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Sleep Bruxism Detection Using Decision Tree Method by the Combination of C4-P4 and C4-A1 Channels of Scalp EEG

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

Biomedical Imaging and Electrophysiology Laboratory, 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)

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ABSTRACT Lack of sleep causes many sleep disorders such as nocturnal frontal lobe epilepsy, narcolepsy, bruxism, sleep apnea, insomnia, periodic limb movement disorder, and rapid eye movement behavioral disorder. Out of all, bruxism is a common behavior, which is found in 8–31% of the population. Bruxism is a sleep disorder in which individuals involuntarily grinds and clenches the teeth. The main aim of this work is to detect sleep bruxism by analyzing the electroencephalogram (EEG) spectrum analysis of the change in the domain of different stages of sleep. The present research was performed in different stages such as collection of the data, preprocessing of the EEG signal, analysis of the C4-P4 and C4-A1 channels, comparison between healthy humans and bruxism patients, and classification using decision tree method. In this study, the channels C4-P4 and C4-A1 of the EEG signal were combined for the detection of bruxism by using Welch technique, which mainly focused on two sleep stages such as S1 and rapid eye movement. The total number of EEG channels of healthy humans and bruxism patients analyzed in this work were 15 and 18, respectively. The results showed that the individual accuracy of the C4-P4 and C4-A1 channels was 81.70% and 74.11%, respectively. The combined accuracy of both C4-P4 and C4-A1 channels was 81.25%. The specificity of combined result was higher than individual. In addition, the value of theta activity during detection is consistent throughout the period, and the accuracy of S1 stage is better than rapid eye movement stage. We proposed that the theta activity of S1 could be taken for the detection of bruxism. The proposed approach in the detection of the bruxism is negligible in noise 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 detection system of the sleep bruxism with high accuracy for medical big data applications.

INDEX TERMS Decision tree, machine learning classifier, neurological disorder, scalp EEG, sleep bruxism.

I. INTRODUCTION

Sleep has a crucial role in the life of zoological species such as animals, amphibians, birds, humans, mammals, and reptiles [1]. Some 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 one eye was closed discovered 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], rapid eye movement behavioral disorder (RBD) [11], nocturnal frontal lobe epilepsy (NFLE) [12], narcolepsy [13], and periodic limb movement disorder (PLMD). In addition, the lack of sleep also affects genes and proteins in human body [14]. It damages several organs including the heart, brain and other organs.

The main signs of the bruxism are flattened, fractured, chipped teeth, and fractured with worn tooth enamel exposing deeper layers of teeth. Other symptoms include Jaw, neck,

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face pain, and headache [5]. The bruxism is mainly found in male children. The factors that increase the risk of bruxism are smoking of tobacco, drinking of alcohol, and side effect of the psychiatric medicines [15]. Moreover, the bruxism was associated with some neurological disorders such as episodes of screaming, intense fear and flailing while still asleep, epileptic seizure, and sleep apnea. 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. The significance of subthreshold symptoms of anxiety in the etiology of bruxism were studied in details by Basson et al. [16]. Bruxism is an under-recognized cause of caregiver concern in patients with Alzheimer's disease [17]. The interhemispheric brain switching of sleep disordered breathing problem in obstructive sleep apnea patients were correlated by Li et al. [18]. The fuzzy entropy was used to estimate a laterality index from C3-A2 and C4-A1 EEG channels. They suggested that inter hemispheric asymmetry of brain activity is more obvious than healthy. Reducing orofacial pain and improving sleep may improve the patient's quality of life to promote healing and optimizing their health [19]. Furthermore, bruxism has been related to sleep disturbances as in case of migraine. 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 [20].

