IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received June 4, 2019, accepted June 17, 2019, date of publication June 21, 2019, date of current version July 9, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2924181

Prognosis of Sleep Bruxism Using Power Spectral Density Approach Applied on EEG Signal of Both EMG1-EMG2 and ECG1-ECG2 Channels

DAKUN LAI, (Member, IEEE), MD BELAL BIN HEYAT, FAEZ IQBAL KHAN, AND YIFEI ZHANG

School of Electronic Science and Engineering, University of Electronic Science and Technology of China, Chengdu 610054, China

Corresponding author: Dakun Lai (dklai@uestc.edu.cn)

This work was supported by the National Natural Science Foundation of China under Grant 61771100.

ABSTRACT Bruxism is a sleep syndrome, in which individual involuntarily grinding and clenching the teeth. If sleep does not complete properly, then it generates many disorders such as bruxism, insomnia, sleep apnea, narcolepsy, rapid eye movement behavioral disorder, and nocturnal frontal lobe epilepsy. The aim of this paper is to draw the results in the form of signal spectrum analysis of the changes in the domain of different stages of sleep. The present research completed in three stages such as the collection of the data, analysis of the electroencephalogram (EEG) signal, and comparative analysis between bruxism patients and normal subjects. Importantly, the channels EMG1-EMG2 and ECG1-ECG2 of the EEG signal were combined for the prognosis of bruxism by using power spectral density, which mainly focused on two sleep stages such as wake (W) and rapid eye movement (REM). The total number of one-minute EEG recordings from bruxism patients and normal subjects analyzed in this work were 149 and 95, respectively. The obtained results show that the average normalized values of the power spectral density of the EMG1-EMG2 and ECG1-ECG2 channels during REM and W sleep stages are several folds higher in case of the bruxism than those in the normal. Moreover, the proposed power spectral density-based method by using the decision tree classifier shows a higher accuracy for the prognosis of sleep bruxism in comparison with previous works. In addition, the proposed approach in the prognosis of the bruxism is noise free and accurate as it is in mathematical form and has taken very less time as compared with the traditional systems. The present research work would provide a fast and effective prognosis system of the human bruxism with high accuracy for medical applications.

INDEX TERMS Bruxism, decision tree (DT), electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), power spectral density, sleep disorder.

I. INTRODUCTION

Sleep has an important role in the life of zoological species such as humans, animals, birds, mammals, reptiles, and amphibians [1]. Some zoological species complete their sleep by closing their eyes such as human beings and most of the animals. Some of them complete it by opening their eyes such as insects, reptiles and amphibians [2]. The phenomenon of sleeping with just one eye closed discovered recently in Wahlberg's epauletted fruit bat [3]. There are two stages of sleep such as non-rapid eye movement (NREM) and rapid eye movement (REM) [2]. If sleep does not complete properly in humans, it leads to several diseases such as bruxism [4], [5], sleep apnea, insomnia [6]–[10], REM behavioral disorder (RBD) [11], nocturnal frontal lobe epilepsy (NFLE) [12], narcolepsy [13], and periodic limb movement disorder. In addition, the poor sleep also affects genes and proteins in human body [14]. It damages several organs including the heart, the brain and other organs. The causes of the bruxism are asymmetrical arrangement of the teeth and sleep disorder. The main symptoms of the bruxism are flattened, chipped, and fractured teeth with worn tooth enamel exposing deeper layers of teeth. Other symptoms include jaw, neck, face pain, and headache [5]. The bruxism can be found in children, and mostly in the male. The factors that increase the risk of bruxism are smoking of tobacco, drinking of alcohol,

The associate editor coordinating the review of this manuscript and approving it for publication was Gang Wang.

and side effect of the psychiatric medicines [15]. Moreover, the bruxism are associated with some neurological disorders such as episodes of screaming, intense fear and flailing while still asleep, epileptic seizure, and sleep apnea.

Till date, many attempts have been made to identify symptom of sleep bruxism by investigating various characteristics of the mental state or different properties of the bioelectrical signal. Basson *et al.* [16] studied the significance of sub-threshold symptoms of anxiety in the etiology of bruxism in details. Bruxism is an under-recognized cause of caregiver concern in patients with Alzheimer's disease [17]. Ohmure *et al.* [18] aimed to assess the efficacy of a proton pump inhibitor (PPI) on bruxism, and examined the gastrointestinal symptoms and endoscopic findings of the upper gastro intestinal tract in bruxism patients. They suggested that the PPI administration leads to a significant reduction in the frequency of electromyography, rhythmic masticatory muscle activity episodes, and grinding noise. Lavigne and Sessle [19] suggests that reducing orofacial pain and improving sleep may improve the patient's quality of life to promote healing and optimizing their health. Furthermore, bruxism has been related to sleep disturbances as in case of migraine [20]. Sleep disturbances are common in postmenopausal women and contribute to increased morbidity and mortality. It is related to anatomical, hormonal, metabolic and psychological factors that can interfere with restorative sleep [21]. On the other hand for more practical diagnosis in clinical, the bioelectrical signals generated from human body such as the electroencephalogram (EEG), the electromyogram (EMG), and the electrocardiogram (ECG) commonly used as useful tools for the brain, muscles, and heart, respectively [22], [23]. Recently, Sten's group reported that the sleep disorder could be diagnosed by the heart rate using the signal of ECG [24]. The single channel EMG was also proposed in the detection of sleep disorder [25]. Previously, a decision support system for automated identification of sleep stages from single channel of EEG signals were proposed [26]. Lei *et al.* [27] proposed a similar framework for the spatial temporal EEG and functional magnetic resonance imaging fusion (STEFF). Wang *et al.* studied that the directed transfer function and the wavelet decomposition system were combined to represent a wavelet-based directed transfer function techniques for the patient-specific seizure recognition [28], [29]. Additionally, the basis of partial directed coherence, analysis was to detect the seizure intervals of epilepsy patients [30]. The author studied that independent component analysis successfully remove the electrooculogram (EOG) artifacts from EEG signals and preserve useful EEG information with little loss [31], [32]. However, there are low accuracy and poor prognosis on the more affected stages of sleep under various disease conditions. Especially for the reasons that the sleep stage of REM is more affected than the sleep stage of wake (W) in EMG1-EMG2 channel. Meanwhile, the stage of W is more affected than the stage of REM in ECG1-ECG2 channel, which is an obstruct for a clinical application at present. As such, a generalized approach for prognosis of sleep bruxism is high beneficial.

In the present study, a new prognostic system by combing the channels of the EMG1-EMG2 and the ECG1-ECG2 extracted from EEG signal is proposed to improve accuracy of the prognosis of bruxism. Initially, both EMG1-EMG2 and ECG1-ECG2 channels were preprocessed by using a hamming window, followed by a low pass filter for the removal of noise in both bruxism patients and normal human. Then, the power spectral density were calculated individually using the Welch method. For both two sleep stages such as W and REM, the corresponding average normalized values of power spectral density of both EMG1-EMG2 and ECG1-ECG2 channels in bruxism patients and normal subjects were fed into the classifier of decision tree (DT) for identification of sleep bruxism. With the proposed approach by combing the signals of EMG1-EMG2 and ECG1-ECG2, the more affected stages of sleep during various disease conditions could be identified more accurately.

