IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 17 May 2022, accepted 16 June 2022, date of publication 4 July 2022, date of current version 11 July 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3188286

Rules-Based and SVM-Q Methods With Multitapers and Convolution for Sleep EEG Stages Classification

IGNACIO A. ZAPATA, YAN LI, AND PENG WEN
School of Sciences, University of Southern Queensland, Toowoomba, QLD 4350, Australia
Corresponding author: Ignacio A. Zapata (ignacio.zapata@usq.edu.au)

ABSTRACT Sleep EEG signals analysis is an approach that helps researchers identify and understand the different phenomena concealed within sleep EEG data. This research introduces a time-frequency analysis approach to untangle the parameters of the sleep stages classification from EEG data. This approach computes the spectral estimation of a signal based on a set of controlled wavelets using a multitaper with convolution (MT&C) method. In this study, the MT&C methods is implemented to extract the features from a single sleep EEG data channel. Then two separated approaches are applied for sleep stage classification. The first one is based on the EEG waves characteristic definitions of sleep stages (named as Rules-based method) to directly classify each 30 second EEG segment after the feature extraction. The second approach uses a support vector machine with quadratic equation (SVM-Q) classifier to classify the sleep stages based on experts' scoring. The experimental results are evaluated, and the outcomes show an overall accuracy of 90% with an average sensitivity of 96.2% and an average specificity of 93.2% using an SVM-Q classifier and an 87.6% accuracy for the Rules-based method on healthy subjects. On the other hand, the accuracy on subjects with abnormal sleep EEG data is of 78.1% with the SVM-Q classifier and 73.4% with the Rules-based method.

INDEX TERMS Multitapers, support vector machine, SVM-Q, spectral estimation, sleep EEG, sleep stages, sleep rules, spectra density estimation (SDE).

I. INTRODUCTION

The electroencephalography (EEG) data represents the neurocognitive process of an individual and the interactions between neurons in the brain [1]–[3]. Its complexity creates a real-world challenge for researchers to generate various algorithms that are able to accurately identify the cognitive dynamics in a certain time frame in which cognition appears. An optimum time to analyse the cognitive dynamics of the human brain is while it is resting, as most of the body functions are partially suspended.

Sleep is essential not just because humans spend one-third of our lives sleeping, but also because it is a recovery process, and its quality dictates the neurological and physiological status of individuals. Therefore, sleep analysis has been a focus of scientific research for many decades, and there are a large number of algorithms dedicated to the analysis of the physiological dynamics of sleep. However, many EEG sleep analysis algorithms face enormous dilemmas due to the variation of their results for individuals and between databases. Often some algorithms perform better than others, yet none of them produces a flawless result [4]–[6].

Manual scoring has been used as the main method for sleep stages classification, and it is still one of the most common practices applied today, although it is time-consuming and subject to expert's fatigue and personal biases [7], [8].

This research introduces a methodology to unveil the characteristics of sleep stages based on EEG data using a time-frequency method, multitapers with convolution (MT&C).

The associate editor coordinating the review of this manuscript and approving it for publication was Mohamed M. A. Moustafa.

TABLE 1. Sleep stages classification criteria and parameters.

Sleep Stage	EEG Waves			Additional criteria
	Frequency (Hz)	Voltage (uV)	Duration (second, s)	
Awake(active)	beta (14–30 Hz)	High Amplitude	-	Active EOG
Awake(relax)	alpha (8–13 Hz) and burst of beta	Low Amplitude	-	Active EOG
Stage 1	theta (4–8 Hz) and burst of alpha	Low Amplitude	<=1.5s. (alpha burst)	Reduced EOG activity
Stage 2	theta with K-complex or spindles or both.	Low Amplitude (Mostly theta) Spindles *and* K − complex	0.5 – 2.5s (Spindles) 0.2 – 1.5s (K-complex)	EOG maps activity of EEG
Stage 3	delta (0.1–4 Hz)	$> 75\ \mu V$	delta > 50% of the epoch	Quiet EOG
REM	Desynchronised mix of frequencies, possible EOG, and *sawtooth waves*	Low Amplitude	delta ~ 40%, theta ~ 30%, alpha ~ 15%, beta < 10%. possible active EOG	~ Active EOG

The MT&C method is used to generate representative features that are linked to specific characteristics found in each sleep stage according to Rechtshaffen and Kales rules (R&K rules) [9].

The main focus of the feature extraction method used in this research is the time-frequency analysis of the signal to identify the presence of specific waves (slow waves, theta, alpha, and beta) in sleep EEG data [10]. The objective is to apply signal analysis methods to decompose the original signal in a multidimensional frame, to uncover the most prominent elements in the signal (frequency, time-duration and power), which will then provide potential prospects of hidden features and characteristics in each sleep stage.

In this paper, the features from sleep EEG signals are extracted using the MT&C, then those features are classified using a support vector machine (SVM) with quadratic equation (SVM-Q) and a proposed Rules-based sleep stage classification method. The results from each classification method are then evaluated and compared with other existing methods [11]–[14] that used the same databases. In the Rules-based method, the classification of sleep stages is implemented based on EEG wave characteristic definitions and parameters (frequency, amplitude, and time duration). Each feature generated by the MT&C method is evaluated for their match with specific waves characteristics of the sleep stages. Table 1 displays the sleep EEG stages characteristic definitions and criteria.

The novelty of this study is the incorporation of the Gabor wavelets together with the MT&C method to extract the key features from Sleep EEG data and the classification of those features using the SVM classifier and the Rules-based classifier. The Rules-based method is also a novelty method because it incorporates the R&K rules to analyse and classify each stage based on already known parameters.

This paper is organised as follows. Section 2 contains an overview on the current related research in sleep classification. Section 3 explains the sleep EEG databases used in this research. Section 4 introduces the MT&C method for feature extraction and the classification methods used. Section 5 reports the experimental results and the evaluation performed in this research. Finally, Section 6 summarizes the research and future work.

II. RELATED WORK

Sleep stages classification has been under development for decades. There are various methods and algorithms capable of classifying sleep stages using diverse approaches based on EEG data, and targeting at different subjects, like healthy subjects [15], older adults [16], [17], newborns [18], patient with Alzheimer [19], epilepsy [20], [21], and many other conditions [17], [22], [23]. The methods are often distinguished by the techniques used to extract the hidden information within data and the classifiers used for the classification. The interpretations and use of available information (like hypnograms) and the assumptions applied play an important role in the methodology design for sleep EEG stages scoring [15].

A. MULTI-TAPERS RELATED APPLICATIONS

Multi-tapers (MTs) related methods have been used for time-frequency analysis and spectral estimation with applications not only in multi-trial EEG data analysis, but also in other areas where an in-depth analysis of signals is fundamental [24], [25].

MTs were first developed by Thomson [26] in 1982 as a novel method to analyse the harmonics in a time series, and then the method was improved by Park *et al.* [27] to estimate the frequency oscillation of the planet Earth. Since then, that method has been widely used in many research areas for signal analysis and signal decomposition. Recently, MTs were used to analyse the spectra density estimation of EEG signals [24], [25], [27], [28] to classify sleep stages and identify abnormal activity on awake subjects [24].

A study by Jeyaseelan and Balaji [29] derived the spectral characteristics of EEG waves using a MTs-based method, and it was reported that the spectral estimation by the MTs method was better than that from fast Fourier transform (FFT). One of their findings was that MTs improved the level of autonomy based on the number of tapers, reducing inconsistencies and producing smoother spectral peaks with a defined estimation of uttermost frequencies.

Babadi and Brown [25] presented a detailed analysis of the MTs spectral and the standard non-parametric spectral estimation. They applied the MTs method to analyse anesthetic and sleep EEG data. Their research showed that by specifying the spectral resolution of the tapers, the frequencies outside

of such resolution became blurry, allowing them to identify only the elements within the spectral resolution. That study gave an insight into how MTs was capable of identifying an accurate spectral estimation for different types of EEG signals.

