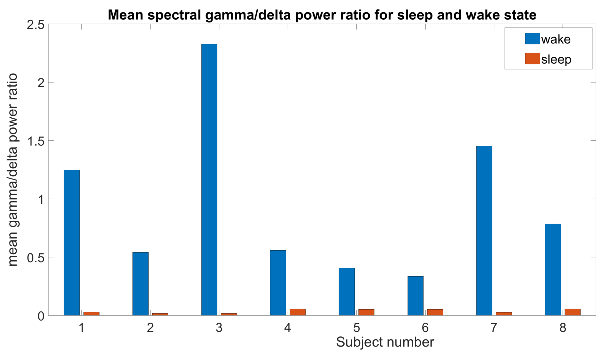

Fig. 6. Ratios of mean powers in the gamma to delta frequency bands for the eight subjects. Blue: from waking state EEG; red: sleep EEG.

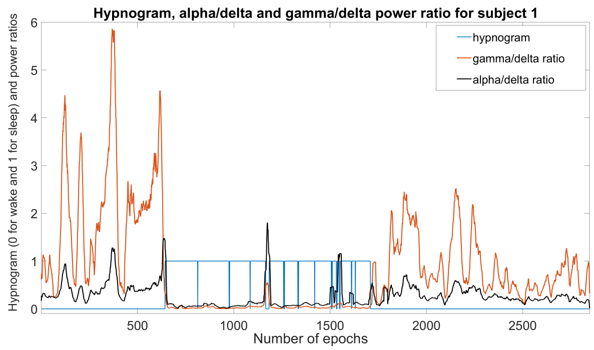

Fig. 7. Epoch-wise values of the gamma to delta and alpha to delta power ratios derived from the EEG of subject 1, along with the hypnogram. Red: gamma to delta power ratios; black: alpha to delta power ratios; blue: Two-state hypnogram.

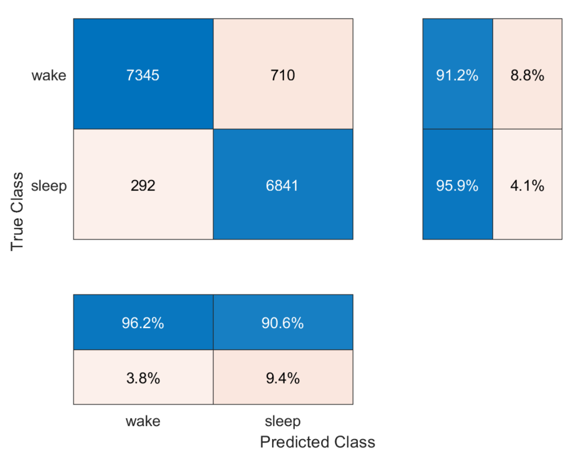

Fig. 8. Confusion matrix between our scoring method using only the complexity measure and the manual sleep scoring.

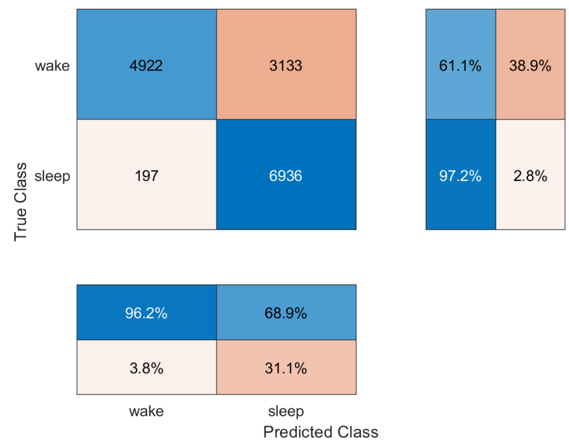

Fig. 9. Confusion matrix between our scoring method using only spectral power ratio features and the manual sleep scoring.

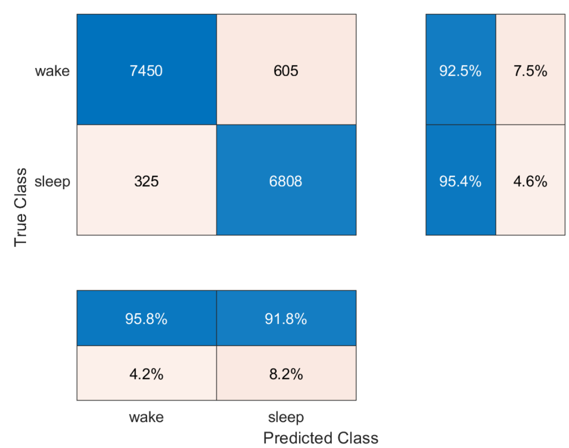

Fig. 10. Confusion matrix between our scoring method using both LZC and spectral power ratio features and the manual sleep scoring.

derived from EOG and EMG signals and/or using classifiers with a nonlinear decision boundary. Further, we would test the prediction accuracy of the trained model on unseen test subjects, which will provide a better estimate of the classifier's performance.

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