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Non-Linear Feature Based Sleep Stage Classification

Anuvitha Chandran VS*, Ashalatha Radhakrishnan**
*(Department of Neurology, Sree Chitra Tirunal Institute for Medical Sciences & Technology, Thiruvanathapuram, India
Email: anuvitha21@gmail.com)
** (Department of Neurology, Sree Chitra Tirunal Institute for Medical Sciences & Technology, Thiruvanathapuram, India
Email: ashalatharadhakrishnan@gmail.com)

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Abstract:

The diagnosis and management of different sleep disorders depend on the categorization of sleep stages. Single channel EEG was used in this study to develop sleep stage classification. The 30-second epochs of EEG data is decomposed into frequency sub-bands using the Butterworth band-pass filter. Non-linear features are extracted and different classifiers are used for classification of sleep stages. Various classifiers were utilized in the classification of sleep stage. Accuracy ranges for 5-stage classification ranged from 89.36% to 92.88%.

Keywords — **Sleep Stage Classification, Single-Channel EEG, Time-Domain Features, Frequency-Domain Features, Random Forest.**

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I. INTRODUCTION

Polysomnography is a non-invasive test to study EEG waves that appear during sleep. Sleep is the physiological process where body movements, temperature, breathing rate, heart rate and responsiveness to external stimuli are reduced. Sleep is necessary for many body functions, including memory consolidation, energy conservation and regulating metabolism [1].

Polysomnography is a technique used to record brain waves, heart rate, eye movements, temperature and muscle activity while sleeping [2]. The polysomnographic recording of EEG is divided into different sleep stages depending on the brain waves that emerge during sleep. Polysomnographic recordings are usually annotated by sleep technicians or the experts with 30 seconds of data to aid doctors in diagnosing of various sleep disorders. The annotations are performed in accordance with the rules established by the R&K [3] or AASM [4] criteria. The R&K rule categorizes sleep into six stages. In the AASM standards, two stages are combined, resulting in a total of five stages. Stage-1 is marked by the theta and alpha waves in brain activity. Alpha waves are visible when eyes are closed, but they disappear in the deeper stages of sleep. Stage-2 is marked by the appearance of K-complexes, which are triggered by external stimuli and sleep spindles, which last for about 1 second. Stage-3 is deep sleep, which is marked by high amplitude delta waves. The last stage is similar to awake or stage-1 sleep. The EEG waves that appear during this stage are sawtooth waves, theta waves and alpha waves. Beta waves are most commonly observed during awake [5].

The classification of sleep stages in machine learning involves three main processing steps. Preprocessing is the initial step, which involves eliminating any unwanted noise from the EEG signals. Commonly used preprocessing methods include band-pass filtering and notch filtering. The next step involves feature extraction, which primarily takes place in time [6], frequency [7] and time-frequency [8] domains. The classification methods include K-Nearest Neighbour [9], Linear Discriminant Analysis, Random Forest [11] and Support Vector Machine [10].

Single channel EEG was utilized in this study, so the following session will describe other works that reference single EEG channels. Gurrala et al. mapped the EEG signals using discrete wavelet transform (DWT). An accuracy of 97.4% was achieved using the support vector machine [13]. Li et al. applied wavelet transform packet to extract features. A classification method using cascaded SVM yielded an accuracy rate of 88.11% for 5 stage classification [14].

Satapathy et al. implemented a stacking classifier model and three different feature selection algorithms. They extracted features from three different domains and compared the classification results with different classifiers [15]. The decomposition of signals into six sub-bands was carried out by Sharma et al. using wavelet decomposition. Features such as fuzzy entropy and log energy were extracted from EEG signals and compared classification results using various classification methods [8].

Zhou et al. implemented a 2-layer stacking model that was based on RF and lightGBM (LGBM). Five features belonging to different domains were extracted and used RF to perform classification [16]. Bakmeedeniya et al. extracted power spectral density and used various classifiers [17]. By employing the stockwell transform, Ghasemzadeh et al. were able to transform EEG signals into the time-frequency domain. Entropy was obtained from the two datasets and different classification methods were utilized [18].

Tzimourta et al. extracted energy from the 30 second epoch of EEG data and used five classifiers for classification [19]. Aboalayon et al. extracted features from the decomposed EEG frequency bands. Discriminating between awake and stage-1 sleep, a support vector machine was used with an accuracy of 95.93% [20]. Diykh et al. utilized both structural graph similarity and K-Means for the six stage classification. Extracted features from the time domain resulted in a classification accuracy of 95.93% [21].

In this work, single EEG channel data is separated into different frequencies using Butterworth band-pass filter. The EEG wave characteristics are then extracted from the decomposed signals. Lastly, classification was implemented using well-known machine learning algorithms.

II. MATERIALS AND METHODS

A. Database

Data was gathered from an online publicly available sleep-EDF extended dataset [22], Physionet [23]. The dataset consists of 197 polysomnographic recordings made by healthy individuals. The recordings are made of Electroencephalography, Electrooculography and Electromyography. As part of the dataset, two EEG channels were recorded with 100 Hz sampling rate. 20 recordings from the Pz-Oz channel were used for this study. The annotations have been identified as w, 1, 2, 3, 4, R to indicate different sleep stages.