Prerau *et al*. [30] presented a review of the neurophysiology of sleep EEG data using the spectral analysis generated by the MTs spectrograms. They demonstrated how the MTs method could be used as an effective tool to present a more defined way to visualize EEG data, producing better and faster results of classifying sleep stages. They found that the spectrograms allowed them to identify the embedded oscillatory mechanisms of each particular sleep stage and create a visual representation that was easier to map with their hypnogram compared to the original signal. Their results showed a very close relationship between expert's labels and the spectrograms produced by the MTs method.

B. EXISTING STUDIES FOR RESULT COMPARISONS

The performance of the proposed methods in this paper are compared against four other similar studies that used the same databases as the ones proposed in this research.

The first study by Zhu *et al.* [3] combined a deep belief networks approach with bi-directional long short-term memory to improve the performance and time efficiency for sleep stages classification using the St. Vincent's University Hospital database. That paper reported an average accuracy of 68.6% with good performance on Stage 2, but very low accuracy on REM stage.

The second study by Chokroverty *et al.* [4] proposed the use of a deep belief network to extract representative features and automatically classify sleep stages. That study reported an average accuracy of 65.3%.

The third study by Diykh *et al.* [5] presented a sleep stages classification method using two-stage networks. In the first step, the network combined the hand-crafted features with a network generated feature. In the second step, the network combined a sequence learning process with a prediction model that classified sleep stages using a training and testing approach. That approach produced an average accuracy of 78.6%.

Aboalayon *et al.* [6] proposed a method based on a U-Network architecture. The aim of that method was to generate a spontaneous temporal scale based on the sequences of the labels produced from mapping sequential inputs of a subjective length. So, the final prediction was given by classifying each single time-point in a signal and attaching those classifications over static intervals. That study used both the St. Vincent's University Hospital database and the CAP Sleep database. That approach produced an average accuracy of 72.8% for the St. Vincent's database and 67.8% for the CAP Sleep database.

III. EXPERIMENTAL DATA

In this study, three databases were used, two open-access from PhysioNet [31] and one private database from our industry partner. The first open-access database is the St. Vincent's University Hospital and the University College Dublin Sleep Apnea Database (St. Vincent's Database) published by Heneghan [32]. The second database is the Cyclic Alternating Pattern of EEG Activity During Sleep Database (CAP Sleep Database) published by Terzano *et al*. [33]. The database from our industry partner known as the Delica Database is for closed access and is used for testing.

A. ST. VINCENT'S DATABASE

The St. Vincent's Database was published in 2007 and revised in 2011. That database contains a full overnight polysomnogram EEG data from a three-channel Holter of 25 adult subjects with suspected sleep disorders. For that database, the subjects were randomly selected from a group of individuals over 18 years of age, who were not under any medication, and did not present any cardiovascular diseases, or dysautonomia.

The hypnograms from the database were manually labelled by a sleep technologist using the R&K rules [9].

TABLE 2. St. Vincent's data information (from 12 subjects).

Sleep Stage	The Number of Stages
Awake	2309
Stage 1	1348
Stage 2	1746
Stage 3 & Stage 4	3309 & 343 (3652)
REM	995
Total:	10051

B. CAP SLEEP DATABASE

The CAP Sleep Database contains the EEG, electrooculography (EOG), electromyography (EMG), respiration signals and electrocardiography (ECG or EKG) polysomnograms of 108 subjects divided into eight groups, from which the non-pathology subject group is used on this research. The hypnograms were made by an expert trained at the Sleep Centre using the R&K rules [9].

The non-pathology datasets from CAP Sleep Database comprise 16 healthy subjects of mixed genders in an age range of 25 to 42, who were not on any medication that could alter the central nervous system. The data of each subject contains around 9 hours of an overnight sleep recording. The datasets are available in a sampling rate of 256 hertz (Hz).

C. DELICA DATABASE

The Delica Database contains the EEG, EOG, EMG and EKG of an overnight sleep from three different healthy subjects from 17 to 23 years old. That database uses a sampling rate of 500Hz in a frequency band of 0.05 to 100Hz. The data from that database has not been filtered or modified. It has five individual EEGs channels (F4, C3, C4, O1, O2, A1, A2), four EOGs (two vertical electrooculograms and two horizontal electrooculograms) and three EKGs (one right and two left).

TABLE 3. CAP Sleep data information (from 11 subjects).

Sleep Stage	The Number of Stages
Awake	985
Stage 1	390
Stage 2	4107
Stage 3 & Stage 4	874 & 1551 (2425)
REM	2174
Total:	10081

TABLE 4. Delica database (from 3 subjects).

Sleep Stage	The Number of Stages
Awake	467
Stage 1	311
Stage 2	934
Stage 3	319
REM	587
Total:	2618

IV. METHODOLOGY

This research uses one main feature extraction method for the general features and one supplementary method to extract the features of muscle movement (MM). Then, the features are classified into stages using two different approaches.

A. EEG DATA AND DATA PROCESSING

This study uses the EEGs from C3-A2 and C4-A1 channels for the MT&C feature extraction method, and the right (R) and left (L) EOGs channels together with the C3-A2 and C4-A1 for the MM feature extraction method. In the case of the EEGs used in MT&C, those bio-signal channels were selected in accordance with R&K [9] as they are the main channels to score sleep stages using sleep EEG data. The data from the EEG channels were filtered using a notch filter and a bandpass filter. The starting frequency of 0.2Hz on the notch filter were selected to avoid negative frequencies as described in [34]–[36], and the top frequency of 50Hz in the notch filter as well as in the bandpass filter were designated to exclude frequencies over 50Hz which were not relevant to this study.

In the case of the MM feature extraction method, additional filters were applied in the right (R) and left (L) EOG channels as well as in the EEG data. Accordingly, considering that the features from the MM method reflect the outsized increase of the amplitudes (over 15Hz) in sleep EEG data whenever there is muscle movement in subjects, all four channels used in this method were filtered above the alpha range (15Hz) using a high-pass filter.

The average of signal to noise ratio (SNR) in the CAP database [33] is around 0.0198 decibels (dBs). For the St. Vincent's database [32] the SNR is around 0.132 dBs and 0.223 dBs for the Delica database. That noise corresponds to the high amplitudes, and high or abrupted frequencies (>30Hz, 50Hz) that are removed from the data for the sleep stages classification. Also, the segments that are flagged as noisy due to constant muscle movement and awake are deducted from the data that is used for sleep analysis. It's unclear what preprocessing and denoising methods were applied in the two open-source EEG databases (CAP and St Vincent's). But we applied xx denoise method before used all the EEG data.

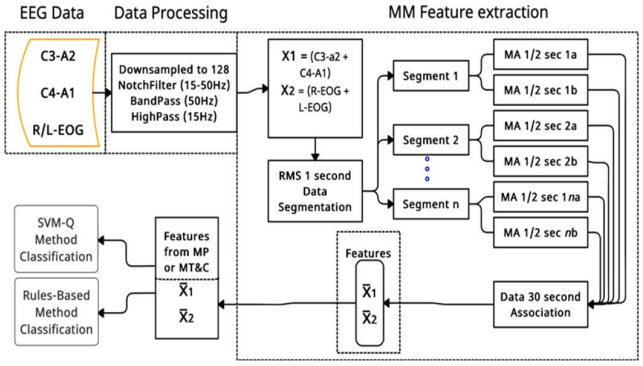

FIGURE 1. MM feature extraction diagram.

B. FEATURE EXTRACTION

Feature extraction was conducted using two individual methods of the MM and MT&C. The features obtained from the MM method are integrated with those from the MT&C. For the MT&C feature extraction, the data was segmented in epochs of 30 seconds to match the hypnograms for the sleep stage scoring. The data were segmented in epochs of one second to compute bipolar differences and then it was grouped back to epochs of 30 seconds to match the hypnograms in the MM feature extraction.

1) MM FEATURE EXTRACTION

The Muscle movement or MM characteristic features were originally defined by the R&K rules [2] and used in many other studies when analysing EEG data for sleep stages classification [7], [8], [10], [23], [24], [35].

