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# AUTOMATIC SLEEP APNEA DETECTION BASED ON ENTROPY OF MULTI-BAND EEG SIGNAL MECHANISM

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## ABSTRACT

*Sleep apnea is a general rest issue influencing an expansive number of individuals everywhere throughout the world. Electroencephalography (EEG) flag investigation is an imperative procedure that empowers neurologists and rest pros to analyze and screen Sleep apnea occasions. In perspective of abusing the variety in irregular attributes of multi-band EEG information amongst apnea and non-apnea occasions, in this paper, an entropy based element extraction plan is proposed. It is demonstrated that the proposed highlight set, removed from five diverse band-restricted EEG signals, offers attractive component quality as far as standard execution criteria, for example, geometric detachability file. With the end goal of order, the K-closest neighborhood (KNN) classifier is utilized. The proposed strategy is tried on a few subjects taken from openly accessible Physionet database. It is found that the proposed strategy offers unrivaled arrangement execution with lower include measurement in contrast with that acquired by existing strategies, as far as affectability, specificity and precision.*

***Keywords: Classification, electroenchephalogram (EEG)signal analysis, entropy, feature extraction, feature quality analysis,sleep apnea***

## I. INTRODUCTION

Sleep apnea is an exceptionally basic rest issue influencing around 4% men and 2% ladies of all inclusive community [1]. It is described by stops in breathing or occasions of shallow breathing amid rest. Each delay, specifically apnea, can keep going for a few moments to a few seconds. Recognizing apnea occasions with the assistance of a specialist is extremely tedious, repetitive and costly. There has been a great deal of endeavors recently to robotize manual identification prepare utilizing attributes of a few physiological signs, for example, electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG) and electrooculogram (EOG). The concentration of this work is the investigation of EEG flag keeping in mind the end goal to recognize Sleep apnea occasions. Electroen-cephalography (EEG), a famous method in the acknowledgment procedure, relates with neural action of mind. As of late, the rest EEG synchronization examination has gotten to be as a skyline to help perceiving cerebrum instruments. Many reviews demonstrate that rest issues can be recognized by utilizing a solitary channel (C3-A2 or C4-A1) of the EEG flag [2]. It is generally used to recognize rest stages and rest

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quality. Sleep apnea seriously irritates rest quality, henceforth it can be related to EEG flag.

An approach for automatic sleep stage scoring and apnea-hypopnea detection is presented in [3] by using EEG, ECG, EOG and EMG signals by Fourier and wavelet transform,derivative dynamic time warping and waveform recognition. detrended fluctuation analysis (DFA) is used to compute EEG scaling exponents and are compared between apnea and healthy subjects during sleep in [4]. Instead of using the full band EEG signal, one effective way is to utilize band limited signals where band limits are chosen according to the well known EEG sub-bands namely delta, theta, alpha, sigma and beta. Energy and variance computed from each frequency sub-band are used as features for apnea classification in [5]. Variation of Hilbert spectrum frequency is used in [6] to detect duration of obstructive sleep apnea. Bispectral characteristics of EEG signal are used in [7] to classify between apnea and healthy subjects. In [8], features from spectral domain of oximetric and EEG signals are used for sleep apnea detection. The accuracy of apnea detection, taking only entropy of power spectral density of EEG signal as a feature, is also reported here. Energy, entropy and standard deviation, computed from different frequency bands of EEG signal, are used as features to classify sleep stages in [9].

The goal of this paper is to build up a productive subject particular rest apnea identification conspire utilizing entropy of recurrence band-constrained signs. Pre-prepared EEG flag is initially isolated into five recurrence groups. Next, entropy of each of the subsequent band-constrained EEG signs is extricated and after that utilized as a part of course to get proposed highlight set. At last, apnea and non-apnea edges are arranged utilizing KNN classifier. The execution of the proposed strategy is tried utilizing a standard rest apnea database.

## II. PROPOSED METHOD

Major steps of the proposed method are shown in Fig. 1 and detailed description is provided in this section. Features are extracted from each pre-processed band-limited EEG signal and then cascaded feature set is used in KNN classifier.