The bioelectrical signals generated from human body such as the electroencephalogram (EEG), the electromyogram (EMG), and the electrocardiogram (ECG) commonly used as beneficial tools for the brain, the muscles, and the heart, respectively [21]. Chai et al. studied that systematic method to select optimal EEG channels for three mental tasks-based brain-computer interface classifications [22]. It is used in different EEG channels such as C3, C4, P3, P4, O1, O2 to P3, O1, C4, O2, with O1 and C4 for the dominant features, which is referenced as the clinic standard 10-20 EEG recording system [23]. Chen et al. proposed the technique to achieve the muscular artifact cancellation for the single-channel EEG event [23]. It is design by the combination of the ensemble empirical mode decomposition and the joint blind source separation techniques. Kuriyama et al. studied a single channel snooze EEG for detection of major depressive syndrome [24]. Additionally, a decision support system for automated identification of sleep stages from single channel of EEG signals was proposed [25]. Similarly, a framework for the spatial temporal EEG and functional magnetic resonance imaging fusion (STEFF) were proposed [26]. Despite, they have low accuracy and poor diagnoses on the more affected stages of sleep during various disease conditions.

On the basis of the complex electrophysiological mechanism of sleep bruxism [27], a common limitation of individually using the above mentioned single EEG channel or recording electrodes far away from the corresponding brain area is that they may not provide a high enough sensitivity, specificity, or either both of them. Thus, our further hypothesis is that, if such channels reflect part of underlying physiological phenomena of jaw movements, they might add complementary information to each other. In the present study, a novel diagnostic system by combing the channels of the C4-P4 and the C4-A1 extracted from EEG signal is proposed to improve accuracy of the detection of bruxism. The combinations of these two channels were more informative and could cover more brain area related sleep bruxism. Specifically, The C electrodes in higher primates are near the central sulcus of the cerebral hemispheres, hence their name. The analogous structure in the domestic species, the cruciate sulcus, is much smaller, much more rostral and much closer to the frontal electrodes than to the C electrodes. The A electrodes deviate from standard terminology in that they are positioned in the low temporal region, rostral to the ear canal. The P electrodes were placed in parietal region of the brain [23], [28]. For distinguishing between sleep bruxism and health subject, the proposed work includes such four steps as below. Initially, both the C4-P4 and the C4-A1 were pre-processed by using a hamming window, followed by a low pass filter for the removal of noise in both healthy humans and bruxism patients. Second, the power spectral density for the both healthy humans and bruxism patients were estimated using the Welch method. Third, the corresponding average normalized values of both bruxism patients and health subjects in two sleep stages such as the S1 and the REM were fed into machine learning based classification for an automatic detection. The results suggested that the average normalized value of healthy humans is higher than bruxism patients in both channels (C4-P4 and C4-A1) of the theta activity. The REM stage is very easy to differentiate the healthy and bruxism. The generalized approach for detection of sleep bruxism is high beneficial. With the proposed approach by combing the signals of C4-P4 and C4-A1, the more affected stages of sleep during various disease conditions could be identified by using theta activity only. the trigeminal somatosensory evoked potential.

II. SUBJECT AND METHODOLOGY

In the present work, the methods proposed for the detection of bruxism are the data collection, preprocessing of the EEG signal, analysis of the C4-P4 and C4-A1 channels of the EEG signal, calculation of the normalized values, comparative analysis of healthy humans and bruxism patients, and classification of the system. The details of methodologies including low pass filter, hamming window, Welch method for the feature extraction and classification using decision tree method of the research are explained as following.

A. DATASET

The EEG data was collected from bruxism patients and healthy individuals from the cyclic alternating pattern (CAP) sleep database of physionet, which offers a free data access for collections of recorded brain signals physio bank, and related open-source software physio toolkit [29]. The waveform of CAP sleep database of physionet includes at least

TABLE 1. Dataset of the proposed work.

Name of the Subjects	Age of the Subjects (Years)	Sleep Stages	Time of the Data (Sec)	Location of the C4-P4 Channel	Location of the C4-A1 Channel
Bruxism Patient 01	34	S1	780	03	13
		REM	1800		
Bruxism Patient 02	23	S1	2400	03	13
		REM	3420		
Healthy Human 01	37	S1	600	05	11
		REM	300		
Healthy Human 02	34	S1	420	03	05
		REM	420		
Healthy Human 03	35	S1	420	03	13
		REM	420		
Healthy Human 04	25	S1	420	04	06
		REM	420		
Healthy Human 10	23	S1	420	03	13
		REM	420		
Healthy Human 11	28	S1	420	03	13
		REM	360		
Mean ± Standard Deviation	29.8 ± 5.39	-	840 ± 872.58	-	-