Fig. 1 shows the algorithmic form diagram in the MM feature extraction. Firstly, the sleep EEG and EOGs data were pre-processed, then the EEGs from C3-A2 and C4-A1 channels were integrated into a single signal (X1), so did the R-EOG and L-EOG channels (X2). After that, the data were segmented into one second epoch and the root mean square (RMS) was calculated for each epoch. The moving average (MA) technique was then used to smooth out the small fluctuations for every 0.5 second of the input data to highlight the outliers from those high amplitudes. Then the data were grouped back into 30 second epochs and the mean ($\bar{x}$) of the entire data was computed and passed as features $\bar{X}1$ and $\bar{X}2$.

The sensitivity analysis surrounding the relationship of the MM features and awake stage was based on the correlation between all awake instances on the hypnogram and the high amplitudes found on the MM features. It was established that

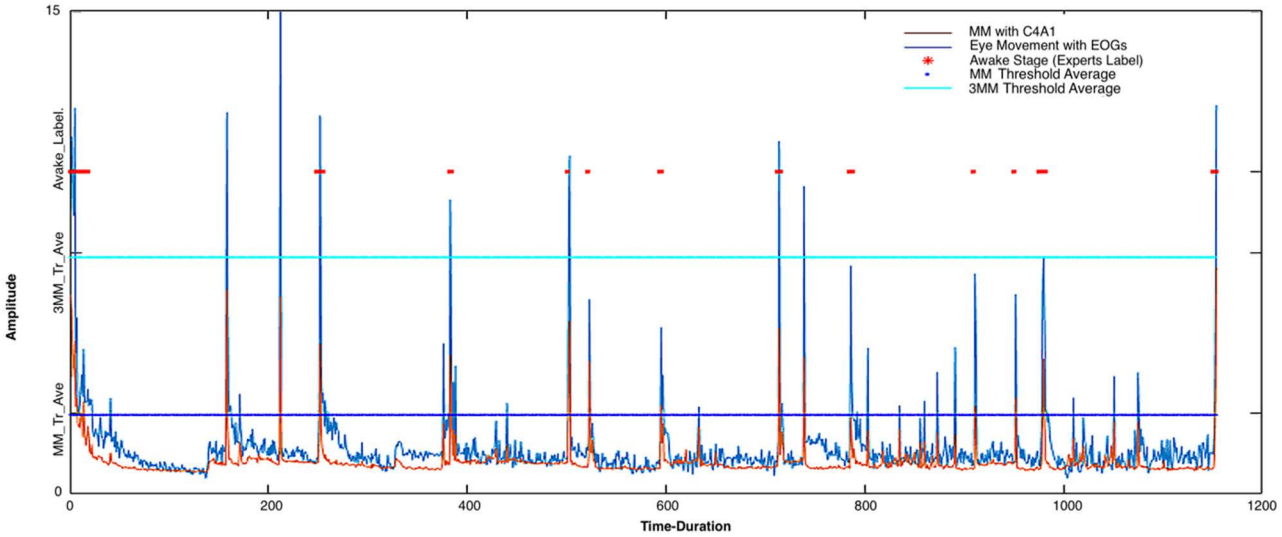

FIGURE 2. Correlation between muscle movement and eye movement using the features from MM method.

awake stages and high amplitudes on frequencies above 15Hz have a significant correlation with the number of instances (artifacts) found on each awake stage. Consequently, by calculating the number of artifacts in each epoch and smoothing them out using a moving average function, most of the awake stages were defined by using the MM features from the EEG bipolar channel (BC) called MM-BC and the EOGs called MM-EOG [37]. Muscle movement was determined when the MM-BC and the MM-EOG surpassed the general average (Tr_Ave) of the MM-BC, as seen in Fig. 2.

Using the features from MM method the muscle movement was determined when the MM-BC was three times larger than its general average (3MM_Tr_Ave) as shown in Fig. 2. Likewise, when the artifacts in one of the surrounding epochs were above the general mean of the signal, and its artifacts on the current epoch were above the mean, that epoch also were given the MM status. Parallel to that analysis, the MM was also validated using the SVM-Q classification method from MATLAB. It was found that the final MM features had a high correlation with the wake stage, and by using the MM from C3-A2 or C4-A1, the classification tool was able to predict an average classification accuracy of 87.7% for awake stages using a support vector machine (SVM).

2) MT&C FEATURE EXTRACTION

This main feature extraction in this study is the MT&C method. It generates a spectra density estimation (SDE) from a signal by convoluting predefined wavelets with a row signal. The predefined wavelets are orthogonal to each other in terms of frequency, and they are generated using the Gabor function.

The Gabor kernel is selected as the main function after intensive literature review [15], [24], [39]–[41] and experiments performed and compared with other kernels like Haar, Laplacian, Sobel, and a combination of them. The Gabor function in (1), which is used to create the wavelets that convolute the signal, is a permutation of a Gaussian function in [15], [38], [39] with an imaginary cosine wave as used in [24], [40].

$$g_k(t) = e^{\left(\frac{(-t^2)}{(2S^2)}\right)} e^{(i2\pi f_k t)} \tag{1}$$

where $g_k(t)$ is the Gabor wavelet, $e^{\left(\frac{(-t^2)}{(2S^2)}\right)}$ is the Gaussian window, $e^{(i2\pi f_k t)}$ is an imaginary cosine wave, t is the time instance which also represents the duration of the wavelet *(1 second with the sample rate* (R) *of the raw signal)* and fk is the frequency, which also refers to a specific the wavelet, meaning that each wavelet is referenced by the frequency used to generate it.

Naturally, a cosine wave ($e^{(i2\pi f_k t)}$) is a constant infinite oscillatory wave, that by itself does not present much meaning to the interpretation of fluctuated signals as the ones presented in EEG sleep data [41], [42], [44]. Therefore, it is used together with the Gaussian function ($e^{\left(\frac{(-t^2)}{(2S^2)}\right)}$), which is a window that transforms the cosine wave into a wavelet with specific characteristics (f_k) that allows to identify specific elements in fluctuating signals. From the Gaussian function, there is an adjustable standard deviation (S) (described in (2)) that allows to modify the size or range of the wavelet, meaning that S in the Gaussian function defines the width of the wavelet.

$$S = \frac{n}{(2\pi f_k)} \tag{2}$$

where n is the number of cycles of the wavelet, and f_k is the frequency of the signal at level k.

The kernel function implemented here is based on Mallat [39], in combination with the one by Cohen [24], [40] in an attempt to reduce the complexity of the wavelet used in

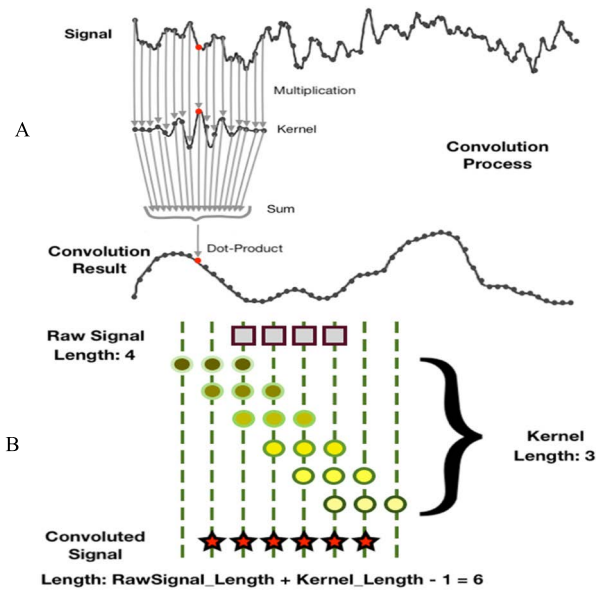

FIGURE 3. (A) Convolution process for a single point (red mark). (B) Convolution process and convolution signal length.

the MT&C by creating a complex wavelet, where redundancy is not compromised, but its size is reduced, improving the computational power, especially for extensive signals decomposition [45].

