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Highlights

- A statistical model and weighted networks are used to identify EEG sleep stages.
- The proposed system requires one input the EEG signals without pre-processing.
- The results showed that the network's characteristics vary with their sleep stages.
- Each sleep stage is best represented using the key features of their networks.

EEG Sleep Stages Identification Based on Weighted Undirected Complex Networks

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Abstract:

Background and Objective: Sleep scoring is important in sleep research because any errors in the scoring of the patient's sleep electroencephalography (EEG) recordings can cause serious problems such as incorrect diagnosis, medication errors, and misinterpretations of patient's EEG recordings. The aim of this research is to develop a new automatic method for EEG sleep stages classification based on a statistical model and weighted brain networks. **Methods**: each EEG segment is partitioned into a number of blocks using a sliding window technique. A set of statistical features are extracted from each block. As a result, a vector of features is obtained to represent each EEG segment. Then, the vector of features is mapped into a weighted undirected network. Different structural and spectral attributes of the networks are extracted and forwarded to a least square support vector machine (LS-SVM) classifier. At the same time the network's attributes are also thoroughly investigated. It is found that the network's characteristics vary with their sleep stages. Each sleep stage is best represented using the key features of their networks. **Results**: In this paper, the proposed method is evaluated using two datasets acquired from different channels of EEG (Pz-Oz and C3-A2) according to the R&K and the AASM without pre-processing the original EEG data. The obtained results by the LS-SVM are compared with those by Naïve, k-nearest and a multi-class-SVM. The proposed method is also compared with other benchmark sleep stages classification methods. The comparison results demonstrate that the proposed method has an advantage in scoring sleep stages based on single channel EEG signals. **Conclusions**: An average accuracy of 96.74% is obtained with the C3-A2 channel according to the AASM standard, and 96% with the Pz-Oz channel based on the R&K standard.

Keywords: Sleep stages, weighted networks, statistical model, EEG single channel.

1. Introduction

Sleep is a dynamic process involved in two main stages: rapid eye movement (REM) and non-rapid eye movement (NREM) [5, 14, 18, 34, 69]. The later includes three stages of Stage 1 (S1), Stage 2 (S2), and slow wave sleep (SWS). These individual sleep stages are connected through different physiological and neuronal characteristics that are used in sleep identification by experts and researchers. The process of discriminating sleep stages visually is called sleep scoring or sleep staging. Normally, it is carried out visually by experts according to either Rechtschaffen or Kales (R&K) [50] or the American Academy of Sleep Medicine (AASM) [9] guidelines. Based on the R&K guidelines, sleep recordings are divided into seven different stages namely: Awake (AWA), S1, S2, S3, S4, REM and movement time. Although, for the past 40 years, the R&K guidelines have been used as the standard for sleep scoring. It has received

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many criticisms for leaving too much room for subjective interpretations, for which a wide variability in the visual evaluation of sleep stages would occur. In 2007, the AASM guidelines were modified to address some revealed issues in the R&K. In the AASM guidelines the allocated time for S1 and SWS were changed, and a minimum of three EEG derivations including F4-M1, C4- M1, and O2-M1 from the frontal, central, and occipital regions must be recorded. The AASM combines S3 and S4 into one stage [9], and considers the body movement as one of the sleep stages.

Although the visual inspection for sleep staging remains the standard method for a number of decades, there has been a surge in demand for developing automatic sleep scorings [10, 13] due to the drawbacks of the manual inspection, such as being subjective and time consuming. Most of automatic sleep staging approaches have been carried out in two phases: (i) to eliminate the undesired information and to extract the key features, (ii) to classify the extracted features for distinguishing the sleep stages [15, 5]. The majority of sleep staging research has been carried out by means of analysing electroencephalography (EEG) signals, for some cases electromyography (EMG) or a combination of the EEG, and Electrooculography (EOG) recordings were used for identifying specific sleep stages [3, 6, 53, 52]. From the literature, the automatic sleep stages classification methods were mainly developed depending on analysing EEG signals recorded from a single EEG channel [15, 16, 17, 24, 49] instead of multiple-channels [42]. Various types of approaches from time domain [44], frequency domain [59, 9], time-frequency domain [16], and graphs domain [1, 14, 15, 16, 72] were utilized for extracting the key features from EEG signals.

The wavelet transform, and fast Fourier transform have been commonly utilized in sleep research compared with their counterparts in time domain [24]. Peker [49] suggested a sleep classification model based on frequency domain where a dual wavelet transform was used to extract features from EEG data. Gao et al. [19] proposed a multi-classifiers system for sleep stages classification based on Fast Fourier transform with a hamming window length equal to the EEG segment length. da Silveira et al. [12] applied a normalized wavelet transform for decomposing EEG signals into different frequency bands. The statistical parameters were obtained from each decomposing level. The extracted parameters were then fed to a random forest classifier. Ebrahimi et al. [17] applied a wavelet packet tree of seven levels to break down an EEG signal into five different bands. A set of statistical features was extracted from the coefficients of those bands and then was used to identify the EEG sleep stages. Kayikcioglu [28] classified a single channel EEG signal based on auto-regressive coefficients. The single EEG channel was normalized and then filtered using a Butterworth band pass filtered. Liang et al. [41] used a multiscale entropy and an autoregressive model for features extraction. A linear discrimination analysis was used to classify the extracted features.

Nonlinear features have been investigated by many researchers. Acharya et al. [3] compared and analysed 29 nonlinear measures such as high order spectra and recurrence quantification analysis to identify the sleep stages. In that study, the extracted nonlinear features were ranked based on f-value. Acharya et al. [2] also used a nonlinear technique based on high order spectra (HOS). In that study, Bispectrum and bicoherence plots were utilized to extract four HOS features to classify EEG sleep stages. Lee et al. [35] applied a nonlinear approach based on detrended fluctuation analysis to study and identify the EEG sleep stages. Zhou et al. [70] used detrended fluctuation analysis to detect apnea using EEG signals.

More recently, Diykh et al. [15, 14], applied the concept of complex networks combined with a statistical model to classify single EEG channel signals for six sleep stages. Zheu et al. [72] discriminated the sleep stages based on a visibility graph algorithm. Each EEG segment was transferred into horizontal and vertical visibility graphs. Seven features were extracted and then fed to a SVM classifier. Liu et al. [42] propounded a multi-domain approach for identifying the EEG sleep stages. Fifteen features were extracted using different techniques including: visibility graphs, frequency domain, detrened fluctuation analysis, natural graph and non-linear analysis. Rodríguez-Sotelo et al. [54] proposed entropy metrics extracted from an EEG signal. The resulting features vector was optimized by a $Q - \alpha$ method and fed to a J-means clustering algorithm. Bajaj et al. [6] classified the EEG sleep stages based on time frequency images (TFIs). TFIs were obtained using a time frequency representation based on Winger-Ville distribution. The statistical features of the histogram of each TFI were utilized to classify the EEG sleep stages. Xia et al. [67] identified the sleep stages using EOG signals. A deep belief network blended with a hidden Markov model was employed to classify each EOG segment into one of these sleep stages. Mousavi et al. [47] developed a methodology based on conventional neural networks to classify EEG sleep stages. Jiang et al. [25] considered multi-channels signals technique to identify EEG sleep stages. Each single EEG channel was segmented into small intervals of 30 second. Covariance matrices were used to extract the most representative features from EEG segments. Two machine learning algorithms were employed to classify the extracted features. Then a HMM- based refinement process was adopted to optimise the classification results. Jiang et al. [26] employed a multi-decomposition approach-based features selection to categorise EEG sleep stages. Ghasemzadeh et al. [20] proposed a logistic smooth transition autoregressive model (LSTAR)to investigate EEG sleep signals. Each 30 EEG segment was decomposed into several bands using a double-density dual-tree discrete wavelet transform. Then the LSTAR with a tensor locality preserving projection was utilised to pull out and select a set of EEG features. Abdulla et al. [1] applied a correlation graphs similarity concept to analyse EEG sleep signals. in that study, an ensemble machine learning algorithm was developed to classify graph features.

EEG signals exhibit nonlinear behaviours. One of the effective non-linear methods is complex networks. Based on our previous research [14, 15], we found that complex networks yielded promising results in EEG signals classification. In this paper, we employed a weighted complex network to further improve the performance. Based on the obtained results, it was found that the weighted complex networks were capable to identify EEG patterns for sleep staging. In this paper, each EEG segment is partitioned into smaller blocks using a sliding window technique. Total 12 statistical features are extracted from each block and are put in one vector to represent a 30 second EEG segment. The vector of the extracted features is then mapped as a weighted undirected complex network. The spectral and structural characteristics of the networks are extracted from each network. Then, extensive simulations and experiments are carried out to analyse the attributes of the networks for sleep stages classification, and to determine the effective characteristics of the network's to represent each sleep stage. A least square support vector machine (LS-SVM) classifier is used to identify the sleep stages. The results obtained by the LS-SVM are compared with those from Naïve Bayes, k-nearest, a multi-class-SVM for the performance evaluation. The performance of the proposed method is also compared with other previous research work. Our findings demonstrated that each sleep stages can be categorized with a specific set of network features.