### 2.1. Pre-processing

The apnea detection task is performed on each subject separately on a frame by frame basis. The mean value of an EEG test frame is subtracted to remove the dc offset as components of other frequencies are of major interest. Sample values of a frame are normalized with respect to the maximum value of that frame. Such a frame normalization step helps to avoid unwanted amplitude variation in different frames even within same class

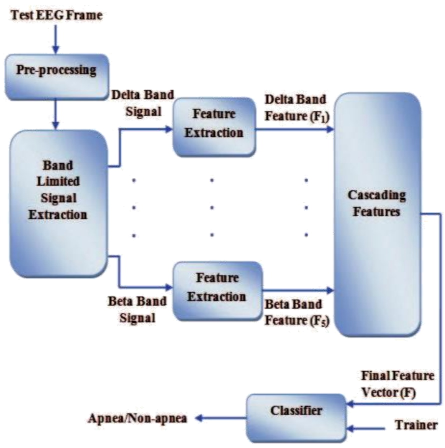


**Fig. 1. Block diagram showing the major steps of the proposed method**

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### 2.2. Band-limited Signal Extraction

When breathing is paused, carbon dioxide builds up in the bloodstream. Chemoreceptors in the bloodstream notice the high carbon dioxide levels and the brains is signaled to wake the person sleeping and breathe in air. Due to change in sleep stages, it is expected that there will be variation in level of activity in different frequency bands of the recorded EEG data. As a result, frequency band-limited signals can preserve more distinct features for detection of apnea events. It is found that multi-band signals preserve local information better in comparison to full single-band EEG signal. Hence, instead of analyzing full band EEG signal, band-limited signal analysis is used to detect apnea events.

EEG signal is divided into five frequency bands [10], namely: delta (0.25-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), sigma (12-16 Hz) and beta (16-40 Hz), by simple spectral filtering in FFT domain where only frequency components of the desired band are preserved.

### 2.3. Proposed Multi-band Entropy Feature

In the proposed method, feature based classification scheme is proposed for subject specific identification of apnea and non-apnea events. Entropy of band-limited EEG data is proposed as a potential feature which is expected to be capable of showing discriminative characteristic during apnea and non-apnea events.

Entropy of a discrete random variable $X$ with $(N + 1)$ number of possible values $\{x_0, x_1, x_2, ..., x_N\}$ is defined as

$$H(X) = E(I(X)) \qquad (1)$$

where$E(.)$ denotes the expectation operator and $I(X)$ repre-sents the information content. For a particular value $x_i$ of $X$, the information content can be expressed as

$$I(X) = -\log_2(p(x_i)) \qquad (2)$$

where$p(x_i)$ denotes the probability of occurrence of $x_i$. Using (2), the entropy in (1) can be re-written as

$$H(X) = -\sum_{i=0}^{N} p(x_i) \times log_2(p(x_i)) \qquad (3)$$

Here, $p(x_i) = n_i/N$ , where, $n_i$ is the number of occurrence of coefficients in a bin in proximity of $x_i$ value among the N number of values, i.e. $\sum_i n_i = N$ .

EEG signal indicates the electrical activity of the brain. It is highly random in nature and contains useful information about different mental/motor-imagery states of the brain. Moreover, when breathing stops, one may make grunting, gasping, or snorting sounds and restless body movements. Hence, random-ness in information content of EEG signal is expected to be more in case of apnea events compared to that of non-apnea events. As entropy is a statistical measure of randomness of information content, it is proposed as a potential feature in detection of apnea events.

It is very difficult to extract useful information from the EEG signal by directly utilizing full-band EEG data in time domain. However, variation in information content, depending on physiological changes and sleep stages, is better visualized in different frequency bands of EEG signal. Energy contents in different frequency bands of EEG signal vary from band to band. During normal sleep (non-apnea event), most energy remains in lower frequency bands. When apnea occurs, there is a significant change in energy in different frequency bands compared to non-apnea events. In particular, it is observed that relative energy contribution of higher frequency bands with respect to that of lower frequency bands increases during apnea events. This observation can be hypothesized as energy being shifted from lower frequency bands to higher frequency bands. In view of incorporating these changes, instead of extracting entropy value from full band signal, entropy values extracted from five different frequency band-limited EEG signals namely, $F_1$, $F_2$, $F_3$, $F_4$ and $F_5$ are combined to obtain the proposed feature vector, F as

$$F = [F_1\ F_2\ F_3\ F_4\ F_5] \qquad (4)$$

The entropy values of beta band of 100 apnea and 100 non-apnea frames for a subject are shown in Fig. 2. It is observed from this figure that a significant number of apnea and non-apnea frames exhibits distinguishable entropy values. As expected, there are also some overlaps in entropy values for some frames within an acceptable limit. For other frequency bands corresponding to the same subject and same 200 frames, similar pattern of entropy values for apnea and non-apnea frames is observed. Due to the randomness of EEG data, apnea and non-apnea frames which are showing very similar entropy values in a particular band, may exhibit significantly different values in other frequency bands. It is expected that the proposed entropy feature set extracted from multi-band EEG signals can provide better feature quality which in the long run can offer satisfactory classification performance.