II. SUBJECT AND METHODOLOGY

In the present work, the following methods have been proposed for the prognosis of bruxism such as the data collection, analysis of the EEG signal, extraction of the EMG1-EMG2 and ECG1-ECG2 channels, calculation of the normalized values of the power spectral density, and the comparative analysis of bruxism patients and normal subjects with the DT classifier, as shown in Fig. 1. The details of methodologies including low pass filter, hamming window, and power spectral density estimation by the Welch method are explained as following.

A. DATA COLLECTION

The EEG data was collected from bruxism patients and healthy individuals from the CAP sleep database of physionet, which offers a free data web-access for collections of recorded physiologic signals Physio Bank, and related open-source software Physio Toolkit [33]. The waveform of CAP sleep database of physionet include at least EEG channels, EOG, EMG of the submentalis muscle, bilateral anterior tibial EMG, respiration signals and ECG [34]. Previously, Hassan *et al.* employed the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) method for automatic sleep staging. They carried experiments using Sleep-EDF database of physionet. Their proposed scheme gives high detection accuracy for sleep stages S1 and REM [35]. The REM and W stage is very helpful in the accuracy of the system [36]–[38]. In this work, a total number of 244 one-minute EEG recordings from two bruxism patients and seven normal subjects were collected, as shown in Table 1. The ages of subjects were 23-42 for normal subjects and 23-34 for bruxism patients, respectively. Importantly, two channels of EEG recordings such as the EMG1-EMG2 channel and the ECG1-ECG2 channel and two sleep stages such as the REM and the W were exacted

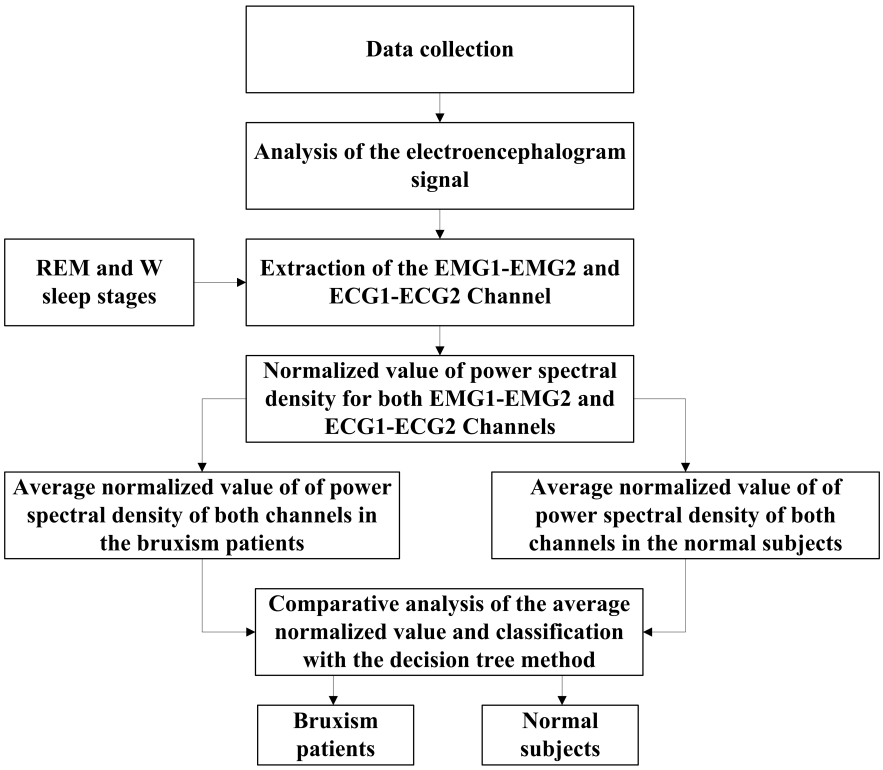


FIGURE 1. Block diagram of the current research work for the prognosis of the bruxism. The two channels of the EEG signal such as EMG1-EMG2 and ECG1-ECG2 used in the current work.

and analyzed. Noted that all of bruxism patients' data in the CAP sleep database was collected in this work, including 96 one-minute segments at REM stage and 53 one-minute segments at W stage. A total of 7 normal subjects were randomly selected from 16 subjects of the CAP sleep database. For each of normal subject, 7 one-minutes segments and 5-7 one-minutes segments were collected randomly during the REM stage and the W stage respectively. The different channel allocation for the EMG1-EMG2 channel and the ECG1-ECG2 channel, there are a total of 149 and 95 EEG recordings collected from the REM and W sleep stages in bruxism patients and normal subjects, respectively (Table 1).

B. LOW PASS FILTER

The low pass filter passes the low frequency signals, and blocks the high frequency signals. The low pass filters can be designed either using resister with inductor or resister with capacitor. Both the models are used for passing low frequency and blocking the high frequency [33]. The low pass finite impulse response (FIR) filters [39] were used for this purpose, which is used for finite duration and operated in the discrete time signal. The filtering was done to overcome aliasing effect in the EEG signals [40]. The other purpose of using filter is to remove undesirable oscillations that are not part of EEG signal [41]. The window based linear phase low pass FIR filter of cut off frequency of 25 Hz were used in this study [11]. This window based linear phase low pass FIR filter has been normalized to obtain a magnitude response with pass band center frequency of zero dB [42]. The low pass FIR filter used in this work is present by equations (1).

$$y(n) = \sum_{k=0}^{M} b_k x(n-k) \tag{1}$$

where y (n) is the output signal, M is the order of the filter, b_k is the value of the response for $0 \leq k \leq M$ and x (n-k) is the unit delay of the signal.

C. HAMMING WINDOW

The Hamming window technique was applied on the collected EEG signals in this work to reduce the side lobe compared to the main lobe. Richard W. Hamming discovered hamming window techniques [7], [43], [44]. It was recommended for smoothing the truncated auto covariance function in the time domain. In place of each constants being same to half within the hanning window. The constant approximations of values ($\alpha = 25/46$) and ($\beta = 21/46$), which cancel the primary aspect-lobe of the hanning window by means of putting a zero at frequency ($5\pi/(N-1)$). Approximation of the constants to two decimal locations notably lowers the extent of side-lobes, to a nearly equal ripple condition. Inside the equal ripple sense, the most reliable values for the coefficients are $\alpha = 0.53836$ and $\beta = 0.46164$. The zero segment

TABLE 1. Experimental data set details.