The number of wavelets used in the MT&C are associated to the frequencies that are desired to be extracted from an EEG signal [46]. Considering that each wavelet (g_k) can offer an autonomous estimation of the spectral density function (SDE(f_k)) of a signal within a time-window. The SDE of the signal is computed with a convolution process as shown in (3), and graphically represented in Fig. 3.

$$SDE(f_k) = \sum_{t=R\left(-\frac{1}{2}R\right)}^{n} (g_k(t)X_{w_t}) \tag{3}$$

where R *is the sampling rate,* t is one second (duration of the wavelet) and it starts from $t - (1/2R)$, and it goes up to $w+(1/2R)$ with increments of $1/R$. $g_k(t)$ is the kernel function in the frequency instance k with t duration. X_{w_t} is the original EEG data with t duration from the total duration w.

Based on SDE(f_k), $g_k(t)$ multiplies the original signal X_{w_t} and generates a dot-product for every point in X_{w_t}. This process is achieved by sliding each wavelet across the signal (X_{w_t}), meaning that if there are five kernels at different frequencies, the convolution will generate five different new signals, where each one contains the information related to the wavelet at the frequency. For instance, if the wavelet has a frequency of 15, the generated signal will show the instance, the power, and the amount of frequency (15) in the evaluated signal [28].

As described in (3), the dot-product between a wavelet and a signal is the sum of all points of the wavelet with a t duration multiplied by the signal of the same duration (red mark in Fig. 3(A). In other words, it is generated by convoluting every point of the kernel against the input signal. Considering that the maximum power a wavelet is in its centre, we must pad a $0.5R$ of zeros at the beginning and at the end of the original signal. Otherwise, if no additional points are added into the original signal, the first and the last 1/2 second of the resulting signal will not have an unbiased meaning. Those new extra points in the signal will have a value of zero to cancelling biased values and noise in the resulting signal, which means that the rightmost point of the kernel will be lined up with the leftmost point of the original signal at the start and the end of the convolution. The size of the resulting signal will be equal to the size of the original signal plus the size of the kernel minus one. The minus one occurs because the kernel overlaps the raw signal by one (Fig. 3(B)).

In general, the MT&C method behaves like a filter, where the signal is passed through a tunnel named kernel, which bypasses the frequencies that are outside it, resulting in a new signal that will only have amplitude wherever the frequency from the kernel is present [24], [46].

C. MT&C FUNCTIONALITY

Fig. 4 shows the algorithm structure for the MT&C feature extraction and classification method, where the data from one sleep EEG channel (C3-A2 or C4-A1) is pre-processed and segmented into epochs of 30 seconds. Subsequently, each epoch is convoluted to generate its SDEs. The resulting SDEs from each epoch are then grouped in wave bands, and their results are the MT&C features.

1) MT&C ALGORITHM

The MT&C algorithm includes four elements: an array that contains the data from one sleep EEG channel, a minimum frequency, a maximum frequency, and the number of frequencies that the algorithm is going to retrieve from the signal. The algorithm creates a linearly spaced vector from the minimum to the maximum frequency. The distance between individual frequencies will vary according to the number of frequencies requested by a user. Based on each element of the linearly spaced vector, the algorithm will then generate one Gabor atom using (3). Each wavelet generated will be convoluted across the signal [47].

The MT&C algorithm returns a matrix with all applied frequencies, a 2D matrix with the average power for each evaluated frequency and a matrix with the spectrogram.

D. FEATURE DIMENSIONALITY REDUCTION

The features generated from the MT&C method are a series of multidimensional descriptive matrices which can become problematic to be applied in the sleep stages classification methods. There is, therefore, a customised dimensionality reduction section for each classifier. The matrices from the MT&C are reduced to 30 features. Each feature represents the power spectrum presence on each of the frequencies, which are sorted in an ascending order based on the frequency.

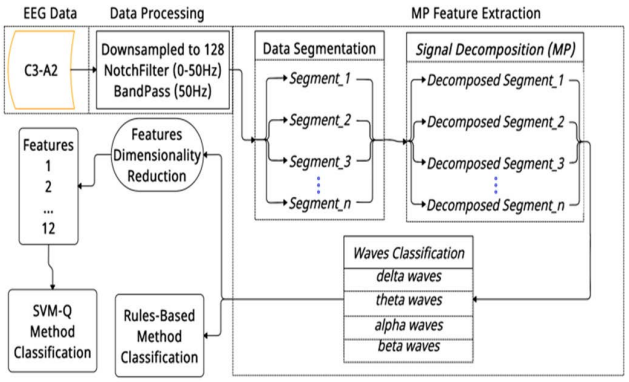

FIGURE 4. Feature extraction and classification using MT&C.

Those features are then grouped with the two features from the MM method before they are passed to the next phase of the classification.

E. SLEEP STAGES CLASSIFICATION WITH THE SVM-Q

The SVM-Q was implemented in this study after carefully analysing other supervised classifiers like decision trees, discriminant analysis, naïve bayes classifier, nearest neighbour classifier and ensemble classifier. It was found that the SVM-Q have better performance and accuracy over the other classifiers. SVM classifiers, also known as binary classifiers, are popular supervised learning algorithms used for regression and classification. The idea behind the SVMs is to find a hyperplane that denotes clear distinction between features into distinctive domains [48]. The quadratic kernel in the (4) is computed using quadratic optimization approach [49].

$$K\,(x, y) = \left(x^T * y + c\right)^2 \tag{4}$$

The SVM-Q classifier is fed with 32 features (30 from the MT&C and two from the MM), along with the expert labels. 70% of the data were used as the training data and the remaining 30% was divided equally for testing and validation. There are five main parameters used by the SVM-Q classifier used are. 1) The regularisation of the 'c' variable that defines the trade-off rate between the model minimization complexity and the minimization of the training error. 2) The box constrain level, that variable changes the number of support vectors (SVs) used in the classification algorithm, it is set individually for each subject and the computational power requirements fluctuates based on the number of the SVs used. 3) The kernel scale, by default it uses heuristic procedure to select the kernel scale value, however, in some instances the kernel scale is manually set. The algorithm splits the elements of the predictor matrix on the number of the kernel scale and then it applies the kernel norm to generate the main matrix. 4) The multiclass method, those variables have two options, ether one-vs-one or one-vs-all. When one-vs-one is applied, the classifier trains one learner for each pair of classes, which allows the learner to distinguish one class from another. When one-vs-all method is applied, the classifier trains one learner against each class, that allows the class to distinguish each class from all others. 5) The standardise data and non-standardise data, that parameter specifies whether or not to scale every coordinated distance. In some cases (for some subjects), where the predictors have a substantial scale difference, standardization improves the prediction.

1) RULES-BASED CLASSIFICATION

Fig. 5 shows the classification workflow diagram in the Rules-based classification method. The first step is to identify clear MM instances from sleep or very relaxed stages. So, any stage that contains a constant beta activity and active EOG movement is scored as Awake.

a: STAGE 3

To identify sleep Stage 3, all the spectral coefficients are analysed against each wave frequency sections. For instance, if the band frequency delta is predominant over every other band (theta, alpha or beta), and theta is smaller than delta but larger than alpha and beta, the stage is scored as Stage 3 [50].

b: STAGE 2

If the power spectrum is predominant between theta and delta (mostly theta), and at the same time are much larger than alpha and beta, then, the epoch is scored as sleep Stage 2.

c: STAGE 1

Stage 1 is scored only when the spectral coefficient of low-alpha (8-10Hz) is smaller than 40%, and the spectral coefficient of theta is higher than 40%.

d: REM

If the power spectrums across alpha, theta and delta bands are considerably low and close to each other, which at the same time are larger than the beta amplitude, the epoch is scored as REM.