The paper is organised as follows: In Section 2, the information regarding to the data used in this paper is presented. Section 3 describes the methodology of the proposed method and the relevant fundamentals. Section 4 presents the experimental and simulation results. In Section 5, the results and findings of this paper are discussed. In Section 6, the conclusions of the paper are drowned.

2. EEG Data

In this work, two publicly available datasets were used to evaluate the proposed method in EEG sleep stages classification. The datasets were acquired from two different channels and scored by either the R&K or the AASM guidelines. The following section gives a brief explanation for the two datasets.

2.1. ISRUC-Sleep database

One set of EEG data used in this paper is from ISRUC-Sleep database acquired at the Hospital of Coimbra University during 2009-2013 [32, 50, 31]. It contains three sub-groups. Each sub-group comprises different subjects, including healthy subjects, subjects with sleep disorders and subjects under effects of medications. The recorded data for those sub-groups were gathered from 8, 10 and 100 participants respectively. Each recording contains 19 channels. The EEG, EMG and EOG signals were sampled at 200 Hz, and they were stored as European Data Format (EDF) files. The EEG signal from C3-A2 channel is used in this paper as it is proven for giving better classification results [32]. The recordings were scored by two experts based on the AASM rules. All the recordings were partitioned into 30 second segments and each segment was assigned into one of the five sleep stages in accordance with the AASM guidelines [9]. The dataset is publically available for sleep research. The EEG recordings from 18 subjects of subject 1 to subject 18 were used in this paper. Their demography information was as follows: 15 males and 4 females, aged between 22-76, with a weight from 41 kg to 110 kg and height from 68cm to 178 cm. Table 1 presents the distribution of the sleep stages used which were carried out by the two experts.

Table 1

Distribution of the sleep stages in the ISRUC dataset

Sleep stage	AWA	S1	S2	SWS	REM	Total number of epochs
No. of epochs	5103	2083	4364	2909	1767	16226

Table 2

Distribution of the sleep stages in the EDF database

Sleep stage	AWA	S1	S2	S3	S4	REM	Total number of epochs
No. of epochs	8055	604	3621	672	627	1609	15188

2.2. Sleep-EDF database

Another set of the EEG data used in this paper was obtained from PhysioNet [22, 30, 46, 64, 29]. The online Sleep-EDF datasets (expanded) were used. In this database, 61 EEG recordings were collected from two studies. 13 subjects were used for simulations in this paper including SC4001E0, SC4011E0, SC4012E0, SC4021E0, SC4022E0, SC4031E0, SC4032E0, SC4041E0, SC4042E0, SC4051E0, SC4002E0, SC4061E0 and SC4062E0.The polysmnographic includes two EEG channels recorded from Fpz-Cz and Pz-Oz, one EOG, one EMG, Resporonasal, EMGSubmenta, Tempbody, and Eventmarker. The datasets were acquired from different volunteers in 1987-1994 from Caucasian males and female. All the recordings were stored in EDF format. The original EEG signals were sampled at 100 Hz. They were scored with segments of 30 second (3000 data points) based on the R&K criteria [43]. The segments were labelled as AWA, S1, S2, S3, S4, REM MVT (movement time), and UNS (unknown state). Table 2 shows the number of segments that were used in this study.

3. Methodology

In this paper, each EEG segment of 30 seconds was further divided into blocks with an overlapping of 0.4 seconds using a sliding window technique. Reducing the dimensionality of EEG segments is an important step to minimize the algorithm complexity and to improve the performance. Total 12 statistical features were extracted from each block. As a result, a vector of statistical features representing one EEG segment of 30 seconds was obtained, and was then transferred into a weighted undirected network. A set of structural and spectral attributes from each network was pulled out and fed to a LS-SVM classifier for identifying the six sleep stages. For further investigation, other three classifiers including a multi-class-SVM, k-nearest and Naive Bayes were also used to discriminate the networks features. The findings from this study show that the networks characteristics varied with the EEG sleep stages. Fig. 1 shows the proposed method to classify the EEG sleep stages.

3.1. Features extraction and signal stratification

As EEG signals vary over time, we processed each EEG segment into quasi stationary by dividing it into sub-blocks using a sliding window technique. A sliding window technique was applied by Li and Wen [38, 39] to trace the depth of anaesthesia (DoA) in EEG signals. Their results showed a satisfactory DoA assessment. Mehmood and Lee [43] also used different a sliding windows with different sizes to figure out the prominent waves in EEG signals.

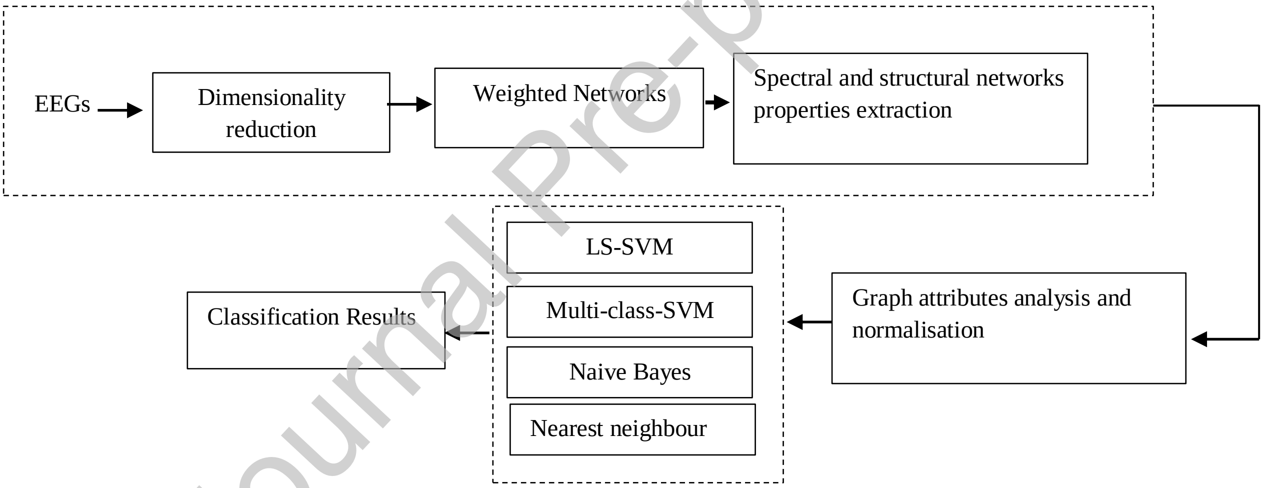


Figure1. Block diagram of the proposed method

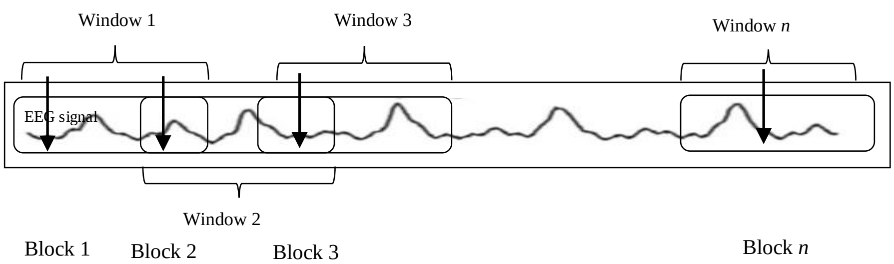


Figure 2. An EEG signal is divided into blocks using a sliding window technique

In this paper, each segment was partitioned into predetermined overlapping intervals called strata or blocks. We kept the original segment length of 30 seconds based on Hypnograms associated with the datasets. The size of the windows was empirically determined. At each stage of the segmentation the statistical features were selected and sent to the proposed method. The segmentation process stopped once the desired classification results were obtained or there were no further improvement in the classification results. A window size of one second was selected with an overlapping of 0.4 seconds. Thus, each segment was partitioned into 49 overlapping blocks. A statistical approach was employed in this work to extract the representative features from each block. Total 12 statistical features were extracted from each block, and all the extracted features were formed as a vector of 588 features to represent each EEG segment.

Considering an EEG signal $X = \{x_1, x_1, \cdots, x_n\}$ of n segments, a vector of features $T \in \mathbb{R}$ was extracted from each segment that includes m statistical features where $T = \{y_1, y_1, \cdots, y_m\}$. The 12 features are *{Mean, Min, Mode, Max, Median, Range, Variation, Skewness, Kurtosis, 1st Quartile, 2nd Quartile, Standard deviation}*. The features selection and ranking were based on our previous work in [14, 15]. In those studies, we investigated different statistical features and we found that the 12 chosen features could reflect the main characteristics of EEG signals. The 12 statistical features include both linear and non-linear features. Kurtosis and skewness are non-linear features and are often considered as high order statistics features while the other features are linear features. The features vector T is mapped into a weighted undirected network. Fig. 2 shows the features extractions from an EEG signal using the sliding window technique.