EEG, EMG, EOG, respiration signals and EKG [30]. Lai et al. used the physionet database for the prognosis of bruxism. Their proposed scheme gives high detection accuracy for sleep stages S1 and REM [31]. In this work, a total number of 224 EEG recordings from eight subjects of two sleep stages such as S1 and REM were collected. The S1 and REM stage is very helpful in the accuracy of the system [32]–[34]. The ages of subjects were 23-37 for healthy humans and 23-34 for bruxism patients (mean age ± standard deviation, 29.8 ± 5.39 year), respectively. The total 224 minutes data per channel (mean time ± standard deviation, 840 ± 872.58 sec) are used in the proposed research, as shown in Table 1. Importantly, the two channels of the EEG signal such as C4-P4 and C4-A1 and two sleep stages such as the S1 and the REM were exacted and analyzed.

B. PRE-PROCESSING OF THE EEG SIGNAL USING LOW PASS FINITE IMPULSE RESPONSE FILTER AND HAMMING WINDOW TECHNIQUE

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. The low pass finite impulse response (FIR) filters [35] 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 [36]. The other purpose of using filter is to remove undesirable oscillations that are not part of EEG signal [37]. The window based linear phase low pass FIR filter of cut off frequency of 25 Hz were used in this study [5]–[9], [11]. This window based linear phase low pass FIR filter has been normalized to obtain a magnitude response with pass band center frequency of 0 dB [38]. The low pass FIR 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.

The Hamming window technique was applied on the collected EEG signals in this work to reduce the side lobe compared to the main lobe. So less artificial long distance spread making the noise free result Richard W. Hamming discovered hamming window techniques [7], [39], [40]. 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 hann window. Approximation of the constants to two decimal locations notably lowers the extent of side-lobes, to a nearly equi-ripple condition. Inside the equi-ripple sense, the most reliable values for the coefficients are $\alpha = 0.53836$ and $\beta = 0.46164$. The zero segment 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 $\beta = 1 - \alpha = 0.46$

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

where, $w_{hc}(n)$ is hamming window, N is the number of samples each frame and n is the real number.

C. FEATURES EXTRACTION USING WELCH TECHNIQUE

The most important part of EEG signal processing is feature extraction. Welch techniques for the measurement of power spectral density were used for feature extraction of the EEG signal. The renowned scientists P.D. Welch discovered the Welch technique for the estimation of power spectral density of the signal [41]. 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 nonrectangular window. The combined use of short data records and nonrectangular windows results in reduced resolution of the estimator [42]. 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 [43]. Equations (4), (5), and (6) can estimate the periodogram spectral.

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

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

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

The discrete random vibration signals with length N are [x(0), x(1), x(2), x(3), …, x (N - 1)]. The segment i with length L data are $x_i(n) = x(n+iD)$. The equation (5) is power parameter factor of window function $w_{hc}(n)$ in order to ensure the estimation no bias intimately. The periodogram of the each segment windowed is proportional to the square of the Fourier transform of the signal.

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

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.

D. DECISION TREE (DT) CLASSIFIER

Moreover, the decision Trees are classifiers that offer interpretable results. Since training the algorithm and selecting the features are performed simultaneously, the DT method is characterized as an implanted method. The classifier of DT is used to distinguish between the normal human 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 [44], [45].

III. RESULTS

A. ANALYSIS OF THE EEG CHANNELS

The total number of EEG channels of healthy humans and bruxism patients were fifteen and eighteen, respectively. Specifically, the EEG signals of healthy humans have Fp2-F4, F4-C4, C4-P4, P4-O2, C4-A1, ROC-LOC, EMG1-EMG2, ECG1-ECG2, DX1-DX2, SX1-SX2, SAO2, HR, PLETH, STAT and MIC channel (Fig. 1(A)). Moreover, 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-F3, F3-C3, C3-P3, P3-O1, F7-T3, T3-T5, C4-A1, ROC-LOC, EMG1-EMG2, ECG1-ECG2, DX1-DX2, and SX1-SX2 channel (Fig. 1(B)). Additionally, the C4-P4 and C4-A1 channels extracted from EEG signal for the both healthy humans and bruxism patients (Fig. 1(C) and Fig. 1(D)), respectively. The healthy humans and bruxism patients for the C4-P4 and C4-A1 channels are represented by black and red color, respectively. As shown in Figs. 2 and 3, the low pass filter of hamming window with the cutoff frequency 25 Hz shows a good capability with less noise [4]–[8], which passed both the C4-P4 and C4-A1 channels of the healthy humans and bruxism patients, and simultaneously blocked the high frequency of the EEG signal. Moreover, the estimation of the power spectral density of the healthy humans and bruxism patients of the C4-P4 and C4-A1 channels 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 (Fig. 4).