2) PERFORMANCE MEASUREMENT METRICS

The performance of this study is evaluated using three measurement metrics: accuracy, sensitivity and specificity [51]. The accuracy metric is based on the number of the correct assessments, true positive (TP) and true negative (TN), divided by the total number of assessments, TP, TN and false positive (FP) and false negative (FN), as shown in (5). The measurement shows the percentage rate of the correct classification in terms of all [52], [53].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

The sensitivity metric, which is defined as the TP divided by the sum of the TP and FN as shown in (6), shows the ability of the algorithm to identify a specific sleep stage in terms of others [52].

$$Sensitivity = \frac{TP}{TP + FN} \tag{6}$$

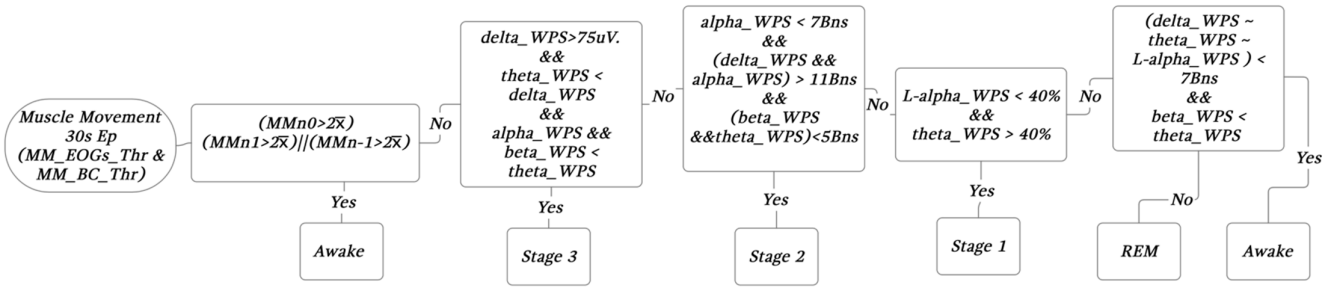

FIGURE 5. Rules-based classification method for MT&C features *(WPS = wavelet power spectrum)*.

The specificity metric, which is based on the TN divided by the sum of FP and TN as in (7), is the ability of the algorithm to exclude specific stage from others [52].

$$Specificity = \frac{TN}{FP + TN} \tag{7}$$

V. EXPERIMENTAL RESULTS

The algorithms presented in this research are evaluated using a set of experiments with the databases mentioned in Section 2. The results from the SVM-Q classifier and the Rules-based classification are compared with one another and with other existing studies that used the same databases. The features used for the classifications are from the MT&C in conjunction with the MM features.

The experiments consisted of four parts: A) graphical analysis using the MT&C against experts hypnograms; B) stages classification using the Rules-based classification and the SVM-Q classifier; C) Results comparisons between the Rules-based method and the SVM-Q; and D) Results comparison with the others in the literature as discussed in Section 2.2.

A. GRAPHICAL ANALYSIS OF THE MT&C

After generating the spectral estimation of the EEG data, it was visualized on a heat-map to identify and analyse the common element between the hypnogram generated by the experts and the spectral estimation generated by the MT&C method, as seen in Fig. 6.

Fig. 6 shows the correlation between the spectral estimation in respect to each sleep stage. The most prominent distinction was on Stages 2 and 3, where the amplitudes were highly concentrated on the delta wave range (green/yellow and red-wide colours in heat-map Fig. 6). Another sleep stage that is highly distinctive is the Awake stage. There the beta waves range (light blue lines between 13 Hz and 30 Hz) becomes evident when the subject enters into Awake stage. In the case of REM, the spectral estimation of the frequencies becomes quiet, with low amplitudes in varying ranges between low-alpha (L-alpha, 8-10 Hz) and delta. It has also been found that during REM, the MM-EOG factor becomes quite active and the MM factor from C4-A1 and C3-A2 remains quiet as seen in Fig. 6 (EOG & MM factors are at the bottom side on Fig. 6). For Stage 1, it was found that the amplitudes in the spectrogram started to do a smooth transition from L-Alpha to theta wave range, the amplitudes on that stage were low and transitory.

B. EXPERIMENTAL RESULTS WITH THE SVM-Q CLASSIFIER AND THE RULES-BASED CLASSIFICATION

The number of features generated by the MT&C was given by the number of specific frequencies which are directly related to the number of wavelets applied. It was found that when the number of specific frequencies were larger than 40, not only did the size of the matrix increase massively but so did the computational power required to generate the spectral estimation. Moreover, when the ''lined spaced vector'' between one frequency to the next was higher than 1, the descriptive values of the frequencies after the convolution did not match the parameters of the sleep stages. The best outcomes were achieved when there was a ''lined spaced vector'' between 1 to 29, and a 0.2 element was attached to that vector. The 0.2 element was incorporated to match the EEG sleep parameters of delta waves. The Rules-based classification for the MT&C features was applied based on the graphical analysis of the MT&C and the classification criteria stated in Table 1.

It was found that the accuracy of the sleep stages classification with the Rules-based method using the features from the MT&C and the datasets from St. Vincent's database was good, however, the accuracy of the sleep stages classification on healthy subjects was considerably better (CAP Sleep Database) [54]. The average accuracy in sleep classification on the St. Vincent's database was 73.4%, with an average specificity of 81.8% and an average sensitivity of 87.7%. While the average accuracy of the sleep stages classification on the CAP Sleep Database was 87.6%, as seen in Fig. 7 with an average sensitivity of 93.1% and an average specificity of 91.6%. In Fig.7 (confusion matrix) it can be seen that most of the stages had a good performance, however, Awake stage and Stage1 had a significant number of FPs (36.5% and 36.4%) compared to the number of the evaluated stages (416 for Awake stage and 264 for Stage1). The performance of the other sleep stages (Stage 2, Stage 3 and REM) in terms of FPs were significantly better with FPs rates between 18.1% and 5% (Fig. 7 far-right column).

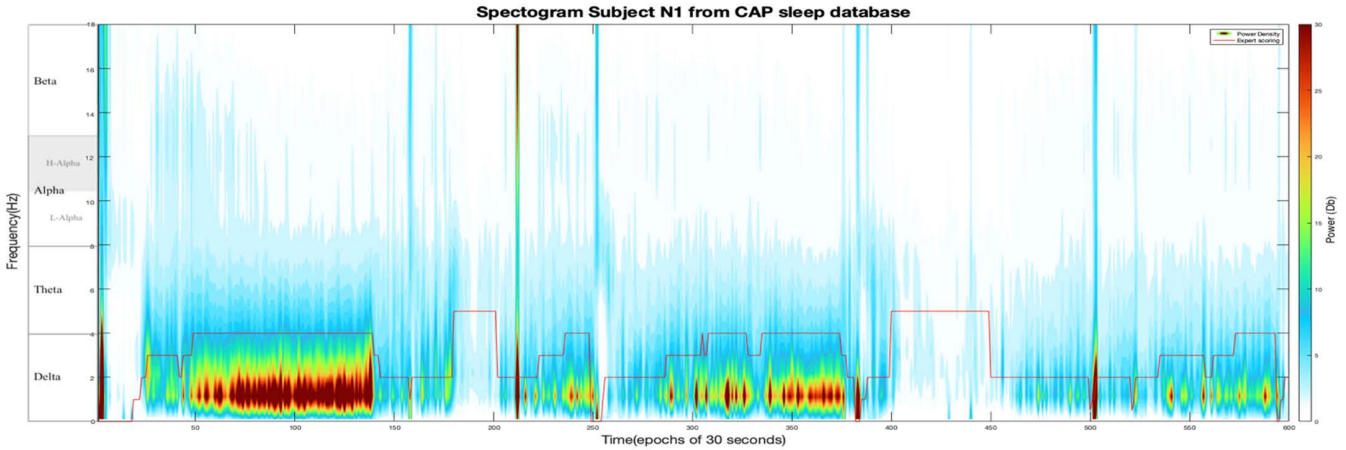

FIGURE 6. Spectrogram generated by the MT&C feature extraction. It shows the distribution of the power across 30 frequencies (1-30Hz) over one night sleep. The distribution of frequencies is contrasted with labels from an expert (red-line: 0 = awake, 1 = stage 1, 2 = stage 2, 3 and 4 = deep-sleep stage, 5 = REM).

TABLE 5. Methods accuracy on St. Vincent's database.