B. Preprocessing

To preserve the important signal, a band-pass filter (0.1-49 Hz) was applied.

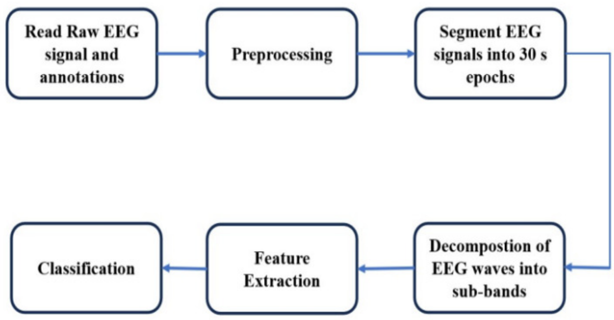

Fig.1 Flowchart of proposed method

The filtered data was separated into 30 second and decomposed into different EEG frequencies using Butterworth filter [20]. Fig.1 displays a demonstration of the proposed method.

C. Feature Extraction

The non-linear characteristics are taken from every frequency sub-band and are given below. Higuchi's fractal dimension [24] is calculating the fractal dimension of time series analysis. It is given by

$$L(t) = \frac{1}{t}\sum_{i=1}^{t} L_i(t) \qquad (1)$$

Where L_i is the length of the curve, t indicates time interval and i indicates initial time. The Higuchi fractal dimension is given by plotting log(L(t)) versus log(1/t).

Katz algorithm [24] is a non-linear algorithm that calculates the complexity of EEG data. The Katz fractal dimension is expressed as

$$\text{Katz Fractal Dimesion} = \frac{\log_{10} N}{\log_{10} N + \log_{10}(\frac{\text{distance}}{\text{Length}})} \qquad (2)$$

The Hurst exponent [25] measures the long memory process of the time series. It provides details on whether the time series is a random process or underlying trends. Hurst values close to 0.5 indicate a random walk. A Hurst value between 0.5 and 1 signifies trending and if it is between $0 \leq H \leq 0.5$ implies mean reverting. Hurst component is given by

$$\text{Hurst Exponent} = \frac{\text{Range Series(n)}}{\text{Standard Deviation(n)}} \qquad (3)$$

Shannon Entropy (SE) [26] calculates the average amount of information using the probability of the event. It is given by

$$SE = -\sum \text{probability} * \log(\text{probability}) \qquad (4)$$

Permutation Entropy (PE) [27] is the combination of Shannon entropy and ordinal pattern series. It is the probabilities of the distribution of permutation patterns and given by

$$PE = -\sum \text{probability}(\pi) * \log(\text{probability}(\pi)) \qquad (5)$$

The Lyapunov exponent [25] measures the stability of the time series from its initial conditions and is expressed as

$$\text{Lyapunov Exponent} = \lim_{n\to\infty} \frac{1}{n} \log \frac{p_i(n)}{p_i(0)} \qquad (6)$$

Where $p_i(n)$ is the length of the ellipsoidal principal axis.

D. Classification

The classification algorithms used in this study are described below. The decision tree algorithm [19] uses a divide and conquer method. It starts at the root node of the dataset in a top-down recursive manner. Based on the available features, the internal nodes form the output at the leaf nodes and this process continues until all the datasets are classified under specific labels.

Random forest (RF) is comprises multiple decision trees that select randomly a subset of data points and features in each phase. This randomness can enhance accuracy by decreasing overfitting and overall variance. The predicted results are returned by each decision tree and the final decision is based on the most voted results [28] . In Support Vector Machine (SVM) algorithm, n-dimensional space can be broken down into classes using a hyperplane. The most commonly used kernel for handling non-linear separation problems for EEG processing is the RBF function, which was used in this study [29].

The K-Nearest Neighbors (KNN) algorithm predicts the new data point by considering the labels or values of its nearest neighbors. The algorithm calculates the distance among the data points and its neighbors to find the nearest neighbors. Finally, the classification is accomplished based on the majority voting [9].

E. Performance Evaluation

In order to avoid overfitting, the use of 10-fold stratified cross validation is employed. To assess the classifier's performance, the following measures are utilized [30].

$$\text{Accuracy} = \sum_{1}^{10} \frac{\text{Correctly classified instances}}{\text{Total number of instances}} \qquad (7)$$

$$\text{Recall} = \sum_{1}^{10} \frac{TP}{TP + FN} \qquad (8)$$

$$\text{Precision} = \sum_{1}^{10} \frac{TP}{TP + FP} \qquad (9)$$

Accuracy is determined by the correctly predicted classes to the total number of classes. Recall/sensitivity measures how accurately positive classes are identified among all positive samples in the dataset. Precision can accurately predict positive classes.

III. RESULTS AND DISCUSSION

After preprocessing the EEG recordings of 20 healthy subjects, six features were extracted from the data. The feature vector was classified into different stages of sleep using various classification methods. The accuracy of 5-2 stages is depicted in Fig.2 based on various classification algorithms. Among other classifier algorithms, random forest has the highest classification accuracy.