Subject Name	Sleep Stages	No. of Segments	Allocation of the EMG Channel	Allocation of the ECG Channel
Bruxism 01	REM	30	15	16
	W	13	15	16
Bruxism 02	REM	66	15	16
	W	40	15	16
Normal 01	REM	07	12	13
	W	05	12	13
Normal 02	REM	07	07	08
	W	07	07	08
Normal 03	REM	07	15	16
	W	07	15	16
Normal 06	REM	07	03	06
	W	07	03	06
Normal 07	REM	07	03	06
	W	07	03	06
Normal 10	REM	07	15	16
	W	07	15	16
Normal 11	REM	07	15	16
	W	06	15	16

models are explained by equations (2) and (3), respectively.

$$w(n) = \alpha - \beta \cos\left(\frac{2\pi n}{N}\right) \tag{2}$$

where $\alpha = 0.54$, and $\beta = 1 - \alpha = 0.46$

$$w_h(n) = 0.54 - 0.46 \cos\left(\frac{2\pi n}{N}\right) \tag{3}$$

where $w_h(n)$ is hamming window, N is the number of samples each frame and n is the real number.

D. WELCH METHOD

P.D. Welch describes the Welch technique for the estimation of power spectral density [45]. It is way to evaluate the control phantom thickness. This strategy is utilized as a part of assessing the intensity of a signal at various frequencies. The average periodogram tends to decrease the variance, and to estimate relative to a single periodogram of the entire data. Although overlap between segments introduces redundant information, this effect is diminished by the use of a non-rectangular window. The combined use of short data records and nonrectangular windows results in reduced resolution of the estimator [46]. There is a tradeoff between variance reduction and resolution. One can manipulate the parameters in Welch's method to obtain improved estimates relative to the periodogram, especially when the signal to noise ratio is low [47]. Equations (4), (5), and (6) can estimate the periodogram spectral.

$$P_{SM}^{(i)}(f) = \frac{1}{LU} \sum_{n=0}^{L-1} \left| w_h(n)\, x(n + iD)\, e^{-j2\pi fn} \right|^2 \tag{4}$$

$$U = \frac{1}{L} \sum_{n=0}^{L-1} |w_h(n)|^2 \tag{5}$$

$$P_{SW}(f) = \frac{1}{K} \sum_{i=0}^{K-1} P_{SM}^{(i)}(f) \tag{6}$$

The periodogram of the each segment windowed is proportional to the square of the Fourier transform of the signal.

$$P_{sw}(f) = \gamma \sum_{m=0}^{K-1} [\{X_a^m\}^2 + \{X_b^m\}^2] \tag{7}$$

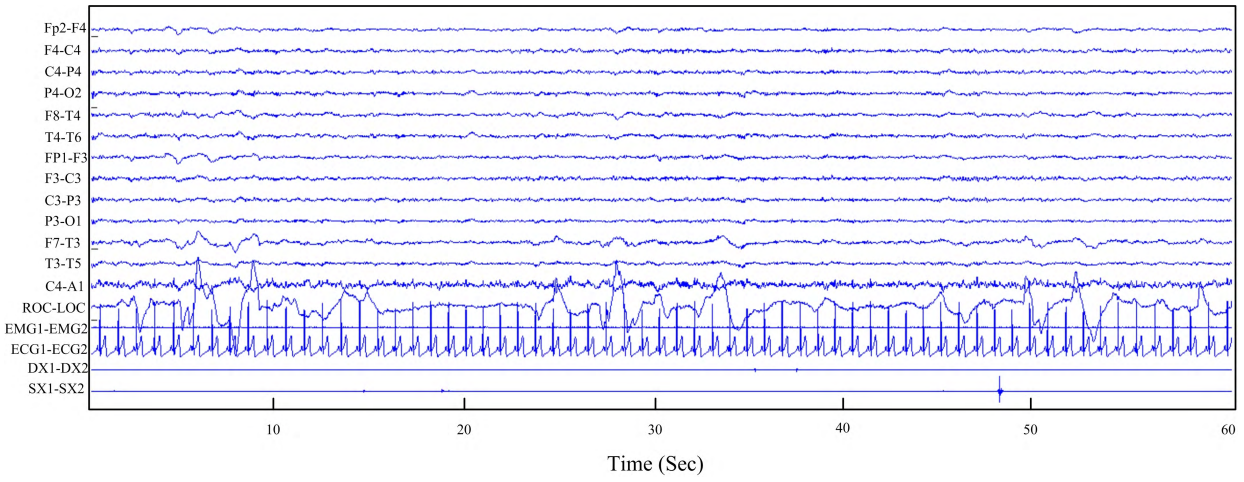


FIGURE 2. An example of one-minute segment of the EEG recording with 18 channels in the bruxism patients during the rapid eye movement (REM) stage. Noted that each of channel is shown as relative amplitude for a better overview of all channels, where the amplitude of the channel of ECG1-ECG2 is shown in 1/5 of that of raw data, while the others channels is illustrated the raw data such as Fp2-F4, F4-C4, C4-P4, P4-O2, F8-T4, T4-T6, FP1-FP3, F3-C3, C3-P3, P3-O1, F7-T3, T3-T5, C4-A1, ROC-LOC, EMG1-EMG2, DX1-DX2, and SX1-SX2. The absolute value of amplitude of each channel was given in [33].

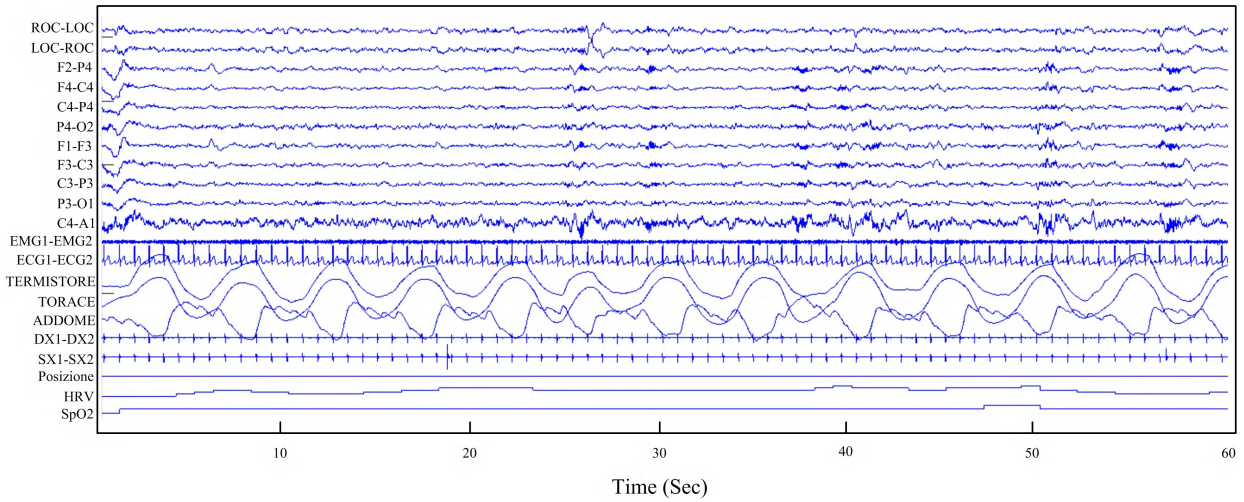


FIGURE 3. An example of one-minute segment of the EEG recording with 21 channels in the EEG signals of the normal subjects. Noted that each of channel is shown as relative amplitude for a better overview of all channels except the HRV in beat per minute and SpO2 in %, where the amplitude of the channel of ECG1-ECG2 is shown in 1/5 of that of raw data, while the others channels is illustrated the raw data such as ROC-LOC, LOC-ROC, F2-F4, F4-C4, C4-P4, P4-O2, F1-F3, F3-C3, C3-P3, P3-O1, C4-A1, TERMISTORE, TORACE, ADDOME, Dx1-Dx2, SX1-SX2, and Posizione. The absolute value of amplitude of each channel was given in [33].