Methods	Main Channel	Other Channels	Features	Average Accuracy	Accuracy /stage (%)				
					Aw	S1	S2	S3	REM
MT&C-rules	**C3A2**	**C3A2**	**32**	**73.4%**	**78**	**63**	**86**	**80**	**83**
MT&C(SVMQ)	**C3A2**	**C3A2**	**32**	**78.1%**	**80**	**60**	**82**	**78**	**67**
qBi-LSTM [11]	------	C3A2, C4A1, EMG, EOG	28 features	68.6%	75	75	90	69	34
DBN [12]	------	C3A2, C4A1, EMG, EOG	28 features	65.38%	68	33	76	88	60
BLSTM+WDBN [13]	C3A2	No mentioned	40 features	78.6%	81	57	83	88	84
U-Time [14]	C3A2	EOG, EMG	No mentioned	72.8%	75	51	79	86	73

TABLE 6. Methods accuracy on CAP Sleep Database.

Methods	Main Channel	Other Channels	Features	Average Accuracy	Accuracy /stage (%)				
					W	S1	S2	S3	REM
MT&C-Rules	**C3A2**	**C3A2**	**32**	**87.6%**	**97**	**84**	**82**	**89**	**86**
MT&C(SVMQ)	**C3A2**	**C3A2**	**32**	**90%**	**92**	**85**	**87**	**89**	**95**
U-Time [14]	C3A2	EOG, EMG	No mentioned	67.8%	78	29	76	80	76
CNN [14]	C3A2	EOG, EMG	No mentioned	68%	77	35	76	78	76
CNN-LSTM [14]	C3A2	EOG, EMG	No mentioned	65%	77	28	69	77	75

In terms of FNs, all stages predictions perform significantly good, with FNs rates between 2.9% and 17.4%, as seen in Fig.7 bottom row. Most of the stages had FNs with the immediately following stage except by Stage 2 which had FNs with Stage 3 and REM.

As seen in Tables 5 and 6, the performance of the SVM-Q classifier was slightly better than the classification with the Rules-based method. The best results were archived with the combination of the SVM-Q classifier with the features generated from the CAP Sleep Database. The average accuracy of the SVM-Q classifier using the MT&C features from the St. Vincent's Database were of 78.1%, with an average sensitivity of 82.2% and average specificity of 93.9%. And the average accuracy of the SVM-Q classifier using the MT&C features with the CAP Sleep Databa was of 90.1%, with an average sensitivity of 96.2% and average specificity of 93.2%.

Fig. 8 (boxplot) shows the accuracy range of each stage on a different test performed in each subject from CAP Sleep Database using the Rules-based method.

Fig. 9 (confusion matrix) shows the classification results of the sleep stages classification on the Delica Database using the SVM-Q classifier, it had an average accuracy of 80%, an average sensitivity of 87% and average specificity of 90.5%. In Delica Database the SVM-Q classifier also performed better than the Rules-based method which archived and average accuracy of just under 78% using the same number of subjects as in the SVM-Q classifier.

Considering the SNR mentioned on section V.A, it is noted that the performance of the algorithms has a high correlation

TABLE 7. Methods performance on all three databases used (St. Vincent's, CAP Sleep and Delica) with the proposed methods.

Methods	Database	Features	Average Specificity (%)	Average Sensitivity (%)	Average Accuracy (%)	SNR (dBs)
MT&C-Rules	St. Vincent's	32	81.8	87.7	73.4	
MT&C(SVM Q)	St. Vincent's	32	93.9	82.2	78.1	0.132
MT&C-Rules	**CAP Sleep**	**32**	**91.6**	**93.1**	**87.6**	
MT&C(SVMQ)	**CAP Sleep**	**32**	**93.2**	**96.2**	**90.1**	**0.0198**
MT&C-Rules	Delica	33	83.4	88.4	77.5	
MT&C(SVMQ)	**Delica**	**33**	**90.5**	**87**	**80**	0.223

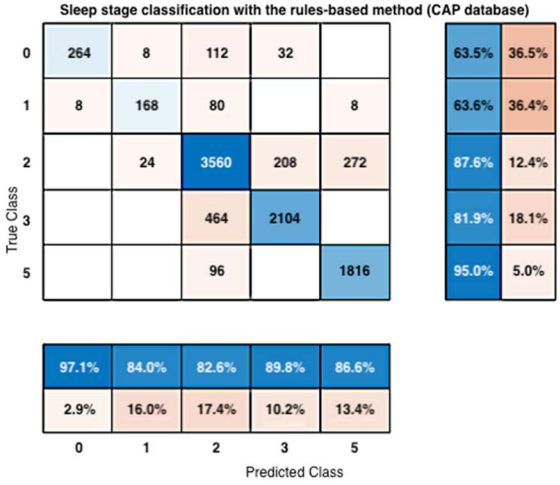

FIGURE 7. Confusion Matrix for 9224 predicted stages from 10 different subjects with features from MT&C using the Rules-based classification method *vs* expert labels for CAP Sleep Database.

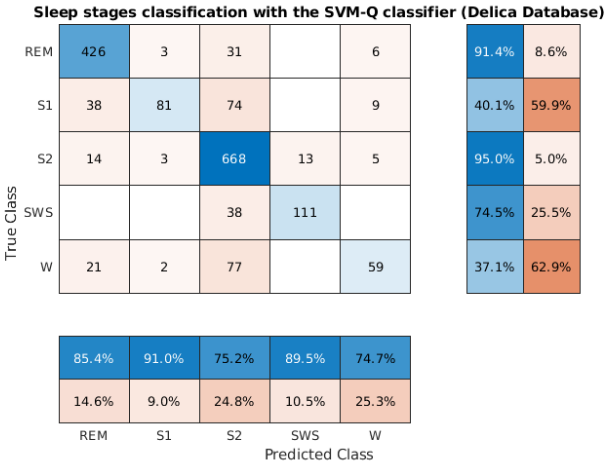

FIGURE 9. Confusion Matrix for 1679 predicted stages from 3 different subjects with features from MT&C using the SVM-Q classifier method *vs* expert labels for Delica Database.

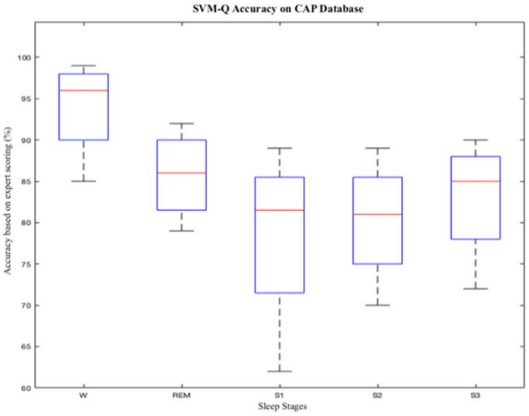

FIGURE 8. Accuracy on the CAP Sleep Database using the Rules-based classifier.

with the SNR of a database. As seen in Table 7, the results from the CAP database with lower SNR (mentioned in section V.A) preformed significantly better that the other databases that have a greater SNR (St. Vincent's and Delica databases).

C. COMPARISONS OF THE PROPOSED METHODS WITH OTHER EXISTING SLEEP CLASSIFICATION STUDIES

To verify the performances of the proposed methods, a comparison with other classification methods that used the same databases was conducted. For the St. Vincent's Database, the studies from Gorriz *et al.* [55], Sun *et al.* [13] and Peslev *et al.* [14] were used. The comparison performances were listed in Table 5. For the CAP Sleep Database, the study from Peslev *et al.* [14] was used, their comparison performances are listed in Table 6. The performances by the proposed methods and those reported in [13] and [14], [55] were very similar with the St. Vincent's Database. It is evidence that the performances of the proposed methods were significantly better than those from [14] for the CAP Sleep Database, as listed in Table 6.

VI. CONCLUSION

This paper applies time frequency analysis methods to sleep EEG data and identifies a significant difference in performance accuracies between healthy subjects and subjects with abnormal sleep patterns. It was found that the both

classification methods, the Rules-based and SVM-Q classifiers, struggled the most in trying to predict Stage 1 in subjects with abnormal sleep EEGs. Even though that the SVM-Q performed better that the Rules-based method in subjects with abnormal sleep EEGs, it had a very low performance in classifying the REM stage compared to the Rule-based method on the same type of subjects [37].