3.2. Transferring statistical features into weighted networks

Complex networks are a natural model that provides global and local quantitative measures to analyse dynamic brain networks [44, 51]. Weighted networks can indicate the connection strengths of neurons in the brain. In this paper, the topological and spectral attributes in the weighted complex networks were used to analyse and classify an EEG signal into the six sleep stages. A thorough investigation was made using the extracted characteristics of the networks to explore the behaviours of the networks at each sleep stage, and to figure out the best combination of the network properties for each sleep stages, (in this paper the terms of "network" and "graph" are interchangeably used).

In this study, we represented the EEG segments by a set of networks features. Each vector of statistical features, $T = \{y_1, y_1, \cdots, y_m\}$, which represents one EEG segment, was transferred into an undirected weighted graph ***G***= (***V***, ***E***, ***W***), where ***V*** denotes the set of nodes, and $\boldsymbol{E} = \{e_{v_i,v_j}\}$ is a set of links among the nodes with weights belonging to ***W*** . In this paper $W_{v_i v_j}$ denotes the weight of the link between the pair of v_i, v_j . The weighted edge was calculated by the following formula.

$$W_{v_i v_j} = \frac{d(v_i v_j)}{D_{max}} \tag{1}$$

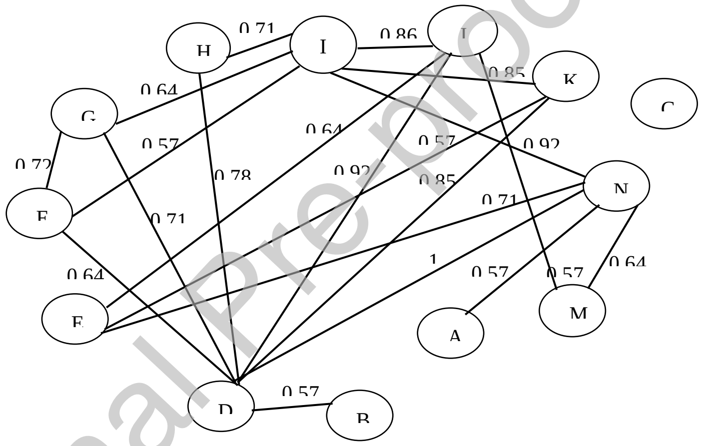
where D_{max} was the longest distance among all the points. The connection between v_i, v_j indicates that there is a relationship between the two nodes [60, 44]. Each data point of the statistical features vector T was considered as a node in an undirected graph. In this paper, each pair of nodes v_{i} and v_{j} were connected according to Zhang and Small [68], and Diykh et al. [14-16].

To eliminate the nodes which had a poor connection, a threshold was used, and each pair of nodes were connected if a distance between any two nodes was less than or equal to the predefined threshold.

$$\begin{cases} if \quad (v_1, v_2) \in E, if\ d(v_1, v_2) \leq \beta \\ else \quad (v_1, v_2)\ elimented\ this\ connection\ from\ G \end{cases} \tag{2}$$

where β is a predefined threshold.

Fig. 3 shows a vector of statistical features being mapped as a weighted undirected graph. Suppose $T = \{A = 4.3, B = 4.1, C = 4.2, D = 4.9, E = 4.5, F = 4, G = 3.9, H = 3.8, I = 3.4, J = 3.6, K = 3.7, M = 4.4, M = 3.6\}$ is a vector of statistical features. To construct a weighted undirected graph, each point in T was considered a node in a graph. For example, A is the first node in the network corresponding to the first point in the vector T with a value of 4.3, and B=4.1 is the second node in the network. The edges between these two points and the others were calculated based on Euclidean distance. The absolute vale of Euclidean distance between A and B was 0.2. Then, the weight of the edge was derived from the distance matrix according to equation (1), and it was assigned the value 0.12. A threshold was set, and each pair of nodes were connected if a link between any two nodes was satisfied the condition in equation 2. As a result, a weighted network was constructed for each EEG segment.



a. A graph G

0	0.2	0.1	0.6	0.2	0.3	0.4	0.5	0.5	0.7	0.6	0.1	0.8
0.2	0	0.1	0.8	0.4	0.1	0.2	0.3	0.7	0.5	0.4	0.3	0.6
0.1	0.1	0	0.7	0.3	0.2	0.3	0.4	0.6	0.6	0.5	0.2	0.7
0.6	0.8	0.7	0	0.4	0.9	1	1.1	0.1	1.3	1.2	0.5	1.4
0.2	0.4	0.3	0.4	0	0.5	0.6	0.7	0.3	0.9	0.8	0.1	1
0.3	0.1	0.2	0.9	0.5	0	0.1	0.2	0.8	0.4	0.3	0.4	0.5
0.4	0.2	0.3	1	0.6	0.1	0	0.1	0.9	0.3	0.2	0.5	0.4
0.5	0.3	0.4	1.1	0.7	0.2	0.1	0	1	0.2	0.1	0.6	0.3
0.5	0.7	0.6	0.1	0.3	0.8	0.9	1	0	1.2	1.1	0.4	1.3
0.7	0.5	0.6	1.3	0.9	0.4	0.3	0.2	1.2	0	0.1	0.8	0.1
0.6	0.4	0.5	1.2	0.8	0.3	0.2	0.1	1.1	0.1	0	0.7	0.2
0.1	0.3	0.2	0.5	0.1	0.4	0.5	0.6	0.4	0.8	0.7	0	0.9
0.8	0.6	0.7	1.4	1	0.5	0.4	0.3	1.3	0.1	0.2	0.9	0

b. distance matrix

0	0.14	0.07	0.42	0.14	0.21	0.28	0.35	0.35	0.5	0.42	0.07	0.57
0.14	0	0.07	0.57	0.28	0.07	0.14	0.21	0.5	0.35	0.28	0.21	0.42
0.07	0.07	0	0.5	0.21	0.14	0.21	0.28	0.43	0.43	0.35	0.14	0.5
0.43	0.57	0.5	0	0.28	0.64	0.71	0.78	0.07	0.92	0.85	0.35	1
0.14	0.28	0.21	0.28	0	0.36	0.42	0.5	0.21	0.64	0.57	0.07	0.71
0.21	0.07	0.14	0.64	0.36	0	0.07	0.14	0.57	0.28	0.21	0.28	0.35
0.28	0.14	0.21	0.71	0.43	0.07	0	0.07	0.64	0.21	0.14	0.35	0.28
0.36	0.21	0.28	0.78	0.5	0.14	0.07	0	0.71	0.14	0.07	0.42	0.21
0.35	0.5	0.42	0.07	0.21	0.57	0.64	0.71	0	0.85	0.78	0.28	0.92
0.5	0.35	0.42	0.92	0.64	0.28	0.21	0.14	0.85	0	0.07	0.57	0.07
0.42	0.28	0.35	0.85	0.57	0.21	0.14	0.07	0.78	0.07	0	0.5	0.14
0.07	0.21	0.14	0.35	0.07	0.28	0.35	0.42	0.28	0.57	0.5	0	0.64
0.57	0.42	0.5	1	0.71	0.35	0.28	0.21	0.92	0.07	0.14	0.64	0

c. weighted matrix

0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	1	1	1	0	1	1	0	1
0	0	0	0	0	0	0	0	0	1	1	0	1
0	0	0	1	0	0	0	0	1	0	0	0	0
0	0	0	1	0	0	0	0	1	0	0	0	0
0	0	0	1	0	0	0	0	1	0	0	0	0
0	0	0	0	0	1	1	1	0	1	1	0	1
0	0	0	1	1	0	0	0	1	0	0	1	0
0	0	0	1	1	0	0	0	1	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0	1
1	0	0	1	1	0	0	0	1	0	0	1	0

d. adjacency matrix

Figure 3. A vector of statistical features is mapped into a weighted undirected

The adjacency matrix **A** of graph **G** was calculated for all **V** to describe the network nodes connection. The adjacent matrix of an undirected weighted graph is symmetric, i.e. **A** (v_1, v_2)= **A** (v_2, v_1)

$$\boldsymbol{A}(v_1, v_2) = \begin{cases} w(\boldsymbol{e}_{v_i, v_j}), if\ (v_1, v_2) \in \boldsymbol{E} \\ 0, \quad otherwise \end{cases} \tag{3}$$

The graph Laplacian matrix was also calculated using the formula of $\boldsymbol{L}$ =*D*-$\boldsymbol{A}$, where *D* is a diagonal degree matrix, and $\boldsymbol{A}$ is the adjacency matrix of graph **G** [7]. Matrix *D* was formed by the degree of each node. The elements of the Laplacian matrix $\boldsymbol{L}$ were produced using the following formula:

$$L(v_i, v_{2j}) = \begin{cases} D_i & if\ i = j; \\ -1 & if\ i\ is\ adjacent\ to\ j; \\ 0, & otherwise, \end{cases} \tag{4}$$

where D_i denotes the degree of the ith node.

From Fig. 3 we can notice that, there is a node, such as *{C}* without any connections with other nodes in the network. This node is isolated points in the network. The number of isolated points in the network was also used as an important feature to distinguish the sleep stages. In this paper all the graphs have been constructed with the same number of nodes.