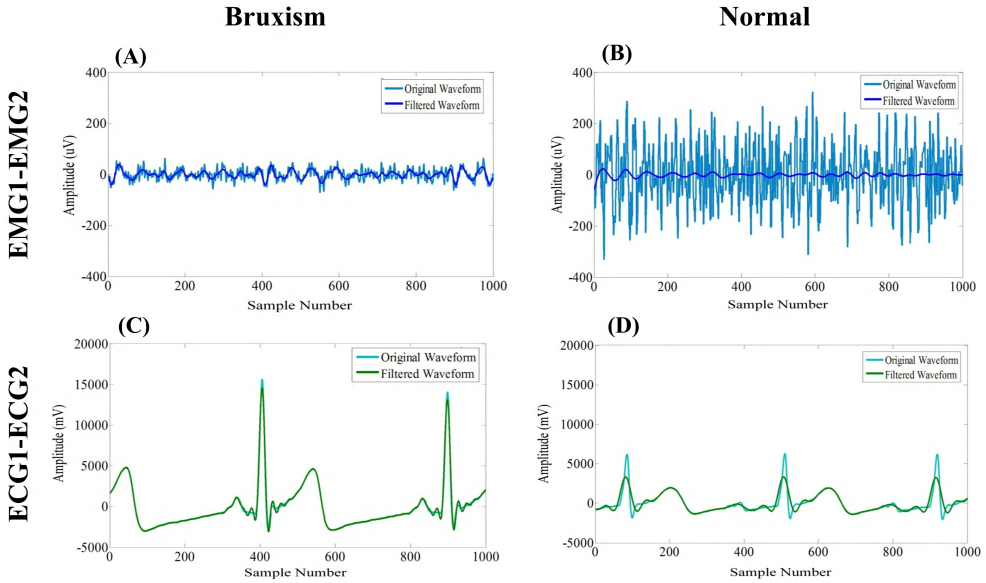


FIGURE 4. The comparative analysis of original and filtered channels of EMG1-EMG2 in (A) bruxism patients and (B) normal subjects. The comparative analysis of original and filtered channels of ECG1-ECG2 in (C) bruxism patients and (D) normal subjects. The original waveform is in blue color and the filtered waveform is in green color.

where $\gamma = \frac{1}{KLU}$ is constant, X_a^m and X_b^m are real and imaginary parts, respectively of Fourier transform for the m^{th} segment and LD is the data of segment.

E. DECISION TREE CLASSIFIER

Furthermore, the classifier of DT [48] is used to distinguish between the normal subject and Bruxism patients in this work. The decision tree classification algorithm is an instance-based induction learning method, which can extract the tree classification model from a given disordered training sample. The decision tree classification algorithm is relatively simple.

III. RESULTS

A. ANALYSIS OF THE EEG SIGNAL

The total number of EEG channels of bruxism patients and normal subjects were eighteen and twenty-one, respectively. Specifically, the EEG signals of bruxism patients were found to have various channels such as Fp2-F4, F4-C4, C4-P4, P4-O2, F8-T4, T4-T6, FP1-FP3, F3-C3, C3-P3, P3-O1, F7-T3, T3-T5, C4-A1, ROC-LOC, EMG1-EMG2, ECG1-ECG2, DX1-DX2, and SX1-SX2 channel, as shown in Fig. 2. And, the EEG signals of normal subject have ROC-LOC, LOC-ROC, F2-F4, F4-C4, C4-P4, P4-O2, F1-F3, F3-C3, C3-P3, P3-O1, C4-A1, EMG1-EMG2, ECG1-ECG2,

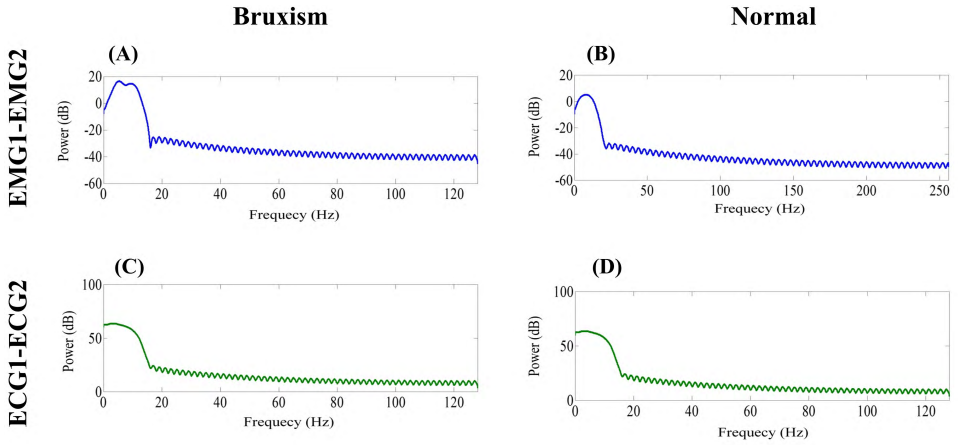


FIGURE 5. The estimation of the power spectral density using welch method for EMG1-EMG2 channels in (A) bruxism patients and (B) normal subjects. The estimation of the power spectral density using welch method for ECG1-ECG2 channels in (C) bruxism patients and (D) normal subjects. This method converts the time domain signal into the frequency domain spectrum.

TERMISTORE, TORACE, ADDOME, Dx1-Dx2, SX1-SX2, Posizione, HR and SpO2 channel, as shown in Fig. 3. Noted that each of channel is shown as relative amplitude for a better overview of all channels, where the amplitude of the channel of ECG1-ECG2 is shown in 1/5 of that of raw data, the HRV in beat per minute and SpO2 in %, while the others channels is illustrated the raw data. The absolute value of amplitude of each channel was given in [33].

In this work, both channel of the EMG1-EMG2 and the ECG1-ECG2 were extracted from EEG recordings for the bruxism patients and normal subjects, as shown in Fig. 4. As shown in Fig. 4, both the filtered EMG1-EMG2 and ECG1-ECG2 channels in the bruxism patients and normal subjects were compared with their corresponding original signals, respectively. The low pass filter of hamming window with the cutoff frequency 25 Hz shows a good capability with less noisy, which passed both the EMG1-EMG2 and ECG1-ECG2 channels of the bruxism patients and normal subjects, and simultaneously blocked the high frequency of the EEG signal. Moreover, the estimation of the power spectral density of the bruxism patients and normal subjects of the EMG1-EMG2 and ECG1-ECG2 channel of the EEG signal were performed by the Welch methods, which converts the signal from time domain into the frequency domain. This method was used for the estimation of the power signal at different frequencies in this study, as shown in Fig. 5.