B. NORMALIZED VALUES OF THE C4-P4 AND C4-A1 CHANNELS OF THE EEG SIGNAL

The normalized values specify the percentage of a particular EEG activity out of whole power. It gives a better indication of measurements of prognostic of features instead of

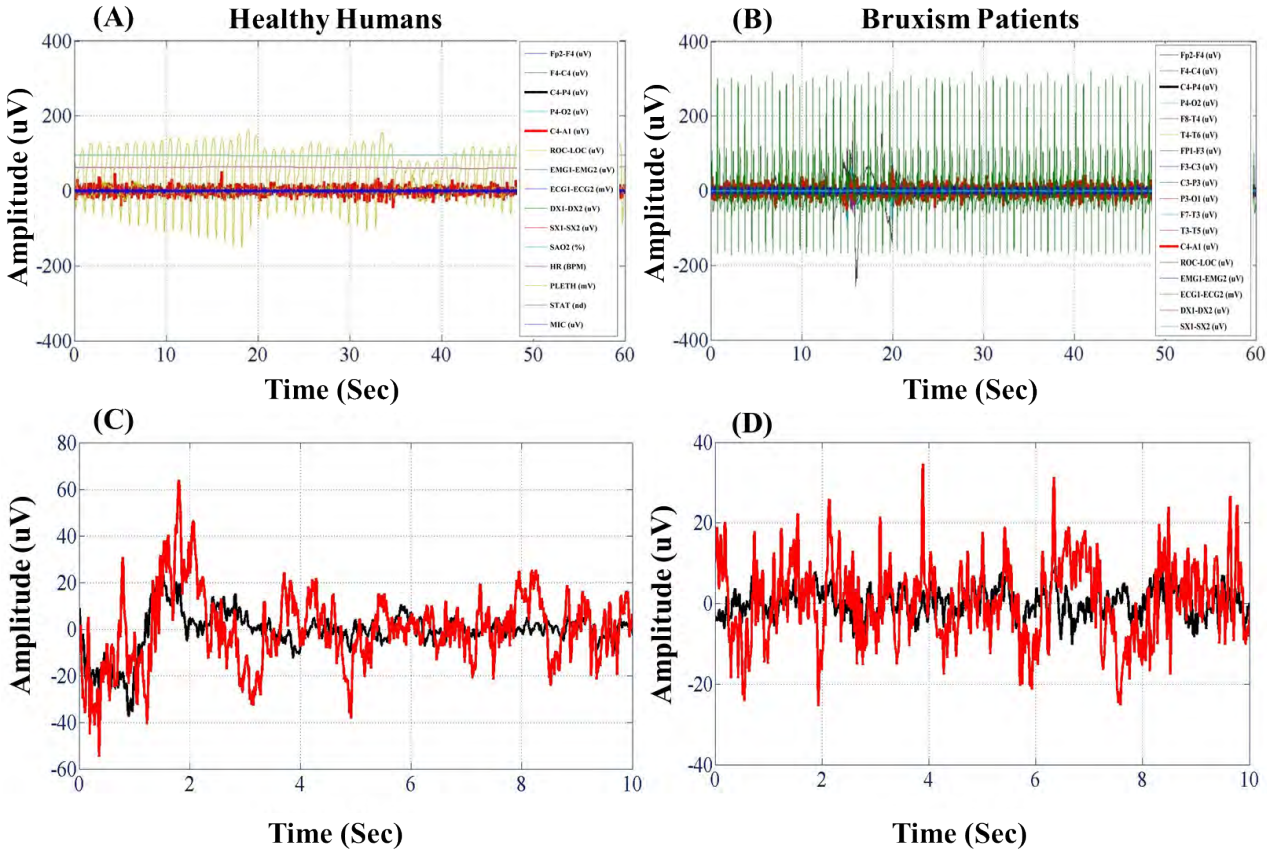

FIGURE 1. The EEG signals of the healthy humans and bruxism patients. (A) The EEG channels of the healthy humans are included such as Fp2-F4, F4-C4, C4-P4, P4-O2, C4-A1, ROC-LOC, EMG1-EMG2, ECG1-ECG2, DX1-DX2, SX1-SX2, SAO2, HR, PLETH, STAT and MIC. (B) The EEG channels of the bruxism patients are included such as Fp2-F4, F4-C4, C4-P4, P4-O2, F8-T4, T4-T6, FP1-F3, F3-C3, C3-P3, P3-O1, F7-T3, T3-T5, C4-A1, ROC-LOC, EMG1-EMG2, ECG1-ECG2, DX1-DX2, and SX1-SX2. (C) Extracted C4-P4 channel colored in black and C4-A1 channel colored in red for the healthy humans. (D) Extracted C4-P4 channel colored in black and C4-A1 channel colored in red for the bruxism patients. In the healthy humans and bruxism patients total fifteen and eighteen channels was found, respectively.

TABLE 2. Normalized value of the C4-P4 Channel of the electroencephalogram signal.

Subjects	Sleep Stages	Theta Activity			Alpha Activity			Beta Activity		
		Max.	Min.	Avg.	Max.	Min.	Avg.	Max.	Min.	Avg.
Healthy Humans	S1	0.361710	0.099102	0.254422	0.791074	0.103621	0.366204	0.08919	0.002911	0.026485