3.2.1. Structural and spectral network features

A set of structural and spectral graph properties were calculated in this paper to represent EEG data [11, 37, 36, 56, 51, 68]. The structural and spectral network attributes can capture the local relationships among nodes. Based on recent studies of analysing brain networks, structural and spectral networks features allow to go through a deeper investigation towards knowledge extraction among brain regions. Our research showed how a combination of structural and spectral attributes of weighted networks could reflect EEG signal patterns.

- **Average degree**

The average degree is defined as the number of edges linking a node in a graph with other nodes. The average degree of a network is the average of the node degrees for all the nodes in the network i.e.

$$\boldsymbol{Av_{deg}}(G) = \sum_{i}^{n} \boldsymbol{deg}(v_i)/n \tag{5}$$

where *n* is the number of nodes in a network, $\boldsymbol{Av_{deg}}$ is the average degree of the network, and $\boldsymbol{deg}(v_i)$ denotes to the degree of node v_i.

- **Average Clustering Coefficient**

Clustering coefficient is commonly used to compute the similarity among nodes based on the fraction of triangles. The clustering coefficient for a node v_i in a graph $\boldsymbol{G}$ is defined as $C_{v_i} = \frac{k_1}{k_2 * 2}$, where k_1 is the number of the actual links between v_i with its neighbours, and k_2 is the number of the neighbours of v_i.

The clustering coefficient of a graph is the average of the clustering coefficients of all the nodes.

$$C = \frac{1}{N}\sum_{i=1}^{N} C_{v_i} \tag{6}$$

where N is the number of nodes in the network and C_{v_i} is the clustering coefficient for node v_i.

- **Shortest path**

Let $\boldsymbol{L}$ be the average of the shortest path length between any pair of the nodes. The length represents the number of steps from node v_i to node v_j. A low number of $\boldsymbol{L}$ indicates that the network has a high level of connections and communication efficiency. This attribute is used to detect the sleep stages.

- **The number of the isolated points**

The number of the isolated points are defined as the number of nodes in a network that have a zero degree. In this paper, the number of the isolated points in a network is used as a feature to differentiate the sleep stages.

- **The maximum eigenvalue**

The eigenvalues of a graph are sorted in a descending order from the smallest to the largest. The graph eigenvalues can represent the most important attributes in a graph. The largest value is selected as a representative for each EEG segment.

- **The second largest eigenvalue**

The second largest eigenvalue of a graph G is also used as a key network characteristic.

- **Spectral radius:** The spectral radius is defined as the largest magnitude eigenvalue for a graph. Let $|\lambda_1|> |\lambda_2| > |\lambda_3| \dots\dots > |\lambda_s|$, be the distinct eigenvalues of graph $\boldsymbol{G}$, sorted by their magnitudes. The spectral radius of the graph $\rho(\mathbf{G})$, is defined as $\rho(\mathbf{G})=|\lambda_1|$.
- **Energy of a graph**

  The energy of a graph is the squared sum of the eigenvalues in a graph. More formally, the energy of a graph $\boldsymbol{G}$ is defined as

$$E(\mathbf{G}) = \sum_{i=1}^{N} \lambda_i^2 \tag{7}$$

3.3. Classification

The network's attributes were forwarded to the LS-SVM classifier and also to multi-class-SVM, k-nearest and Naive Bayes for performance comparison. This section briefly introduce those classifiers.

3.3.1. Least Square Support Vector Machine (LS-SVM)

The least square support vector machine (LS-SVM) was first developed by Suyken and Vandewalle [61, 62] as a modified version of the original support vector machine [5, 6]. It was used by Siuly et al. [38] for the motor image classification, also by Al Ghayab et al. [4] for detecting the epileptic EEG signals.

Two main parameters, γ *and* σ, should be carefully tuned in the LS-SVM for obtaining the desired classification results. The two parameters can positively or negatively affect the performance of the proposed method. The LS-SVM was employed to classify different pairs of sleep stages, the values of γ and σ were empirically set during the training set. The best performance for the proposed method for identifying the awake and sleep (AWA-Sleep) pair was obtained when $\gamma = 1$ and $\sigma = 1$. For the other pairs of (S3, S4), ((S1, S2), SWS), (S1, S2), (S1, REM), (AWA-REM), the best recorded results were achieved when the values of γ and σ were set as (10, 1), (2, 1), (10, 10) (10, 10), (1, 1) respectively.

3.3.2. Multi-class SVM classification

The SVM was originally a binary classification method developed by Vapink and colleagues at Bell laboratories [8, 39, 47]. It was then developed for the multi-class classification [45]. However, it is still an ongoing challenge to use the multi-class SVM for the classification task. For the sleep stages classification, it is required to discriminate each individual sleep stage from the total six sleep stages of (AWA, S1, S2, S3, S4 and REM). To target the multi-class problem, a common approach to use the SVMs is to decompose the multi-class problems into several binary problems. The most popular strategies are one-against-all (OAA) and one-against-one (OAO) [37]. The OAA is a simple method for the multi-class classification, which consists of a binary SVM to recognise each class from other classes. The OAO requires to train two-way classifiers for all possible pairs of classes. Thus, the OAA needs k (k-1)/2 binary SVMs, while the OAO requires k binary SVMs, where k is the number of the classes. In this work, the OAO (multi-class- SVM) is used as a classifier to discriminate EEG sleep stages.

3.3.3. K-nearest neighbour classifier

The k-nearest neighbour is one of the simplest and widely used classifiers in pattern recognition [66]. It uses Euclidian distance to compute the similarity between the training case and the case in the classification record. A record is maintained in order to store the classification performance and similarity results. In order to classify a sample, the similarities with k-nearest neighbours are computed and the class corresponding to the maximum number of votes is assigned as the output class of the sample.

3.3.4. Naive Bayes

Naive Bayes is frequently used in pattern recognition. It works based on the applications of Bayes' rules and posterior hypothesis. Naive Bayes provides a simpler approach based on the probabilistic knowledge to precisely predict the classes. This algorithm assumes that each attribute influences differently on a given class. Assume **Y**= $\{g_1, g_2, \ldots\ldots g_n\}$ is a sample set that includes a set of n attributes. Let **H** represents the hypothesis that each set of **Y** belongs to a specific class. In Naive Bayes rules, we considered **Y** the evidence and seek to assign each attribute in **Y** to the highest posteriori probability class [27]. In this paper, Naive Bayes is also employed to classify the characteristics of the complex networks.

3.4. Performance Evaluation

Four measures including K-cross validation, sensitivity, kappa coefficient, and confusion matrix are utilized to assess and examine the performance of the proposed method [14, 58].

3.4.1.K-fold cross validation: it is a popular approach to assess the performance of a classification algorithm. It is used to estimate the quality of a classification method by dividing the number of correctly classified results by the total of the cases. The datasets in Section 2 were divided into k exclusive subsets in an equal size. One subset was considered as the testing set, while others were used as the training sets. All the subsets were alternatively used and the classification accuracies were reported. In this work, the 10-fold cross-validation is used. The average of the overall results for the subset testings is computed.

$$\text{Performance}=\frac{1}{10}\sum_{1}^{10}\text{accuracy}^{(k)} \tag{8}$$

where $\text{accuracy}^{(k)}$ is the accuracy for (k=1, 2,….10).

3.4.2. Sensitivity: a statistical measure by which the performance of a classification algorithm is assessed by computing the proportion of the actual positive classification. It is defined as

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{9}$$

where TP is the number of the positive classification for all the subset testings, FN is the number of incorrect classification for the subsets.

3.4.3. Confusion matrix: it is a statistical method in which the performance of an algorithm is described by means of comparing the actual and predication classification results by the algorithm. In this paper, the actual predication is from the experts scoring while the predication is by the proposed method.

Classification accuracy: it is defined by the number of the samples correctly classified divided by the total number of the samples.

$$\text{Accuracy} =\frac{N_{cn}}{N_{tn}} \tag{10}$$

where N_{cn} is the number of correctly classified samples and $N_{tn}$is the total number of samples

3.4.4. Kappa coefficient: is a statistical measure that evaluates the agreement between two classification results, those by the proposed method and the expert.

$$\text{Kappa coefficient} =\frac{Pre(a)-Pre(e)}{1-Pre(e)} \tag{11}$$

where, $Pre(a) = \frac{TP+TN}{N}, Pre(e) = \frac{TP+TN}{N} \cdot \frac{TP+FP}{N} + \left(1-\frac{TP+FN}{N}\right).\left(1-\frac{TP+FP}{N}\right), and\ N = TP+FP+TN+FN$ (12)

3.4.5. Receiver operating characteristics (ROC): it is a significant tool to evaluate the quality of classification algorithms by comparing sensitivity against specificity across a range of instances. It is represented by a graph in which the false positive rate is plotted on *x-axis* while the true positive rate is plotted on *y-axis.*

4. Experimental results and complex network analysis

A series of experiments were made to evaluate the performances of the proposed method. The datasets described in Section 2 were used in the experiments. To identify the sleep stages through complex networks, the behaviours of the networks were analysed. It was found that each sleep stages could be categorized with a specific set of graph characteristics. All the experimental results were obtained in a MATLAB 2015b environment on a computer with the following settings: 3.40 GHz Intel(R) core(TM) i7 CPU processor machine, and 8.00GB RAM. The testing and training phases were performed by means of 10-fold cross validation method.