B. NORMALIZED POWER OF THE EMG1-EMG2 AND ECG1-ECG2 CHANNELS

The normalized power specifies the percentage of a particular EEG activity out of whole power. It gives a better indication of measurements of prognostic of features instead of taking average power of specific EEG activity [49]. The comparative analysis of the average normalized values of the EMG1-EMG2 and ECG1-ECG2 channels for the bruxism patients and normal subjects in the REM and W sleep stages were presented in Table 2. The normalized value of bruxism

TABLE 2. Comparison between bruxism and normal human for the EMG1-EMG2 and ECG1-ECG2 channels.

EEG Channels	Sleep Stage	Subject	Normalized Value		Average of the Normalized Value
			max	min	
EMG1-EMG2	REM	Bruxism	0.9770	0.9082	0.9404
		Normal	0.9472	0.7727	0.8893
	W	Bruxism	0.9820	0.5906	0.8904
		Normal	0.9696	0.7293	0.8836
ECG1-ECG2	REM	Bruxism	0.7159	0.4239	0.5612
		Normal	0.7649	0.3341	0.5420
	W	Bruxism	0.6346	0.4924	0.5758
		Normal	0.7579	0.2797	0.5467

patients and normal subjects of EMG1-EMG2 channel for the REM sleep stage are in the range of 0.9082-0.9770 and 0.7727-0.9472, respectively. While, the normalized value of bruxism patients and normal subjects in the W sleep stage are in the range of 0.5906-0.9820, and 0.7293-0.9696, respectively. It has been found that the average normalized values of the EMG1-EMG2 channel for bruxism patients and normal subjects during REM were 0.9404 and 0.8893, respectively. While, average normalized values of the bruxism patients and normal subjects during W stage were found to be 0.8904 and 0.8836, respectively.

Furthermore, The normalized value of bruxism patients and normal subjects for the ECG1-ECG2 channels in the REM sleep stage are in the range of 0.4239-0.7159 and 0.3341-0.7649, respectively. While, the normalized value of bruxism patients and normal subjects in the W sleep stage are in the range of 0.4924-0.6346, and 0.2797-0.7579, respectively. It has been found that the average normalized values of the ECG1-ECG2 channel for bruxism patients and normal

TABLE 3. Performance of the proposed work by using the decision tree classifier.

Testing Fold	EMG1-EMG2 Channel of the W and REM Sleep Stages			ECG1-ECG2 Channel of the W and REM Sleep Stages			Combination of the EMG-EMG2 and ECG1-ECG2 Channels in the W and REM Sleep Stages		
	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy
1	88.61%	95.35%	90.98%	94.67%	91.49%	93.44%	98.65%	97.92%	98.36%
2	94.29%	84.62%	90.16%	93.24%	91.67%	92.62%	94.67%	97.87%	95.90%
3	98.63%	95.92%	97.54%	98.65%	91.49%	95.08%	97.40%	97.78%	97.54%
4	94.74%	93.48%	94.26%	96.25%	100.0%	94.26%	97.33%	100.0%	96.72%
5	97.40%	91.11%	95.08%	89.61%	97.78%	92.62%	96.10%	100.0%	97.54%
Mean ± Standard	94.734% ± 3.463%	92.096% ± 4.098%	93.604% ± 2.714%	94.484% ± 3.026%	94.486% ± 3.664%	93.604% ± 0.956%	96.830% ± 1.348%	98.714% ± 1.050%	97.212% ± 0.836%

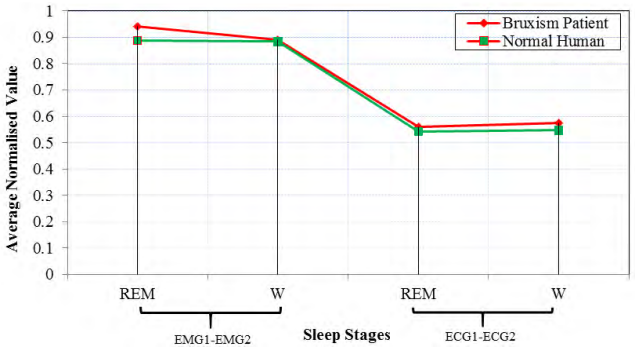


FIGURE 6. The comparison of the average normalized values of power spectrum density between in bruxism patients and normal subjects for the EMG1-EMG2 and ECG1-ECG2 channels, respectively. The value of the estimated power spectral density in the bruxism is higher than that in the normal during both sleep stages such as the REM and the W.

human during REM were 0.5612 and 0.5420, respectively. While, the average normalized values for bruxism patients and normal subjects during the W stage were found to be 0.5758 and 0.5467, respectively.

In summary, the calculated average normalized value of the power spectral density in normal subjects is smaller than that of bruxism patients in both EMG1-EMG2 and ECG1-ECG2 channels, as illustrated in Fig. 6.

C. CLASSIFICATION AND EVALUATION OF THE PERFORMANCE OF THE PROPOSED METHOD

In this work, the classifier of DT are used to distinguish between the normal subjects and bruxism patients, where 149 EEG recordings from the bruxism patient and 95 EEG recordings from the normal subjects were extracted at both channels of EMG1-EMG2 and ECG1-ECG2. To train and test the proposed DT model, 5-fold cross validation was employed in this study. All data was random divided into 5 subsets, each time 4 subsets were used for training the DT model and the remaining one subset was used for test. The evaluation of classification is processed in three conditions (ECG1-ECG2, EMG1-EMG2, and the combination of ECG1-ECG2 and EMG1-EMG2 channels) with the same process. Moreover, the performance of the proposed method for prognosis of bruxism was evaluated by specificity, sensitivity, and accuracy, which are computed by following equations below:

$$\text{Sensivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{8}$$

$$\text{Specifity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{9}$$

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{TP} + \text{FP} + \text{FN}} \tag{10}$$

where, TP is the true positive, TN is the true negative, FP is the false positive and FN is the false negative. As a result, five models were obtained in this work and the performance of the proposed method could be determined by the average performance of the five DTs models, as shown in Table 3.