Bruxism Patients		0.365649	0.071120	0.158845	0.751676	0.119723	0.488041	0.056630	0.010397	0.034400
Healthy Humans	REM	0.401503	0.228289	0.335529	0.363270	0.055881	0.155609	0.035448	0.001070	0.008987
Bruxism Patients		0.358595	0.149363	0.282709	0.318959	0.072971	0.147224	0.014241	0.001231	0.004477

taking average power of specific EEG activity [46]. The comparative analysis of the normalized values of the C4-P4 and C4-A1 channels for the healthy humans and bruxism patients in the S1 and REM sleep stages were presented in Table 2 and Table 3. In Table 2, the normalized value of healthy humans and bruxism patients for C4-P4 channels of the theta activity in the S1 sleep stage are in the range of 0.099102 - 0.36171 and 0.07112 - 0.365649, respectively. While, the normalized value of healthy humans and bruxism patients for C4-P4 channels of the theta activity in the REM sleep stage are in the range of 0.228289 - 0.401503, and 0.149363 - 0.358595, respectively. The normalized value of healthy humans and bruxism patients for C4-P4 channels of the alpha activity in the S1 sleep stage are in the range of 0.103621 - 0.791074, and 0.119723 - 0.751676, respectively. While, the normalized value of healthy humans and bruxism patients for C4-P4 channels of the alpha activity in the REM sleep stage are in the range of 0.05588 - 0.36327,