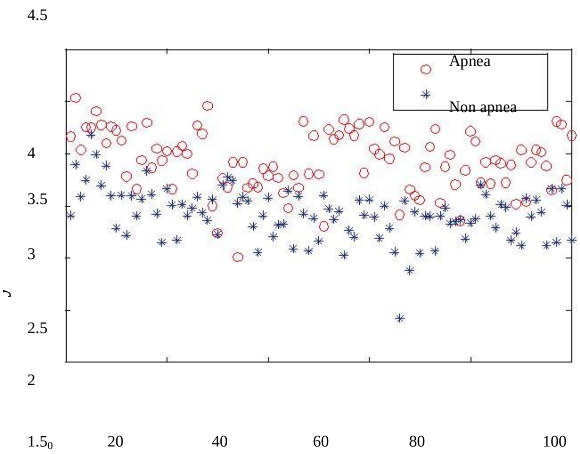


**Fig. 2. Variation of entropy values for apnea and non-apnea frames in beta band**

## 2.4. Classification

For classification purpose, the K-nearest neighborhood (KNN) classifier is used which is one of the simplest but efficient classifiers. It considers a distance function which is computed among the features belonging to the EEG pattern in the test set and K neighboring EEG patterns from both apnea and non-apnea group in the training set. The EEG pattern from the test set is classified based on the class labels of K closer EEG patterns in the train set. In the proposed method, the cosine distance is used in KNN classifier. It is required to find a suitable value of K for achieving the best classification performance. In the proposed method, the value of K is varied within a large range and it is found that because of the better feature quality, consistent performance is achieved for all K values. For the purpose of performance evaluation, leave-one-out cross validation technique is employed.

## III. RESULTS AND DISCUSSIONS

### 3.1Database and Simulation Setup

A dataset containing overnight polysomnograms collected from adult subjects who are previously diagnosed with sleep disordered breathing is used for the analysis, which is publicly available in the Physionet database [11]. The EEG data are sampled at 128 samples/sec. The ground truth (starting and ending point of apnea events) in the recorded EEG data is provided in the database based on physical inspection by an experienced sleep technologist.

For the purpose of experimentation, 5 different subjects having wide variations in apnea hypopnea index (AHI) are taken into consideration. AHI<5 corresponds to healthy; 5-15 is mild; 15-30 is moderate, and more than 30 is severe [12]. Information of 5 subjects used in this paper is given in Table I along with total number of frames to be considered. For the purpose of testing the classification performance, all the apnea frames and corresponding equal number of non-apnea frames of each subject are taken. In this paper, among two EEG channels of the database, C3-A2 channel is considered. It is found that the duration of apnea event varies between 10 seconds to 25 seconds in most of the cases. In this experiment, a frame duration of 10 seconds is considered, which ensures that a frame consists of only apnea or non-apnea condition.

**Table I Information of the Subjects Used in the Experiment**

| Subject Number (Sub. No.) | AHI | Height (cm) | Weight (kg) | Gender | Total Number of Frames |
|---|---|---|---|---|---|
| UCDDB007 | 12 | 183 | 84 | M | 214 |
| UCDDB010 | 34 | 174 | 119 | M | 488 |
| UCDDB011 | 8 | 188 | 101 | M | 88 |
| UCDDB021 | 13 | 161 | 87 | F | 184 |
| UCDDB024 | 24 | 172 | 99.9 | M | 390 |

The proposed method is compared with existing method (EM-1) in [5], existing method (EM-2) with only spectral entropy of full band EEG signal in [8], multi-band spec-tral entropy method (MBSE) and single-band entropy (SBE) method. In MBSE, entropies are extracted from power spectral density of multi-band EEG data, whereas in the SBE, entropy is extracted from the full single-band (0.25-40 Hz) of time domain EEG data.

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### 3.2. Feature Quality Analysis using Geometric Separability Index (GSI)

Geometrical separability index (GSI), also known as Thorn-tons separability index, is useful to understand the separability of clusters. It is defined as the fraction of a set of data points whose classification labels are the same as those of their nearest neighbours. According to [13] it is computed as

$N \quad (f(x_i)) + f(x\ ) + 1)\ mod\ 2$

$i=$

$1 \quad I$

$$s = \frac{\quad}{N} \qquad (5)$$

wherex is the nearest neighbour of $x$ and $N$ is the number of points. GSI values of proposed method, existing method-1 (EM-1), existing method-2 (EM-2), multi-band spectral en-tropy method (MBSE) and single-band entropy method (SBE) are shown in Fig. 3. It is clearly observed from this figure that