IV. DISCUSSION AND CONCLUSION

Previously, sleep disorder from normal and affected person using time frequency analysis of power spectral density approach applied on EEG signals using right of central – left of central (ROC-LOC) channels were applied. The analysis and calculation were performed in all stages of sleep of power spectral density of each EEG segment. The results indicated the possibility of recognizing insomnia events based on delta, theta, alpha and beta segments of EEG signals [11]. Fulgencio *et al.* [4] presented that the prognosis of bruxism based on the Poisson regression with robust variance and chi square test. Barbosa *et al.* [25] presented that portable single channel EMG device were able to detect bruxism by the gold standard criteria method. A further clarification and comparative analysis on sleep bruxism between patients and normal human are required for better analysis. In the present work, 244 one-minutes EEG recordings were collected from two bruxism patients and seven normal subjects from CAP sleep database, and a power spectrum density based approach by using the DT classifier for prognosis of sleep bruxism were presented. We have calculated normalized value of power spectral density both of the EMG1-EMG2 and ECG1-ECG2 channels recorded in patients and normal subjects during the REM and W sleep stages. The average normalized values of the normal human are lower than bruxism patient

in the EMG1-EMG2 and ECG1-ECG2 channels. Moreover, the performance of the proposed approach for distinguishing between the bruxism patients and normal subject was evaluated and presented.

In the present work, we have developed a prognosis system of the bruxism using the channel EMG1-EMG2 and the channel ECG1-ECG2 of EEG signal. A total number of EEG channels of bruxism patients and normal subjects obtained were eighteen and twenty-one, respectively. The obtained average normalized values of the power spectral density of bruxism patients were higher than that of normal subjects in both the channel of EMG1-EMG2 and ECG1-ECG2. The EMG1-EMG2 and ECG1-ECG2 channels during REM and W sleep stages of the bruxism are several folds higher than those of the normal as indicated in Fig. 6. In this method, the hamming window was helpful in the accuracy of the system as it has negligible noise. The proposed method in the prognosis of the bruxism has taken very less time as compared with the traditional systems. Importantly, comprised with the accuracy of 62.20% reported in the previous work on prognosis of sleep bruxism [50], the proposed PSD based approach by using the DT classifier shows a higher accuracy of 97.212%. Specifically, the obtained sensitivity, specificity and accuracy of the EMG1-EMG2 channel are 94.734%, 92.096% and 93.604%, respectively. Meanwhile, the obtained sensitivity, specificity and accuracy of the ECG1-ECG2 channels are 94.484%, 94.486% and 93.604%, respectively. Importantly, the obtained sensitivity, specificity and accuracy for the combination of the both EMG1-EMG2 and ECG1-ECG2 channels are 96.830%, 98.714% and 97.212%, respectively, which present a higher accuracy as compared with either the EMG1-EMG2 or ECG1-ECG2. The reason of the proposed method providing a better performance could be addressed as that the sleep stage REM is more affected than the sleep stage W in EMG1-EMG2 channel, and the sleep stage W is more affected than the REM stage in ECG1-ECG2 channel [24], [25].

The present work showed potential applications in the prognosis of bruxism by using the EMG1-EMG2 and ECG1-ECG2 channel of the EEG signal. The research work would provide a fast and effective prognosis system of the human bruxism with high accuracy for medical applications, especially for the more affected stages of sleep during various disease conditions. The main application of the current research is to diagnose the psychological patients in short time with high accuracy.

The present work has certain limitations that the data from the PhysioNet database used in this paper was relatively small for statistical evaluation. Further work could be required to collect a great number of clinical data to evaluate the proposed approach for a higher accuracy. Another limitation includes the careful interpretations of results from EEG recording, since EMG1-EMG2 and ECG1-ECG2 channels of the EEG signal were not be able to monitor the all signals of the brain. Additionally, the third limitations are related to filter used in this work. The low pass FIR filter were used for finite range. In order to design a better filter, both the finite impulse response (FIR) and the infinite impulse response (IIR) in the same time should be implemented in both continuous and discrete time signals.

ABBREVIATIONS

Continuous Positive Airway Pressure (CPAP); Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN); Decision Tree (DT); Electroencephalogram (EEG); Electrocardiogram (ECG); Electromyogram (EMG); Finite Impulse Response (FIR); Infinite Impulse Response (IIR); Non Rapid Eye Movement (NREM); Nocturnal Frontal Lobe Epilepsy (NFLE); Power Spectral Density (PSD); Rapid Eye Movement (REM); Proton Pump Inhibitor (PPI); REM Behavioral Disorder (RBD); Sleep Bruxism (SB); Spatial Temporal Electroencephalogram and Functional magnetic resonance imaging Fusion (STEFF).

ACKNOWLEDGEMENTS

The authors are grateful to Xinyue Zhang, Xinshu Zhang, Faiz ul Hassan and Pan Meng Li for assistance in data preprocessing and suggestive discussion of the research. The authors would like to acknowledge National Natural Science Foundation of China under grant 61771100. Authors also acknowledge Biomedical Imaging and Electrophysiology laboratory, University of Electronic Science and Technology of China or providing computational and biomedical equipment. *(Dakun Lai and Md Belal Bin Heyat contributed equally to this work.)*

REFERENCES

[1] N. Alperin, J. Wiltshire, S. H. Lee, A. R. Ramos, R. Hernandez-Cardenache, T. Rundek, R. C. Cid, and D. Loewenstein, "Effect of sleep quality on amnestic mild cognitive impairment vulnerable brain regions in cognitively normal elderly individuals," *Sleep*, vol. 42, no. 3, 2018, Art. no. zsy254.

[2] Y. M. Hasan, M. B. B. Heyat, M. M. Siddiqui, S. Azad, and F. Akhtar, "An overview of sleep and stages of sleep," *Int. J. Adv. Res. Comput. Commun. Eng.*, vol. 4, no. 12, pp. 505–507, Dec. 2015.

[3] C. T. Downs, A. Awuah, M. Jordaan, L. Magagula, T. Mkhize, C. Paine, E. Raymond-Bourret, and L. A. Hart, "Too hot to sleep? Sleep behaviour and surface body temperature of wahlberg's epauletted fruit bat," *PLoS One*, vol. 10, no. 3, 2015, Art. no. e0119419.

[4] L. B. Fulgencio, P. Corrêa-Faria, C. F. Lage, S. M. Paiva, I. A. Pordeus, and J. M. Serra-Negra, "Diagnosis of sleep bruxism can assist in the detection of cases of verbal school bullying and measure the life satisfaction of adolescents," *Int. J. Pediatric Dentistry*, vol. 27, no. 4, pp. 293–301, 2017.

[5] M. B. B. Heyat, F. Akhtar, and S. Azad, "Comparative analysis of original wave & ltered wave of EEG signal used in the detection of bruxism medical sleep syndrome," *Int. J. Trend Sci. Res. Develop.*, vol. 1, no. 1, pp. 7–9, Nov./Dec. 2016.

[6] M. B. B. Heyat, "Insomnia: Medical sleep disorder & diagnosis," Anchor Academic Publishing, Hamburg, Germany, Tech. Rep. V337729, 2016.

[7] M. B. B. Heyat, "Hamming window is used in the detection of insomnia medical sleep syndrome," in *Proc. Int. Seminar Present Scenario Future Prospectives Res. Eng. Sci. (ISPSFPRES)*. Lucknow, Uttar Pradesh: Integral Univ., 2017, pp. 65–71.