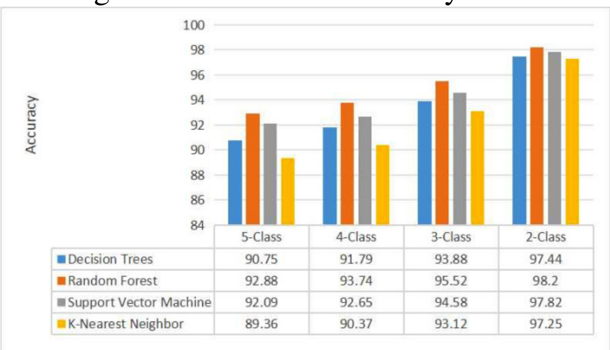

Fig.2 Classification accuracy of sleep stages using various classifiers

Table I shows that the recall/sensitivity of stage-1 is poorly performed, and the decision trees showed the best score. From this table, we can see that the recall and precision of the stage-1 are less than those of the other sleep stages. The imbalance in data distribution resulted in most of stage-1 being misclassified. Since stage-1 is the state between awake and stage-2 stages, the percentage of stage-1 in the total sleep epochs is lower. Due to this reason, the precision and recall for the stage-1 stage were less than those for the other sleep stages.

TABLE I
RECALL AND PRECISION (PR) OF 5-CLASS CLASSIFICATION FOR VARIOUS CLASSIFIERS

	Decision Trees		Random Forest		Support Vector Machine		K-Nearest Neighbor	
	Recall	PR	Recall	PR	Recall	PR	Recall	PR
Awake	0.98	0.98	0.99	0.98	0.99	0.97	0.98	0.98
Stage1	0.19	0.35	0.18	0.6	0.04	0.41	0.24	0.27
Stage2	0.84	0.83	0.89	0.86	0.88	0.86	0.8	0.81
Stage3	0.76	0.81	0.79	0.87	0.78	0.86	0.74	0.75
REM	0.77	0.64	0.84	0.72	0.83	0.67	0.67	0.63

In Fig.3, you can see the confusion matrix for 5-stage. The row represents the percentage of classified instances and the correct rate of every class is displayed on the main diagonal. The rest of the values in that row are indications of incorrect categorization.

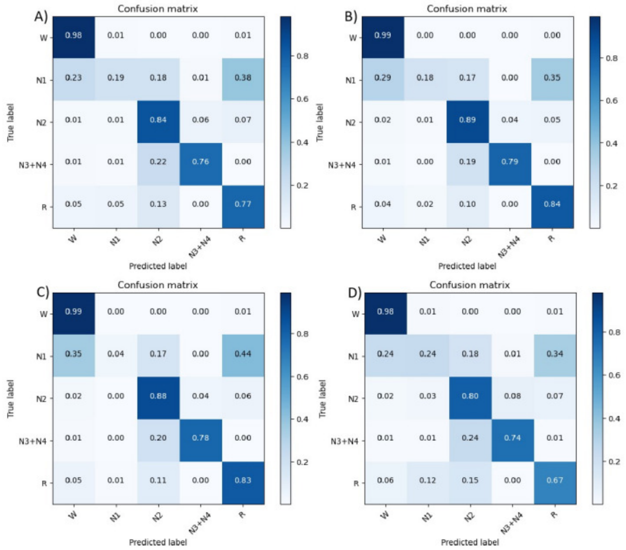

Fig. 3 Confusion matrix of A) Decision Trees, B) Random Forest, C) Support Vector Machine D) K-Nearest Neighbor

Comparisons with other works are presented in Table II. Braun et al. used normalized EEG data and then divided them into 30 seconds epochs. They extracted eight statistical features related to frequency using FFT and used four decision tree related algorithms available in the WEKA software for classification [31]. Da Silveira et al. used sleep-EDF data and implemented DWT to decompose the EEG waves. They extracted variance, kurtosis and skewness and random forest was used as the classifier [32].

TABLE III
COMPARISON WITH OTHER WORKS

Authors	Classifiers	Accuracy
Braun et al.	Random Forest	5-stage: 91.8% 4-stage: 92.4% 3-stage: 94.3% 2-stage: 97.1%
Da Silveira et al.	Random Forest	5-stage: 91.5% 4-stage: 92.3% 3-stage: 93.9% 2-stage: 97.3%
Proposed Method	Random Forest	stage: 92.88% 4-stage: 93.74% 3-stage: 95.52% 2-stage: 98.2%

IV. CONCLUSIONS

From a publicly available database, the single channel EEG data was gathered and divided into 30 second intervals. The Butterworth band-pass filter was used for feature extraction and extracted 30 no-linear features related to the frequency of interest. The classification process involved using random forest and evaluating it against other classification methods. The result shows that random forest performs well compared to the other classifiers. In the sleep cycle, stage-1 lasts only 5-10 minutes and the number of EEG samples recorded during polysomnography is less than that of other stages. As the result, the stage-1 classification has low accuracy and other performance metrics. Moreover, EEG waves that occur during stage-1 are also observed in other stages of sleep. Due to this, most of stage-1 are misclassified as other stages.

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