4.1. Significant characteristics of network properties and networks behaviour analysis

EEG signals are often contaminated with noise and non-stationary [53, 46]. Inappropriate features could not result in the desirable results for EEG sleep stages classification. We conducted extensive experiments to investigate and select suitable features to represent individual sleep stages. We investigated the effectiveness of each graph attributes on sleep stages classification and its relationship with each stage. It was found that a sleep stage was better classified with separated
network attributes. For example, the shortest path can be used as one of the important network characteristics to identify the AWA stages while it has a little influence on the recognition of S1 or S2.

Table 3 shows the network features best representing each sleep stages based on the experimental results. The network features for each sleep stages in Table 3 were selected based on the binary classification results during the training stage. The classifiers were trained with balanced data (50% of EEG epochs were used for the training and the other 50% of EEG epochs were used for the testing).The results in Table 3 were obtained through extensive experiments. An equal number of segments were used for each pair of sleep stages to avoid inconsistency. The network's features in Section 3.1 were extracted and the LS-SVM was also employed to classify each pair of the sleep stages. The parameters of the LS-SVM were selected during the simulation session. As a result, for identifying {AWA, Sleep}, the LS-SVM parameters were set as $\gamma = 1$ and $\sigma = 1$, while the other pairs of {S3, S4}, {(S1, S2), SWS}, {S1, S2}, {S1, REM}, {AWA, REM}, the best classification results were achieved when the values of γ and σ were set as (10, 1), (2, 1), (10, 10) (10, 10) and (1, 1) respectively. At each iteration, different graph attributes were used and the accuracy of the LS-SVM classifier was recorded.

Once the accuracy started to increase, the optimum features set was updated. The procedure was applied for each pair of the sleep stages to discover the best graph attributes representing their sleep stages. The obtained results revealed that not all the sleep stages could be represented with the same network features. For example, the features of *{average degree,*

Table 3

The selected weighted network features for each sleep stage pairs after the training phase

Sleep stages	network characteristics
{AWA, Sleep}	*average degree, average of clustering coefficient , spectrum radius, shortest path, graph energy*
{AWA, REM}	*average degree, average of clustering coefficient, graph energy, spectrum radius, shortest path*
{S1, REM}	*energy of graph, average of clustering coefficient, maximum eigenvalue, average degree, second maximum eigenvalue*
{S1, S2}	*average degree, average of clustering coefficient maximum eigenvalues and second maximum eigenvalue*
{(S1,S2), SWS}	*average degree, average of clustering coefficient, maximum eigenvalues and second maximum eigenvalue, energy of graph and number of isolated points*
{S3, S4}	*average degree, average of clustering coefficient, maximum eigenvalue, shortest path, spectrum radius and number of isolated points*

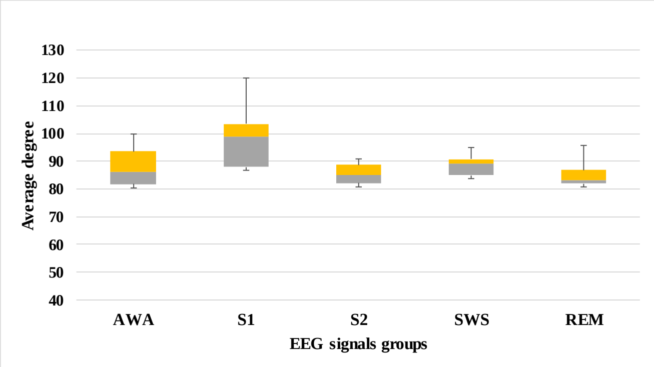


Figure 4. Box plot of the average degree

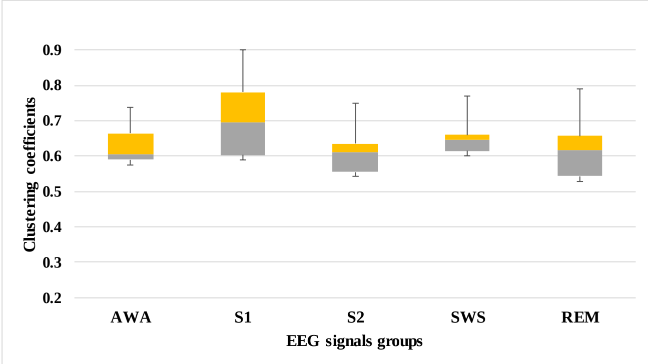


Figure 5. Box plot of the clustering coefficients

average of clustering coefficient, spectrum radius, shortest path, graph energy} were used to identify the pair {AWA, Sleep}. That means, using the same features to classify all the sleep stages could not give the promising results. One of the interesting results, we found in this paper is that the network's characteristics vary with their sleep stages.

During the experiment, it was noticed that some attributes of the networks, such as clustering coefficients and degree distribution, were more significant compared to other network attributes to recognize the sleep stages. To investigate the effectiveness of the attributes on the identification of sleep stages, box plots were used. In each box plot, the upper part of the box denotes the 75% percentile, the lowest part of the box represents the 25% percentile and the line on the middle refers to the median 50% percentile (also called centre). The highest and lowest values are marked by the lines extending from the top to the bottom of the box.

From Figs. 4 and 5 we can see that the clustering coefficients, and degree distribution can be used as the key attributes to differentiate the sleep stages. The statistical mean degree of the clustering coefficients, and the degree distribution that are associated with the five sleep stages are shown in Fig. 4 and Fig. 5. The results in Figs. 4 and 5 support the research findings in Table 3 in which the clustering coefficients and the degree distribution are the key features to represent all the sleep stages. A statistical analysis for all the network's characteristics was also conducted to evaluate the differences of the networks attributes among the individual sleep stage pairs using Wilcoxon rank sum test. It was found that the average of cluster coefficients of the networks changed over the sleep stages transition, and the links of networks were significantly stronger during the AWA, and the light sleep stage compared with the REM and SWS stages. The results in Tables 4 and 5 indicate that the attributes of *{Cluster coefficient, graph energy, spectrum radius, shortest path, graph energy}* for the {AWA, Sleep} stage pair were different from those of other pairs. These networks characterises can be used to distinguish between the pairs of {AWA, Sleep} and {AWA, REM}.

Table 6 depicts another example. It presents a set of networks characteristics of *{cluster coefficients, graph energy, spectrum radius, maximum eigenvalue, second maximum eigenvalue}* that indicate the significant differences between the pairs of {S1, REM}. Table 7 shows p-values for 4-state, 5-state and 6-state sleep stages. The results in Tables 4, 5, 6 and 7 show that each pair of the sleep stages can be represented by a specific set of the network characteristics. The same procedure was conducted for all the sleep stage pairs to study the network behaviours. Such findings are significant at ($\rho > 0.05$) in terms of statistics.

Table 4

Differences in networks attributes for separating {AWA, Sleep}

Network features	AWA		sleep		P-value
	Mean	SD	Mean	SD	
Cluster coefficient	0.54	0.7	0.63	0.74	2.43e-16
Graph energy	1.2	1.02	0.91	0.21	0.6e-05
Spectrum radius	1.4	1.1	1.7	1.42	0.372e-13
Graph energy	0.99	0.69	1.8	1.81	6.12e-10
Shortest path	3	1.9	4	1.79	0.000213

Table 5

The differences of the networks attributes for separating { AWA, REM}

Network features	Stage 1		Deep sleep (REM)		P-value
	Mean	SD	Mean	SD	
Cluster coefficient	0.45	0.43	0.49	0.48	0.00421
Graph energy	2.5	0.12	2.71	0.19	0.0059
Spectrum radius	1.9	1.5	1.7	1.23	0.51e-13
Graph energy	1.9	0.89	2.8	2.9	0.120e-10
Shortest path	3	1.9	4	2.1	0.000978

Table 6

The differences of the networks attributes for separating {S1, REM}

Network features	S1		Deep sleep (REM)		P-value
	Mean	SD	Mean	SD	
Cluster coefficient	0.82	0.79	0.87	0.78	0.404e-11
Graph energy	2.2	1.1	1.11	0.99	0.305e-9
Spectrum radius	0.89	1.02	0.97	0.93	0.00723
Maximum eigenvalue	1.9	0.89	2.8	2.9	0.00210
2^{nd} maximum eigenvalue	0.2	1.1	1.9	1.8	0.00810

Table 7

The differences of the networks attributes for separating {4-state, 5-state, and 6-state}

Sleep stage	features	p-value
4-state	*Average degree, average of clustering coefficient, maximum eigenvalue, shortest path, spectrum radius and number of isolated points.*	0.214e-11
5-state	*Spectrum radius, average degree, average of clustering coefficient, maximum eigenvalue, shortest path.*	0.71e-13
6-state	*Graph energy, Spectrum radius, average degree, average of clustering coefficient, maximum eigenvalue, shortest path*	0.851-19

4.2. Sleep stages classification results

After testing and analysing the network's behaviour through their attributes during the training phase, different experiments were conducted in the testing phase to investigate the relationships between the EEG sleep stages and the networks characteristics. The network's characteristics were forwarded to the LS-SVM. The results were reported in Table 8.