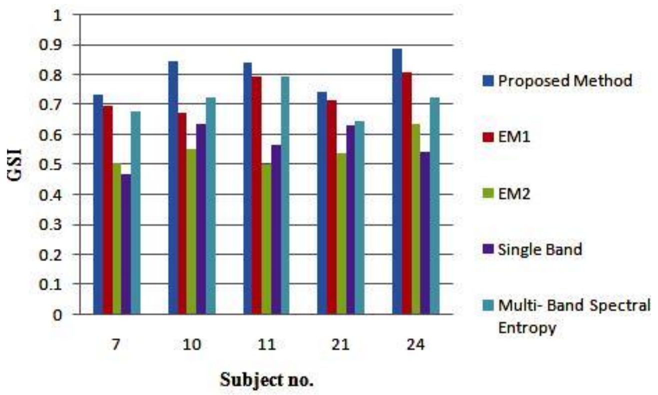


**Fig. 3. Comparison of GSI values among different methods**

**TABLE II Comparison of Apnea Detection Results of Proposed Method with Other Methods**

| Sub. No. | Sensitivity( %) | | | | | Specificity (%) | | | | | Accuracy( %) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | EM-1 | EM-2 | MBSE | SBE | Prop. | EM-1 | EM-2 | MBSE | SBE | Prop. | EM-1 | EM-2 | MBSE | SBE | Prop. |
| 1 | 72.90 | 47.66 | 58.88 | 57.01 | 80.37 | 83.18 | 63.55 | 66.36 | 50.47 | 82.24 | 78.04 | 55.61 | 62.62 | 53.74 | 81.31 |
| 2 | 89.34 | 53.28 | 75.41 | 62.70 | 96.72 | 83.61 | 65.57 | 55.74 | 67.62 | 86.07 | 86.48 | 59.43 | 65.57 | 65.16 | 91.39 |
| 3 | 79.55 | 45.45 | 79.55 | 50.00 | 90.91 | 77.27 | 70.45 | 81.82 | 63.64 | 88.64 | 78.41 | 57.95 | 80.68 | 56.82 | 89.77 |
| 4 | 79.35 | 52.17 | 75.00 | 48.91 | 84.78 | 79.35 | 54.35 | 63.04 | 70.65 | 82.61 | 79.35 | 53.26 | 69.02 | 59.78 | 83.70 |
| 5 | 86.15 | 65.13 | 69.74 | 54.87 | 92.31 | 91.28 | 71.79 | 76.41 | 60.00 | 91.79 | 88.72 | 68.46 | 73.08 | 57.44 | 92.05 |
| Mean | 81.46 | 52.74 | 71.72 | 54.70 | 89.02 | 82.94 | 65.14 | 68.67 | 62.48 | 86.27 | 82.20 | 58.94 | 70.19 | 58.59 | 87.64 |

the proposed method offers better geometric separability than the other methods. Thus proposed method is showing better feature quality than the other methods.

### 3.3. Classification Result

The performance of the proposed method is evaluated using standard measures, such as accuracy, sensitivity and specificity which are defined as

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \qquad (6)$$

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \qquad (7)$$

T N +F P

where TP = True Positive (Apnea detected as apnea),
FP = False Positive (Non-apnea detected as apnea),
TN = True Negative (Non-apnea detected as non-apnea) and
FN = False Negative (Apnea dected as non-apnea)

Performance comparison of the proposed method (Prop.)with the existing methods arepresented in Table II. It is to be mentioned that for fair comparison,KNN classifier is used in all cases. It is clearly observed in this table that the proposed method outperforms all four methods with respect to all benchmarks of sensitivity, specificity and accuracy. Only the method EM-1 shows comparative results but it uses a feature dimension of 10, whereas only 5 features are used in the proposed method. Although EM-2 and SBE methods use lesser feature dimension, they in comparison to proposed method offer poorer performance. The method MBSE which has a similar feature dimension as the proposed method alsoshows poorer performance than the proposed method. Hence, proposed method is offering better performance with reduced 98 % computational complexity which is a significant achievement.

## IV. CONCLUSION

In this paper, a simple but efficient automatic sleep apnea classification scheme is proposed based on entropy analysis of multi-band EEG signal. Proposed multi-band entropy basedmethod provides much better classification performance in comparison to single-band method no matter that utilizes time domain entropy or spectral domain entropy of EEG data. Feature quality test, such as GSI also confirms that the proposed method offers better feature quality than other methods. Moreover, this method offers a feature dimension of only five which indicates low computational complexity. From extensive experimentation on several apnea patients with wide variation in AHI, it is shown that the proposed method,with a very low computational complexity, offers superior subject specific classification performance in comparison to some existing methods in terms of sensitivity, specificity and accuracy.

## V. ACKNOWLEDGEMENT

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