It can be concluded that the features from the MT&C with the data from healthy subjects were more descriptive in terms of the correlation to the sleep stages that the ones from subjects with abnormal sleep. The performance of both classifications was considerably better when using the data from the CAP Sleep Database and the data from Delica Database.

It is very clear that the SVM-Q classifier performs better in accuracy over the Rules-based method. However, the Rules-based classifier has lots of potential for future improvements. For instance, as new descriptive features are incorporated into the Rules-based classifier algorithm, it has the possibility to identify more detailed elements from each stage, which at the same time will improve the classification of stages that are uncleared or controversial. The Rules-based classifier algorithm has the potential to show a graphical interpretation of the events that took place in each particular stage, which will also help experts on identification of particular characteristics.

More importantly, this study suggests that by using similar principles as the ones applied by the MT&C, sleep stages classification can be improved. For instance, this method could use an additional descriptive wavelet method to identify specific characteristics in sleep stages like spindles and k-complexes, improving the performance and the accuracy of this sleep EEG classification method.

In summary, the applied methods in this research not only produce a good sleep stages classification on different sleep EEG databases as show in table 7, but it can also display the actual events that take place in each stage by visualizing the features produced by the MT&C method. This means that the sleep stages predictions are performed by the spectral estimation generated and then displayed in the spectrogram, which gives a graphical description of the events inside each stage.

REFERENCES

[1] Y. Li and P. Wen, "Identification of motor imagery tasks through CC-LR algorithm in brain computer interface," *Int. J. Bioinf. Res. Appl.*, vol. 9, no. 2, pp. 156–172, 2013.

[2] N.-K. Tai, Y. Li, and P. Wen, "Consciousness and depth of anaesthesia assessment using Bayesian techniques," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 6, pp. 1488–1498, Jan. 2013.

[3] G. Zhu, Y. Li, P. Wen, and S. Wang, "Analysis of alcoholic EEG signals based on horizontal visibility graph entropy," *Brain Informat.*, vol. 1, nos. 1–4, pp. 19–25, Dec. 2014.

[4] S. Chokroverty, R. Thomas, R. K. Malhotra, and A. Y. Avidan, "Sleep stages and scoring technique," in *Atlas of Sleep Medicine*. London, U.K.: Elsevier, 2013, p. 416.

[5] M. Diykh, Y. Li, and S. Abdulla, "EEG sleep stages identification based on weighted undirected complex networks," *Comput. Methods Programs Biomed.*, vol. 184, Feb. 2020, Art. no. 105116.

[6] K. A. I. Aboalayon, M. Faezipour, W. S. Almuhammadi, and S. Moslehpour, "Sleep stage classification using EEG signal analysis: A comprehensive survey and new investigation," *Entropy*, vol. 18, no. 272, pp. 1–31, 2016.

[7] M. Younes, W. Thompson, C. Leslie, T. Egan, and E. Giannouli, "Utility of technologist editing of polysomnography scoring performed by a validated automatic system," *Ann. Amer. Thoracic Soc.*, vol. 12, no. 8, pp. 1206–1218, 2015.

[8] Y. Kim, M. Kurachi, M. Horita, K. Matsuura, and Y. Kamikawa, "Agreement of visual scoring of sleep stages among many laboratories in japan: Effect of a supplementary definition of slow wave on scoring of slow wave sleep," *J. Sleep Res.*, vol. 47, no. 1, pp. 91–97, Mar. 1993.

[9] A. Rechtschaffen and A. Kales, "A manual of standardized terminology, techniques and scoring system of sleep stages in human subjects," Los Angeles: Brain Inf. Service/Brain Res. Inst., Univ. California, Los Angeles, CA, USA, Tech. Rep., 1968, vol. 26.

[10] V. Bajaj and R. B. Pachori, "Automatic classification of sleep stages based on the time-frequency image of EEG signals," *Comput. Methods Programs Biomed.*, vol. 112, no. 3, pp. 320–328, 2013.

[11] I. N. Yulita, M. I. Fanany, and A. M. Arymuthy, "Bi-directional long short-term memory using quantized data of deep belief networks for sleep stage classification," *Proc. Comput. Sci.*, vol. 116, no. 14, pp. 530–538, 2017.

[12] M. Längkvist, L. Karlsson, and A. Loutfi, "Sleep stage classification using unsupervised feature learning," *Adv. Artif. Neural Syst.*, vol. 2012, pp. 1–9, Jul. 2012.

[13] C. Sun, J. Fan, C. Chen, W. Li, and W. Chen, "A two-stage neural network for sleep stage classification based on feature learning, sequence learning, and data augmentation," *IEEE Access*, vol. 1, pp. 1–12, 2017.

[14] M. Perslev, M. H. Jensen, S. Darkner, P. J. Jennum, and C. Igel, "U-time: A fully convolutional network for time series segmentation applied to sleep staging," 2019, *arXiv:1910.11162*,

[15] P. J. Durka, U. Malinowska, M. Zieleniewska, C. O'Reilly, P. T. Różański, and J. Żygierewicz, "Spindles in svarog: Framework and software for parametrization of EEG transients," *Frontiers Hum. Neurosci.*, vol. 9, pp. 1–12, May 2015.

[16] B. Edwards, D. O'Driscoll, A. Ali, A. Jordan, J. Trinder, and A. Malhotra, "Aging and sleep: Physiology and pathophysiology," *Seminars Respiratory Crit. Care Med.*, vol. 31, no. 5, pp. 618–633, Oct. 2010.

[17] M. Radha, P. Fonseca, A. Moreau, M. Ross, A. Cerny, P. Anderer, X. Long, and R. M. Aarts, "Sleep stage classification from heart-rate variability using long short-term memory neural networks," *Sci. Rep.*, vol. 9, no. 1, p. 14149, Dec. 2019.

[18] V. Gerla, M. Bursa, L. Lhotská, K. Paul, and V. Krajca, "Newborn sleep stage classification using hybrid evolutionary approach," *Int. J. Bioelectromagnetism*, vol. 9, no. 1, pp. 25–26, 2007.

[19] D. Al-Jumeily, S. Iram, F. B. Vialatte, P. Fergus, and A. Hussain, "A novel method of early diagnosis of Alzheimer's disease based on EEG signals," *Sci. World J.*, pp. 1–11, Jan. 2015.

[20] C. W. Bazil and T. S. Walczak, "Effects of sleep and sleep stage on epileptic and nonepileptic seizures," *Epilepsia*, vol. 38, no. 1, pp. 56–62, Jan. 1997.

[21] D. Minecan, A. Natarajan, M. Marzec, and B. Malow, "Relationship of epileptic seizures to sleep stage and sleep depth," *Neurologic Disorders*, vol. 25, no. 8, pp. 56–61, Dec. 2002.

[22] M. Zieleniewska, A. Duszyk, P. Rozanski, M. Pietrzak, M. Bogotko, and P. Durka, "Parametric description of EEG profiles for assessment of sleep architecture in disorders of consciousness," *Int. J. Neural Syst.*, vol. 29, no. 3, pp. 1–17, 2019.

[23] A. Roebuck, V. Monasterio, E. Gederi, M. Osipov, J. Behar, A. Malhotra, T. Penzel, and G. D. Clifford, "A review of signals used in sleep analysis," *Nat. Inst. Health*, vol. 35, no. 1, pp. 1–73, 2014.

[24] M. X. Cohen, *Analyzing Neural Time Series Data. Theory and Practice*. Cambridge, MA, USA: Massachusetts Institute of Technology, 2014.

[25] B. Babadi and E. N. Brown, "A review of multitaper spectral analysis," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 5, pp. 1555–1564, May 2014.

[26] D. J. Thomson, "Spectrum estimation and harmonic analysis," *Proc. IEEE*, vol. 70, no. 9, pp. 1055–1082, Sep. 1982.

[27] J. Park, C. R. Lindberg, and D. J. Thomson, "Multiple-taper spectral analysis of terrestrial free oscillations: Part I," *Geophys. J. Int.*, vol. 91, no. 3, pp. 755–794, Dec. 1987.