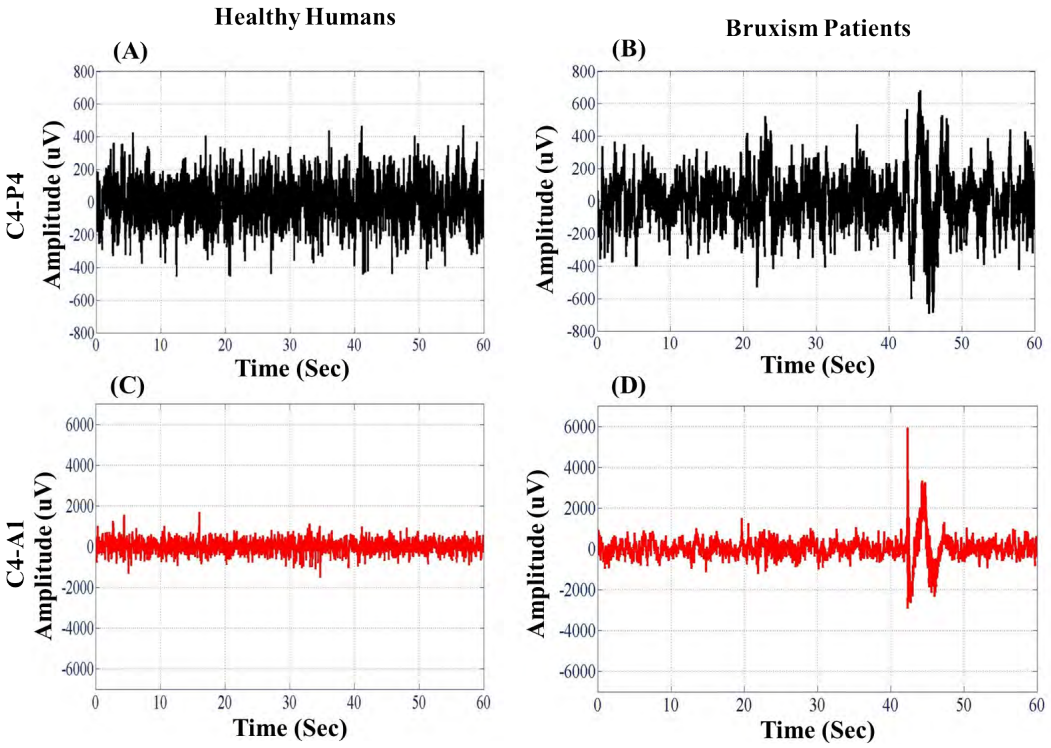

FIGURE 2. The filtered EEG channels of the healthy humans and bruxism patients. (A) Healthy humans for C4-P4, (B) bruxism patients for C4-P4, (C) healthy humans for C4-A1, and (D) bruxism patients for C4-A1. The low pass finite impulse response filter was used in the work.

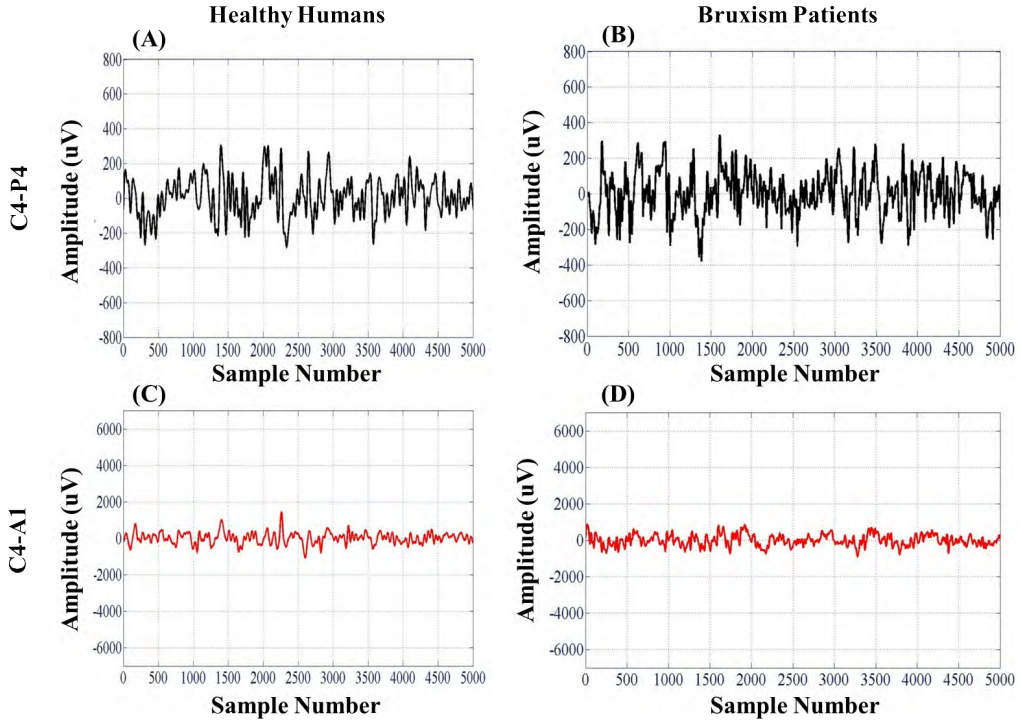

FIGURE 3. (A) Healthy humans for C4-P4, (B) bruxism patients for C4-P4, (C) healthy humans for C4-A1, and (D) bruxism patients for C4-A1. The hamming window was used in the work to obtained results with negligible noise.