[8] M. B. B. Heyat, S. F. Akhtar, and S. Azad, "Power spectral density are used in the investigation of insomnia neurological disorder," in *Proc. Pre-Congr.Symp., Organized Indian Acad. Social Sci. (ISSA) King George Med. Univ. State Takmeelut-Tib College Hospital*, Lucknow, Uttar Pradesh, 2016, pp. 45–50.

[9] M. B. B. Heyat, F. Akhtar, A. Mehdi, S. Azad, A. B. Hayat, and S. Azad, "Normalized power are used in the diagnosis of insomnia medical sleep syndrome through EMG1-EMG2 channel," *Austin J. Sleep Disorders*, vol. 4, no. 1, pp. 1–3, 2017.

[10] M. B. B. Heyat and S. A. Siddiqui, "An overview of dalk therapy and treatment of insomnia by dalk therapy," Nat. Seminar Res. Methodol. Ilaj-Bit-Tadbeer, State Takmeel-ut-Tib-College & Hospital, Lucknow, India, Tech. Rep. 2, 2015.

[11] M. M. Siddiqui, G. Srivastava, and S. H. Saeed, "Diagnosis of insomnia sleep disorder using short time frequency analysis of PSD approach applied on EEG signal using channel ROC-LOC," *Sleep Sci.*, vol. 9, no. 3, pp. 186–191, 2016.

[12] O. Farooq, T. Rahman, M. B. B. Heyat, M. M. Siddiqui, and F. Akhtar, "An overview of NFLE," *Int. J. Innov. Res. Elect., Electron., Instrum. Control Eng.*, vol. 4, pp. 209–211, Mar. 2016.

[13] T. Rahman, O. Farook, B. B. Heyat, and M. M. Siddiqui, "An overview of narcolepsy," *Int. Adv. Res. J. Sci., Eng. Technol.*, vol. 3, no. 3, pp. 85–87, 2016.

[14] S. N. Archer and H. Oster, "How sleep and wakefulness influence circadian rhythmicity: Effects of insufficient and mistimed sleep on the animal and human transcriptome," *J. Sleep Res.*, vol. 24, no. 5, pp. 476–493, 2015.

[15] E. Bertazzo-Silveira, C. M. Kruger, I. P. De Toledo, A. L. Porporatti, B. Dick, C. Flores-Mir, and G. De Luca Canto, "Association between sleep bruxism and alcohol, caffeine, tobacco, and drug abuse: A systematic review," *J. Amer. Dental Assoc.*, vol. 147, no. 11, pp. e4-859–e4-866, 2016.

[16] R. A. Basson, K. Mwaba, R. J. Rossouw, G. A. Geerts, T. J. Kotze, and M. E. Stuhlinger, "The significance of sub-threshold symptoms of anxiety in the aetiology of bruxism," *South Afr. J. Psychol.*, vol. 40, no. 2, pp. 174–181, 2010.

[17] T. Mathew, S. Venkatesh, and M. Srinivas, "The approach and management of bruxism in Alzheimer's disease: An under-recognized habit that concerns caregivers (innovative practice)," *Dementia*, pp. 1–3, Feb. 2017, Art. no. 1471301217694249.

[18] H. Ohmure, K. Kanematsu-Hashimoto, K. Nagayama, H. Taguchi, A. Ido, K. Tominaga, T. Arakawa, and S. Miyawaki, "Evaluation of a proton pump inhibitor for sleep bruxism: A randomized clinical trial," *J. Dental Res.*, vol. 95, no. 13, pp. 1479–1486, 2016.

[19] G. J. Lavigne and B. J. Sessle, "The neurobiology of orofacial pain and sleep and their interactions," *J. Dental Res.*, vol. 95, no. 10, pp. 1109–1116, 2016.

[20] L. B. Fulgencio, P. Corrêa-Faria, C. F. Lage, S. M. Paiva, I. A. Pordeus, and J. M. Serra-Negra, "Diagnosis of sleep bruxism can assist in the detection of cases of verbal school bullying and measure the life satisfaction of adolescents," *Int. J. Pediatric Dentistry*, vol. 27, no. 4, pp. 293–301, 2017.

[21] C. Geyer, "In search of a good night's sleep: Hormones, mind, movement, and breath," *Amer. J. Lifestyle Med.*, vol. 12, no. 2, pp. 120–123, 2017.

[22] M. B. B. Heyat and M. M. Siddiqui, "Recording of EEG, ECG, EMG signal," *Int. J. Adv. Res. Comput. Sci. Softw. Eng.*, vol. 5, no. 10, pp. 813–815, 2015.

[23] U. Lee and H. Shin, "Study on compressed sensing of ECG/EMG/EEG signals for low power wireless biopotential signal monitoring," *J. Inst. Electron. Inf. Eng.*, vol. 52, no. 3, pp. 89–95, 2015.

[24] P. K. Stein and Y. Pu, "Heart rate variability, sleep and sleep disorders," *Sleep Med. Rev.*, vol. 16, no. 1, pp. 47–66, 2012.

[25] J. Stuginski-Barbosa, A. L. Porporatti, Y. M. Costa, P. Svensson, P. César, and R. Conti, "Diagnostic validity of the use of a portable single-channel electromyography device for sleep bruxism," *Sleep Breathing*, vol. 20, no. 2, pp. 695–702, 2016.

[26] A. R. Hassan and A. Subasi, "A decision support system for automated identification of sleep stages from single-channel EEG signals," *Knowl.-Based Syst.*, vol. 128, pp. 115–124, Jul. 2017.

[27] X. Lei, C. Qiu, P. Xu, and D. Yao, "A parallel framework for simultaneous EEG/fMRI analysis: Methodology and simulation," *NeuroImage*, vol. 52, no. 3, pp. 1123–1134, 2010.

[28] D. Wang, D. Ren, K. Li, Y. Feng, D. Ma, X. Yan, and G. Wang, "Epileptic seizure detection in long-term EEG recordings by using wavelet-based directed transfer function," *IEEE Trans. Biomed. Eng.*, vol. 65, no. 11, pp. 2591–2599, Nov. 2018.

[29] G. Wang, D. Ren, K. Li, D. Wang, M. Wang, and X. Yan, "EEG-based detection of epileptic seizures through the use of a directed transfer function method," *IEEE Access*, vol. 6, pp. 47189–47198, 2018.

[30] G. Wang, Z. Sun, R. Tao, K. Li, G. Bao, and X. Yan, "Epileptic seizure detection based on partial directed coherence analysis," *IEEE J. Biomed. Health Inform.*, vol. 20, no. 3, pp. 873–879, May 2016.

[31] G. Wang, C. Teng, K. Li, Z. Zhang, and X. Yan, "The removal of EOG artifacts from EEG signals using independent component analysis and multivariate empirical mode decomposition," *IEEE J. Biomed. Health Inform.*, vol. 20, no. 5, pp. 1301–1308, Sep. 2016.