The results for each sleep stage were reported in terms of the accuracy and kappa coefficient. The best performance for each stage was highlighted in bold. The obtained results demonstrate that the proposed method yielded superior performance with an average accuracy of 96.0% and 96.74% for the Sleep-EDF database and ISRUC-Sleep database, respectively. The highest accuracy was achieved for the stages pair of {REM , AWA} compared with the other sleep stages pairs. The best performance for the identification of {AWA, Sleep} was obtained when the LS-SVM parameters were $\gamma = 1$ and $\sigma = 1$.

For the other sleep stages pairs of {S3, S4}, {(S1, S2), SWS}, {S1, S2}, {S1, REM}, {AWA, REM}, the best recognition results were achieved when the values of γ and σ were set at (10, 1), (2, 1), (10, 10) (10, 10), (1, 1), respectively.

From the results in Table 8 , it was noticed that when S3 and S4 were combined as one stage of SWS, the classification accuracy by the proposed method was improved. The accuracy for identifying the stages of S3 and S4 in Table 8 are 94.1% and 91.0%, respectively. S3 and S4 had similar features that make them difficult to separate. However, when they were combined together as the SWS stage according to the ASSM guidelines the proposed method achieved an accuracy of 95% for the SWS stage for ISRUC-Sleep database as shown in Table 8. The proposed method achieved an average of 87% and 90% of kappa coefficients for the Sleep-EDF database and ISRUC-Sleep database, respectively.

Table 8

Classification accuracy for Sleep-EDF database

Sleep stages	AWA	S1	S2	S3	S4	REM	Average
Accuracy	**99.0%**	97.0%	97.0%	94.1%	91.0%	98.0%	96.0%
Kappa coefficient	**0.97**	0.90	0.89	0.82	0.80	0.89	0.87

Classification accuracy for ISRUC-Sleep database

Sleep stages	AWA	S1	S2	SWS	REM	Average
Accuracy	**99.5%**	97.0%	95.5%	95.0%	96.7%	96.74%
Kappa coefficient	**0.98**	0.87	0.90	0.89	0.87	0.90

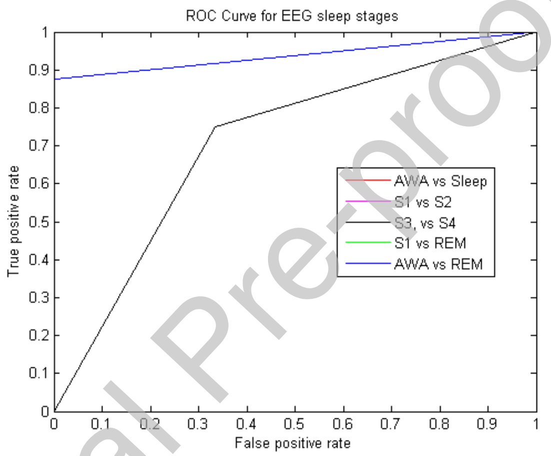


Figure 6 the ROC curves created based on the selected network's feature

Table 9 Performance evaluation based on AUC

AWA-Sleep	AWA-REM	S1-REM	S1-S2	(S1, S2)-SWS	S3-S4
0.99	0.96	0.98	0.99	0.92	0.89

To assess the discrimination or classification capability of network's features for each pair of the sleep stages, the receiver operating characteristics (ROC) curves were established. The ROC is a suitable metric in studying the dependency of sensitivity and specificity. The relationships among true positive rate, false negative rate, false positive rate and true negative rate were investigated in this paper using the ROCs. Fig.6 shows the performance of the proposed method based on the ROCs. In Fig. 6, the ROCs for the pairs of AWA vs Sleep, S1 vs S2, S1 vs REM and AWA vs REM are too close to be visually distinguished. It shows that the proposed method correctly predicts most of the pairs of the sleep stages, and supports our findings in Section 4.1. The area under the resulting ROC (AUC) for the most of the stages pairs except {S3, S4} was calculated and used as a summary of the ROC curves in order to identify how well those networks features could discriminate each pair of EEG sleep stages. The AUC is a portion of the area under the ROC curves. The AUC values ranges from 0.5 (without discrimination) to 1.0 (ideal discrimination). Table 9 shows the AUC values obtained from each classification pair. The maximum AUC value was 0.99 for the pair of {AWA, sleep}, while the minimum value was 0.89 for the pair of {S3, S4} due to the sleep stages S3 and S4 often have similar networks features.

4.3. Performance analysis using confusion matrix

The confusion matrix was used to identify the degree of agreement between the proposed method and the experts scoring. Tables 10 and 11 show the confusion matrix and sensitivity for the experiments on both datasets. It was noticed that there was an accuracy consistency between the proposed method and the expert's scoring. As shown in Tables 10 and 11, an average sensitivity of 93% and 90% was obtained using the proposed method for ISRUC-Sleep and Sleep-EDF database respectively. The highest sensitivity was achieved for identifying the pair of {AWA, S2}. The results in Table 11 were obtained from Sleep-EDF database in which the sleep stages were scored based on the R&K criteria. The agreement between the proposed method and the experts was slightly lower than the results in Table 10. As mentioned before, the main reason is that the features of S3 and S4 were very similar.

For each pair of the sleep stages, the performance of the 10-fold cross validation was calculated. Fig.7 shows the box plots of the performance from the proposed method with the sleep stages pairs. It was noticed that the performances of all the pairs of the sleep stages exceeded 93%. As shown in Fig. 7, the centre of the box plots for {AWA, Sleep} and {(S1, S2), SWS} is between 96% and 97% for all runs of 10-fold cross validation compared to the others. However, the centre of {AWA, REM}, {S1, REM} and {{S1, S2}, SWS} is about 95%, 95% 94% 95.5% respectively.

Table 10
The confusion matrix and sensitivity of ISRUC-Sleep database

		Expert's Scoring				
		AWA	S1	S2	SWS	REM
The proposed method	AWA	2504	2	45	4	19
	S1	5	890	13	50	12
	S2	11	50	2062	4	0
	SWS	1	60	10	1352	36
	REM	31	22	52	45	817
Sensitivity		0.99	0.86	0.95	0.93	0.92

Table 11
The confusion matrix and sensitivity of Sleep-EDF database

		Expert's Scoring					
		AWA	S1	S2	S3	S4	REM
The proposed method	AWA	3857	2	28	31	15	5
	S1	2	250	35	12	10	22
	S2	17	2	1706	2	11	20
	S3	65	45	21	290	5	42
	S4	70	2	12	1	270	16
	REM	17	1	9	0	0	700
Sensitivity		0.95	0.83	0.94	0.86	0.85	0.87

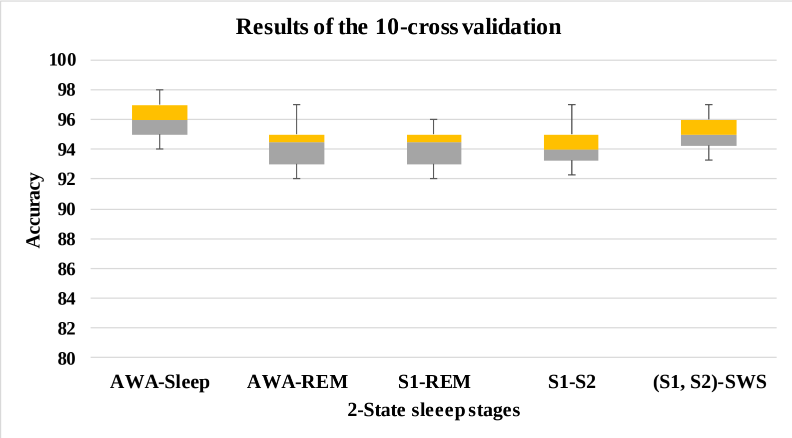


Figure 7. Boxplot of 10 cross validation of 5-sleep stages

Table 12

Performance evaluation using different classifiers

Classifier	Average accuracy		Average Sensitivity		Kappa coefficient	
	C3-A2 channel	Pz-Oz channel	C3-A2 channel	Pz-Oz channel	C3-A2 channel	Pz-Oz channel
LS-SVM	**96.7%**	**95.8%**	**95%**	**94%**	**0.89**	**0.87**
Naïve Bayes	89.8%	92.3%	81%	80%	0.82	0.80
k-nearest	88.5%	91.5%	92%	91%	0.86	0.84
Multi-class-SVM	**94.7%**	**95.8%**	**94%**	**93%**	**0.87**	**0.86**