[28] J. Park, C. R. Lindberg, and F. L. Vernon III, "Multitaper spectral analysis of high-frequency seismograms," *J. Geophys. Res.*, vol. 12, pp. 12675–12684, Nov. 1987.

[29] A. S. Jeyaseelan and R. Balaji, "Spectral analysis of wave elevation time histories using multi-taper method," *Ocean Eng.*, vol. 105, pp. 242–246, Sep. 2015.
[30] M. J. Prerau, R. E. Brown, M. T. Bianchi, J. M. Ellenbogen, and P. L. Purdon, "Sleep neurophysiological dynamics through the lens of multitaper spectral analysis," *Physiology*, vol. 32, no. 1, pp. 60–92, Jan. 2017.
[31] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. e215–e220, Jun. 2000.
[32] C. Heneghan, P. de Chazal, S. Ryan, C. P. Chua, L. Doherty, P. Boyle, P. Nolan, and W. T. McNicholas, "Electrocardiogram recording as a screening tool for sleep disordered breathing," *J. Clin. Sleep Med.*, vol. 4, no. 3, pp. 223–228, Jan. 2008.
[33] M. Terzano, L. Parrino, A. Sherieri, R. Chervin, S. Chokroverty, C. Guilleminault, M. Hirshkowitz, M. Mahowald, H. Moldofsky, A. Rosa, R. Thomas, and W. A., "Atlas, rules, and recording techniques for the scoring of cyclic alternating pattern (CAP) in human sleep," *Sleep Med.*, vol. 2, no. 6, pp. 537–553, 2001.
[34] L. Hu and Z. Zhang, *EEG Signal Processing and Feature Extraction*. Singapore: Springer, 2019.
[35] R. R. Gharieb and A. Cichocki, "Segmentation and tracking of the electroencephalogram signal using an adaptive recursive bandpass filter," *Med. Biol. Eng. Comput.*, vol. 39, no. 2, pp. 237–248, Mar. 2001.
[36] P. Kim and Y. Jeong, "Wideband bandpass filtering branch-line balun with high-isolation," *Int. J. RF Microw. Comput.-Aided Eng.*, vol. 30, no. 6, Jun. 2020, Art. no. e22193.
[37] E. Aserinsky and N. Kleitman, "Regularly occurring periods of eye motility, and concomitant phenomena, during sleep," *Science*, vol. 118, no. 3062, pp. 273–274, Sep. 1953.
[38] U. Malinowska, H. Klekowicz, A. Wakarow, S. Niemcewicz, and P. J. Durka, "Fully parametric sleep staging compatible with the classical criteria," *Neuroinformatics*, vol. 7, no. 4, pp. 245–253, Dec. 2009.
[39] S. G. Mallat and Z. Zhang, "Matching pursuits with time-frequency dictionaries," *IEEE Trans. Signal Process.*, vol. 41, no. 12, pp. 3397–3415, 1993.
[40] M. X. Cohen, "A better way to define and describe Morlet wavelets for time-frequency analysis," *NeuroImage*, vol. 199, pp. 81–86, Oct. 2019.
[41] A. Ahmed, T. Natarajen, and R. K. Rao, "Discrete cosine transform," *IEEE Trans. Comput.*, vol. C-23, no. 1, pp. 90–93, Jan. 1974.
[42] J. Zhou, "Discrete cosine transform," *Nigerian J. Technol. Res.*, vol. 7, 2011.
[43] B. Zeng and J. Fu, "Directional discrete cosine transforms—A new framework for image coding," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 18, no. 3, pp. 305–313, Mar. 2008.
[44] J. Zhou, "On discrete cosine transform," 2011, *arXiv:1109.0337*.
[45] H.-I. Choi and W. J. Williams, "Improved time-frequency representation of multicomponent signals using exponential kernels," *IEEE Trans. Acoust., Speech, Signal Process.*, vol. 37, no. 6, pp. 862–871, Jun. 1989.
[46] L. Cohen, "Time-frequency distributions-a review," *Proc. IEEE*, vol. 77, no. 7, pp. 881–941, Jul. 1989.
[47] X.-K. Wan, H. Wu, F. Qiao, F.-C. Li, Y. Li, Y.-W. Yan, and J.-X. Wei, "Electrocardiogram baseline wander suppression based on the combination of morphological and wavelet transformation based filtering," *Comput. Math. Methods Med.*, vol. 2019, pp. 1–7, Mar. 2019.
[48] Y. Li and P. Wen, "Classification of EEG signals using sampling techniques and least square support vector machines," in *Rough Sets and Knowledge Technology* (Lecture Notes on Computer Science), vol. 5589. Berlin, Germany: Springer, 2009, pp. 375–382.
[49] I. Dagher, "Quadratic kernel-free non-linear support vector machine," *J. Global Optim.*, vol. 41, no. 1, pp. 15–30, 2006.
[50] B. Kemp, A. H. Zwinderman, B. Tuk, H. A. C. Kamphuisen, and J. J. L. Oberye, "Analysis of a sleep-dependent neuronal feedback loop: The slow-wave microcontinuity of the EEG," *IEEE Trans. Biomed. Eng.*, vol. 47, no. 9, pp. 1185–1194, 2000.
[51] D. Chavarría-Bolaños, L. Rodríguez-Wong, D. Noguera-González, V. Esparza-Villalpando, M. Montero-Aguilar, and A. Pozos-Guillén, "Sensitivity, specificity, predictive values, and accuracy of three diagnostic tests to predict inferior alveolar nerve blockade failure in symptomatic irreversible pulpitis," *Pain Res. Manage.*, vol. 2017, pp. 1–8, 2017.
[52] X.-H. Zhou and N. A. Obuchowski, "Chapter 1," in *Statical Methods in Diagnostic Medicine*. New York, NY, USA: Wiley, 2002, pp. 1–56.
[53] M. Marino, Y. Li, M. N. Rueschman, J. W. Winkelman, J. M. Ellenbogen, J. M. Solet, H. Dulin, L. F. Berkman, and O. M. Buxton, "Measuring sleep: Accuracy, sensitivity, and specificity of wrist actigraphy compared to polysomnography," *Sleep*, vol. 36, no. 11, pp. 1747–1755, Nov. 2013.
[54] R. Boostani, F. Karimzadeh, and M. Nami, "A comparative review on sleep stage classification methods in patients and healthy individuals," *Comput. Methods Programs Biomed.*, vol. 140, no. 1, pp. 77–91, 2017.
[55] M. Längkvist, L. Karlsson, and A. Loutfi, "Sleep stage classification using unsupervised feature learning," *Adv. Artif. Neural Syst.*, vol. 2012, pp. 1–9, Jul. 2012.
[56] P. J. Durka, A. Matysiak, E. M. Montes, P. V. Sosa, and K. J. Blinowska, "Multichannel matching pursuit and EEG inverse solutions," *J. Neurosci. Methods*, vol. 148, no. 1, pp. 49–59, 2005.

IGNACIO A. ZAPATA was born in Bogotá, Colombia, in 1987. He received the bachelor's degree in information technology from Central Queensland University, Australia, in 2014, and the master's degree in software engineering and information technology from the University Southern Queensland (USQ), Australia, in 2018, where he is currently pursuing the Ph.D. degree in the area of data science. His research interests include the fields of machine learning, EEG signal processing, data analysis, and programming.

YAN LI received the Ph.D. degree from the Flinders University of South Australia, Australia. She is currently a Full Professor with the School of Sciences, University of Southern Queensland, Australia. She has published more than 195 publications and supervised dozens of Ph.D. completions. Her research interests include the areas of artificial intelligence, machine learning, big data technologies, internet technologies, and signal/image processing.

PENG (PAUL) WEN received the B.E., M.E., and Ph.D. degrees in electrical and electronic engineering from the Huazhong University of Science and Technology, Wuhan, China, and the Ph.D. degree in biomedical engineering from the Flinders University of SA, Adelaide, Australia. He is currently a Professor with the University of Southern Queensland, Australia. His research interests include control systems, biomedical engineering, signal processing, brain modeling, pattern recognition, and machine learning.