[32] G. Wang and D. Ren, "Effect of brain-to-skull conductivity ratio on EEG source localization accuracy," *BioMed Res. Int.*, vol. 2013, Mar. 2013, Art. no. 459346.

[33] A. L. Goldberger, L. A. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, 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, 2000.

[34] M. G. Terzano, L. Parrino, A. Sherieri, R. Chervin, S. Chokroverty, C. Guilleminault, M. Hirshkowitz, M. Mahowald, H. Moldofsky, A. Rosa, R. Thomas, and A. Walters, "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, Nov. 2001.

[35] A. R. Hassan and M. I. H. Bhuiyan, "Computer-aided sleep staging using complete ensemble empirical mode decomposition with adaptive noise and bootstrap aggregating," *Biomed. Signal Process. Control*, vol. 24, pp. 1–10, Feb. 2016.

[36] A. R. Hassan and M. I. H. Bhuiyan, "An automated method for sleep staging from EEG signals using normal inverse Gaussian parameters and adaptive boosting," *Neurocomputing*, vol. 219, pp. 76–87, Jan. 2017.

[37] A. R. Hassan and M. I. H. Bhuiyan, "A decision support system for automatic sleep staging from EEG signals using tunable Q-factor wavelet transform and spectral features," *J. Neurosci. Methods*, vol. 271, pp. 107–118, Sep. 2016.

[38] A. R. Hassan, M. Imamul, and M. Bhuiyan, "Automated identification of sleep states from EEG signals by means of ensemble empirical mode decomposition and random under sampling boosting," *Comput. Methods Programs Biomed.*, vol. 140, pp. 201–210, Mar. 2017.

[39] D. Ahn, J. S. Park, C. S. Kim, J. Kim, Y. Qian, and T. Itoh, "A design of the low-pass filter using the novel microstrip defected ground structure," *IEEE Trans. Microw. Theory Techn.*, vol. 49, no. 1, pp. 86–93, Jan. 2001.

[40] A. Chandra and S. Chattopadhyay, "A novel approach for coefficient quantization of low-pass finite impulse response filter using differential evolution algorithm," *Signal, Image Video Process.*, vol. 8, no. 7, pp. 1307–1321, 2012.

[41] X. Qian, Y. P. Xu, and X. Li, "A CMOS continuous-time low-pass notch filter for EEG systems," *Analog Integr. Circuits Signal Process.*, vol. 44, no. 3, pp. 231–238, Sep. 2005.

[42] M. Teplan, "Fundamentals of EEG measurement," *Meas. Sci. Technol.*, vol. 2, no. 2, pp. 1–11, 2002.

[43] M. O. T. Cole, "A class of low-pass FIR input shaping filters achieving exact residual vibration cancelation," *Automatica*, vol. 48, no. 9, pp. 2377–2380, 2012.

[44] A. Basit, I. M. Qureshi, W. Khan, S. U. Rehman, and M. M. Khan, "Beam pattern synthesis for an FDA radar with Hamming window-based nonuniform frequency offset," *IEEE Antennas Wireless Propag. Lett.*, vol. 16, pp. 2283–2286, 2017.

[45] S. Zhang, "Signal-processing apparatus with a filter of flexible window design," U.S. Patent 6 707 869 B1, Mar. 16, 2004.

[46] M. Aboy, O. W. Marquez, J. McNames, R. Hornero, T. Trong, and B. Goldstein, "Adaptive modeling and spectral estimation of nonstationary biomedical signals based on Kalman filtering," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 8, pp. 1485–1489, Aug. 2005.

[47] K. Umebayashi, K. Moriwaki, R. Mizuchi, H. Iwata, S. Tiiro, J. J. Lehtomäki, M. López-Benítez, and Y. Suzuki, "Simple primary user signal area estimation for spectrum measurement," *IEICE Trans. Commun.*, vol. E99.B, no. 2, pp. 523–532, 2016.

[48] J. R. Quinlan, "Simplifying decision trees," *Int. J. Man-Mach. Stud.*, vol. 27, no. 3, pp. 221–234, Sep. 1987.

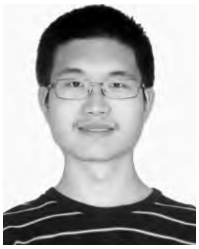
[49] X.-W. Zhu, S.-J. Zhang, and Q.-L. Liu, "Determination to the confidence level of PSD estimation with given D.O.F. based on WELCH algorithm," in *Proc. 4th Int. Conf. Inf. Technol. Manage. Innov.*, Moscow, Russia, 2015, pp. 617–622.

[50] T. Castroflorio, A. Bargellini, G. Rossini, G. Cugliari, A. Deregibus, and D. Manfredini, "Agreement between clinical and portable EMG/ECG diagnosis of sleep bruxism," *J. Oral Rehabil.*, vol. 42, no. 10, pp. 759–764, 2015.

DAKUN LAI (M'11) received the Ph.D. degree in biomedical engineering from Fudan University, Shanghai, China, in 2008. He received the three-year postdoctoral fellowship in biomedical engineering from the University of Minnesota, Minneapolis, MN, USA. Since 2012, he has been on the Faculty of the University of Electronic Science and Technology of China (UESTC), China, where he is appointed as an Associate Professor of electrical engineering and biomedical engineering and also the Director of the Biomedical Imaging and Electrophysiology Laboratory (BMI-EP). He is currently working in the field of cardiac arrhythmia, neurological disorder and sleep disorders. He has published more than 40 peer-reviewed papers in these areas. His current research interests include bioelectromagnetism, neuroengineering, and cardiac electrophysiology. He has pioneered the development of noninvasive cardiac electric source imaging, and made significant contributions to deep learning-based bioelectrical signal analysis, detection and prediction of severe cardiac arrhythmias and neuro disorder, and numerical modeling and simulation of bioelectromagnetism. He also serves as a Reviewer of several international journals.

MD BELAL BIN HEYAT received the B.Tech. degree in electronic and instrumentation and the M.Tech. degree in electronics circuit and system from Integral University, Lucknow, India, in 2014 and 2016, respectively. He is currently pursuing the Ph.D. degree with the University of Electronic Science and Technology of China (UESTC). His current research interest includes developing diagnosis systems of the neurological disorder and sleep disorders. He is an Editor and a Reviewer of several international journals.

FAEZ IQBAL KHAN received the B.Sc. and M.Sc. degrees in biomedical science and bioinformatics and the Ph.D. degree in computational chemistry in collaboration with the Department of Biotechnology and Food Technology, Durban University of Technology, South Africa, in 2015. He is currently a Postdoctoral Research Fellow, where he focuses on atrial fibrillation and other heart related diseases using both experimental and computational techniques.



YIFEI ZHANG received the B.S. degree in electronic information science and engineering from the University of Electronic Science and Technology of China (UESTC), Chengdu, China, in 2017, where he is currently pursuing the master's degree in electronic science and engineering. His current research interests include ventricular fibrillation and other malignant ventricular arrhythmia using machine learning.