4.4. Performance evaluation by the comparisons with different classifiers

To investigate the performance of the proposed method, baseline classifiers were used including: multi-class-SVM, k-nearest and Naive Bayes. The extracted characteristics of the networks from both channels of (C3-A2, and Pz-Oz) were forwarded to those classifiers. The training parameters of all the classifiers were set as: the LS-SVM { $\gamma = 1, \sigma = 1$, $\gamma = 10, \sigma = 1$, $\gamma = 2, \sigma = 1$, $\gamma = 10$ and $\sigma = 10$, and $\gamma = 1$ $\sigma = 1$ for each sleep stages pairs, {AWA, Sleep}, {S3, S4}, {(S1, S2), SWS}, {S1, S2}, {S1, REM}, RBF kernel used for all the pairs}, k-nearest{ *k*=7, one parameter (*k*) is selected which denotes to the number of nearest neighbours}, Multi-class-SVM{ RBF kernel, $\gamma = 1, \sigma = 10$}, and Naïve Bayes{ The class node denotes the EEG sleep stages and feature nodes representing the networks characteristics}. The comparisons were made in terms of accuracy, sensitivity and kappa coefficients. The comparisons were to figure out the best suitable classifier for the graph's features and to validate the performance of the proposed method. Table 12 reports the comparisons among the four classifiers. The results in Table 12 demonstrate that the LS-SVM yields the best performance compared with the other classifiers based on the accuracy, sensitivity and kappa coefficients. The findings show that, the LS-SVM yields the highest accuracy than the multi-class-SVM, k-nearest and Naive Bayes. The performance by the multi-class-SVM is the second highest in term of accuracy and sensitivity, and kappa coefficient. However, the performances of k-nearest and Naive Bayes were scored lower for the classification accuracy.

The ROC was also used in this paper to assess those classifiers. Based on ROC curves in Fig. 8, we can notice that the LS-SVM classified most of the pairs of the sleep stages correctly as the curves of the ROC rise vertically from the point (0, 0) to (0,1). That indicts that the LS-SVM achieved the perfect classification performance compared with other classifiers. The Multi-class-SVM was ranked as the second in the classification performance evaluation while the k-nearest was the last.

In order to evaluate the proposed method, the complexity and processing time were studied. Assume that the number of the segments is **M**, and the consuming time to build a graph and extract its characteristics of the graph is **N**. The total classification time (**T**) can depend on the processing time (L) of the classifier used. The total complexity and processing time (**T**) are T=**N*****M**+**L**.

For computing the performances of the four different classifiers, the same computer having the same settings was used, with the same number of input data segments. The complexity time by the proposed method was recorded for each classifier. Fig.9 illustrates the comparisons of the complexity time by the proposed method with the LS-SVM, k-means and Multi-class-SVM. The results showed that the Multi-class-SVM took the lowest execution time compared with the others and the Naïve Bayes was recorded the second lowest complexity time. However, k-nearest was recorded the highest execution time among the selected classifiers.

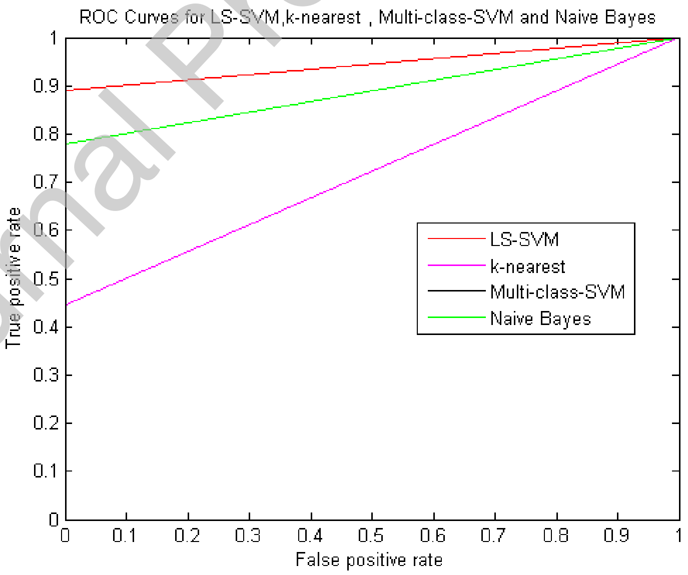


Figure 8. Performance evaluation using ROC curves for the LS-SVM, Multi-class-SVM, k-nearest and Naïve Bayes

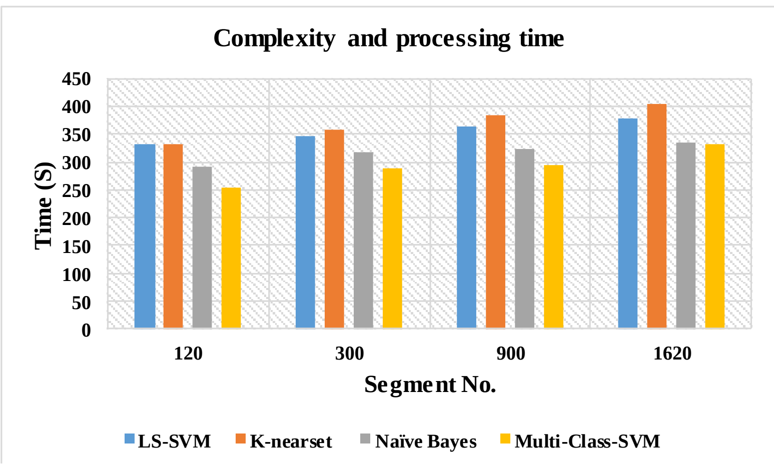


Figure 9. A comparison of the complexity and processing times

5. Discussions

In this study a novel method is developed for the sleep stages classification. The core of this paper is to study the effectiveness of using weighted complex networks on sleep stage classification. Based on the obtained results, it was found that the weighted complex networks could be used to identify the relations and patterns in sleep EEG stages signals. Those relationships are difficult to be identified using unweighted complex networks. The effectiveness of the topological and structural weighted networks features on sleep stages identification is investigated. As a result, we found that individual sleep stages could be better classified using different network features. The proposed weighted complex network method can improve the accuracy of the sleep stages classification compared with our previous studies [13, 14].

As mentioned before, each 30 seconds of EEG was divided into blocks using a sliding window technique. Total 12 statistical features were extracted from each block and then put in one vector to represent an EEG segment. The extracted vector was then mapped into a weighted graph. The behaviours of the graph networks for each sleep stage was studied using the spectral and structural features. The LS-SVM was used as the classifier to discriminate the graphs features. Three other classifiers of multi-SVM, k-nearest, and Naïve Bayes were also implemented for comparisons.

A summary based on this research is described below:

1. In this paper, we present for the first time the weighted complex networks concept combined with the statistical features to analyse EEG signals. The proposed method classified EEG signals with a high accuracy using a simple approach compared with other state of the art approaches in which different transformation techniques were used.
2. The proposed method achieved a high classification accuracy and sensitivity in classifying the sleep stages of AWA, S1, S2, SWS and REM, while it showed a relatively lower performance in identifying S3 and S4 due to their similarities. S3 and S4 stages are considered as deep sleep that occur in the first half of the night. During those stages, the human body starts to release new hormones to restore the muscles damaged from stress and fatigues. Therefore, one is not easy to be waked up. The similarity between S3 and S4 was investigated using the confusion matrix because they could be easily misclassified to each other. These two sleep stages are categorised as slow wave sleep, and the corresponding EEG waves have high amplitudes. The human brain produces similar waves during S3 and S4, for which 50% of those are delta waves, which makes it difficult to distinguish them. Consequently, our research showed that when EEG signals were transferred into brain network graphs, S3 and S4 produce similar network features. Regarding the pair of {REM, AWA}, the REM is associated with a unique brain wave pattern, and the brain waves exhibit a combination of alpha, beta, and de-synchronised waves. During the REM stage, the skeletal muscles of a person are effectively paralysed, and the breathing becomes more rapid, irregular and slow. During this stage, waking could easily happen and the person could be able to remember the dream if the waking period is too long. However, during the AWA stage

brain waves become slower, and more synchronous with an increased amplitude. Thus, EEGs during REM and AWA exhibit different characteristics, which makes the separation of those stages more accurate. These differences between REM and AWA stages were shown in our research where the brain networks exhibited different behaviours during those stages. The best performance of the proposed method was obtained for the identification of {AWA, Sleep}. The pair of {S1, S2} stages was also investigated. These two sleep stages are considered as light sleep. The brain waves during S1 transit from unsynchronized beta (12-30Hz) and gamma (25-100Hz) waves to more synchronised beta and gamma ones. During this stage, the blood pressure and brain temperature are decreased. In the meantime, the range of theta waves during S2 are similar to those in S1, and the blood pressure is also decreased. The main differences between S1 and S2 are that the brain waves during S2 pass through two distinguishing phenomena: sleep spindles and K-complexes. Sleep spindles are defined as short bursts of brain activities in the range of 12-14 Hz for about half a second, while K-complexes exhibit short negative high voltage peaks followed by a slower positive k-complexes. Our research showed that the behaviours of networks during S1 and S2 were different and those differences were reflected by networks features.

3. Because of the EEG epochs for the training and testing phases were selected randomly and most of the EEG epochs were belonged to the AWA stage, there is a high chance of inconsistency in these EEG segments. For example, the AW stage features could be varied for the first and second EEG recordings while these features could mislead when we they were used to identify the AW stage of other EEG recordings. In this paper, we found that the most misclassified pair of EEG sleep stages was AW against S1. Our results showed that about 10% false negatives for each stage were accounted for by the other. We made a thorough investigation, and it was found that the root of this problem is the similarity in the characteristics of EEG. To solve the class imbalance problem, a leave-one-out cross-validation (LOSO) approach was used. Based on LOSO, the training set was formed from the features of all subjects and features from the last remaining subject was used as the testing set. This procedure was repeated until all subjects included in the testing set. An average accuracy, of 96% was obtained based on LOSO, and false negatives were decreased to 5% for each sleep stage.
4. Based on the obtained results we noticed that the networks exhibited a low communication efficiency (shortest path feature) during the deep sleep stages compared with the awake stages. The shortest path was used to examine the efficiency of the network. Our findings are consistent with the results reported by Uehara et al. [63] who found that deep sleep stages revealed a low level of communication efficiency compared with the AWA stage.
5. During the experiments, it was noticed that the networks showed a higher local efficiency (clustering coefficients) during the deep sleep stages compared with the AWA stage.
6. The local clustering increased and the path length decreased significantly in SWS stages compared to the REM, S1, S2 and AWA. The results were compatible with those in Czisch et al. [12]
7. The number of the isolated points can be employed as a key feature in sleep stages classification. Based on the results in Table 3, it was found that the number of the isolated points could be used with other features to discriminate the S1 and SWS.

The proposed method was compared with the other state of the art sleep classification methods reported in the literature. Table 13 reports the comparisons among the proposed method and other sleep classification methods. The average of the classification accuracy for those methods, involving 5-sleep stages, was in the range of 80-95% [15, 14, 19, 50, 59, 72]. Most of the approaches that classified 6-sleep stages had the accuracy around 90%-93% [12, 16, 13]. The obtained results demonstrated that the proposed method produces better results compared to the existing methods even though the proposed method was conducted using two different channels of EEG data. Hassan and Bhuiyan (2017) proposed a sleep classification based on an ensemble Empirical Mode Decomposition (EEMD). Different features were extracted and investigated in that study. An average accuracy of 93% was achieved. Kuo et al. (2014) developed a sleep classification model based on EOG signals. Multiscale entropy, autoregressive model, and multiscale line length were used to extract representative features form EOG signals and were fed to a classifier. An average accuracy of 83.33% was obtained in that study. Ghasemzadeh et al. (2019) proposed a logistic smooth transition autoregressive model (LSTAR)for features extraction. Each EEG epoch was decomposed using e double-density dual-tree discrete wavelet transform. Then, LSTAR was used to extract EEG features. An average accuracy of 93% was achieved in that study. The proposed model attained better classification accuracy in comparison with those methods. Based on the results presented in Table 13, the proposed method obtained an average accuracy of 96.74% and 96.0% with ISRUC-Sleep database (C3-A2 channel) and Sleep-EDF database (Pz-Oz channel) respectively. A 3.0% and 1.3% increase compared to those that used Pz-Oz and C3-A2 channels separately can make significant improvement in medical diagnostics. Other existing methods used in this comparison were only tested with a single channel EEG signal (Pz-Oz) while the proposed method in this paper was tested with both C3-A2 and Pz-Oz channels of EEGs and with different datasets.

The purpose of this work was to investigate changes in weighted network's behaviours during the sleep cycle based on a combination of the weighted networks features including spectral attributes *{shortest path, the number of isolated points, the maximum eigenvalue, the second eigenvalue, spectral radius, energy of graph},* which did not use in our previous work in Diykh et al. [14] and Diykh et al. [15]. In Diykh et al. [14], the EEG sleep stages were identified based on two network characteristics of (Jaccard coefficients and average degree) derived from unweighted networks, while in Diykh et al., [14] we investigated the influence of using the degree distribution on the accuracy of EEG sleep stages classification.

The changes in the spectral and structural weighted network attributes during sleep stages were not taken into the consideration in our previous studies. Our fundamental hypothesis is that classification and analysing sleep stages can be improved by using spectral and structural weighted network characteristics. Those network's feature were studied and their behaviours were investigated during each sleep stage in this work. The theme of this work is to show that individual sleep stages could be better classified using different network features from weighted networks. The proposed method showed that using weighted networks reveals the hidden patterns in EEG signals during sleep cycle that could be difficult to identify using unweighted networks. It was found that human sleep stages were better analysed using a combination of spectral and structural networks features than those network features in Diykh et al. [14] and Diykh et al. [15]. The proposed method illustrated that not all the network attributes had the same influence on the recognition of sleep stages. For example, the shortest path can be used as one of the important network characteristics to identify the AWA stage while it has a little influence on the recognition of S1 or S2.

Table 13

The accuracy comparison with the existing methods in the literature

Authors	Sleep stages	EEG channel	Method and main characteristics	Number or type of features	Accuracy
Zhu et al. [72]	AWA, S1, S2, S3, S4 and REM	Pz-Oz	The differences of mean degrees between horizontal and vertical visibility graphs were used to classify sleep EEG signals	Seven features extracted from Visibility graphs	87%
Peker et al. [50]	AWA, S1, S2, SWS, REM	C3-A2	Combining a duel tree complex wavelet (DTCWT) and a complex-valued neural network	The statistical features of DTCWT coefficients	95.42%, 93.84 with AASM and R&K criteria respectively
Da Silveira et al. [13]	AWA, S1, S2, S3, S4 and REM	PZ-OZ	A normalized wavelet transform and a random forest classifier	The statistical features of the discrete wavelet transform	91%
Shi et al. [58]	AWA, S1, S2, S3, S4 and REM	C3-A2, C3-A1	A join collaborative representation model	Seven features extracted from visibility graphs	80.29%
Sinha et al. [59]	AWA, REM and sleep spindles	N/A	Combined Discrete wavelet (DW) with neural networks	DW coefficients	95.35%
Ebrahimi et al. [17]	AWA, S1, S2, SWS and REM	Pz-Oz, Fpz-Cz	Wavelet package coefficients combined with a neural network.	Five statistical features were extracted from Wavelet package coefficients	93.0±4.0%
Fraiwan et al. [18]	AWA, S1, S2, S3, S4 and REM	C3-A2, Fpz-Cz	Continuous wavelet transform and a linear discrimination analysis.	Time Frequency Entropy features	84%
Hsu et al. [24]	AWA, S1, S2, SWS and REM	Pz-Oz, Fpz-Cz	Energy features of EEG signals with an Elman recurrent neural network	Six energy feature extracted from six characteristic waves of EEGs	90.93%
Hassan and Bhuiyan [23]	AWA, S1, S2, S3, S4 and REM	C3-A2	ensemble Empirical Mode Decomposition	Statistical features	93%
Kuo et al. [33]	AWA, S1, S2, SWS and REM	EOG signals	Butterworth band-pass filter	MSE, AR, and MLL	83.33%
Ghasemzadeh et al. [20]	AWA, S1, S2, S3, S4 and REM	C3-A2, Pz-oz	D3TDWT based on LSTAR	LSTAR coefficients	93%
Diykh et al. [14]	AWA, S1, S2, S3, S4 and REM	C3-A2	Structural graph features combined with k-means	Three networks features	95.93%
Diykh et al. [15]	S1, S2, S3, S4 and REM		Undirected complex networks combined with statistical features	Four networks features	92.16
The proposed method	AWA, S1, S2, S3, S4 and REM	Pz-Oz	Weighted networks and LS-SVM	8 network features	96.0%
The proposed method	AWA, S1, S2, SWS and REM	C3-A2	Weighted networks and LS-SVM	8 network features	96.74%

6. Conclusion

In this paper, the characteristics of complex networks which were constructed from 12 statistical features of EEG signals were extracted to identify the sleep stages. The study examined the efficiency of the topological and structural attributes of the weighted undirected networks in the sleep stages classification. Different networks attributes were used and tested. One of the most important findings in this paper was that the behaviours of networks could vary from one sleep stage to the others. The effectiveness of the proposed method was tested with two datasets that were acquired from different EEG channels. The proposed method achieved a high classification accuracy according to the AASM compared with the R&K guidelines.

In this work, the obtained results showed that using imbalance EEG data had negative effects on classification accuracy and the performance of the proposed method. Our future work will focus on testing different approaches such as oversample the minority, under-sample the majority classes, and synthesize them both to tackle this issue. In addition, more balanced EEG dataset will be employed to evaluate the proposed method. Big data technologies will also be applied to further improve the algorithm. The proposed method can contribute to develop a system tool for automatic sleep stages scoring which can be useful to assist doctors and neurologists for the diagnostics and treatment of sleep disorders and for sleep research.

Conflict of interest

Authors declare that there is no conflict of interest in this paper.

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