and 0.072971 - 0.318959, respectively. The normalized value of healthy humans and bruxism patients for C4-P4 channels of the beta activity in the S1 sleep stage are in the range of 0.002911 - 0.08919, and 0.010397 - 0.05663, respectively. While, the normalized value of healthy humans and bruxism patients for C4-P4 channels of the beta activity in the REM

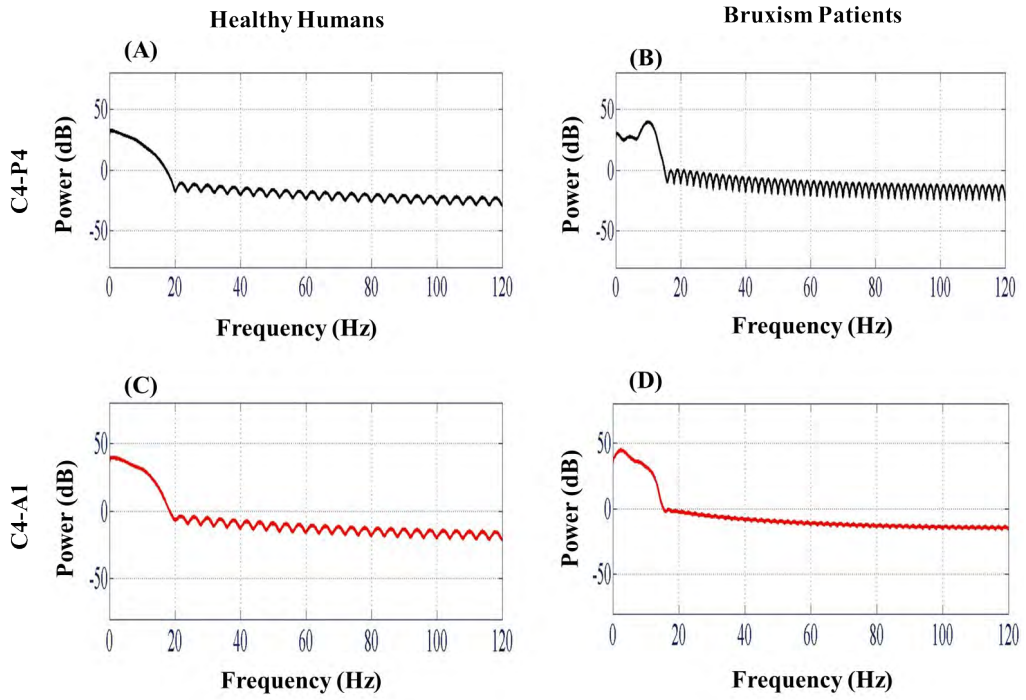

FIGURE 4. The estimation of the power spectral density using Welch method for EEG channels for the bruxism patients and normal humans. (A) Healthy humans for C4-P4, (B) bruxism patients for C4-P4, (C) healthy humans for C4-A1, and (D) bruxism patients for C4-A1. This method converts the signal time into frequency domain.

TABLE 3. Normalized value of the C4-A1 channel of the electroencephalogram signal.

Subjects	Sleep Stages	Theta Activity			Alpha Activity			Beta Activity		
		Max.	Min.	Avg.	Max.	Min.	Avg.	Max.	Min.	Avg.
Healthy Humans	S1	0.348288	0.128995	0.266235	0.302043	0.115432	0.195376	0.058768	0.001259	0.016861
Bruxism Patients		0.371894	0.139708	0.214213	0.582068	0.114305	0.389380	0.035648	0.006976	0.022301
Healthy Humans	REM	0.394262	0.202071	0.320878	0.326502	0.047994	0.129919	0.027218	0.000793	0.006801
Bruxism Patients		0.356066	0.194454	0.284903	0.287076	0.064385	0.124461	0.010795	0.001268	0.004649

sleep stage are in the range of 0.00107 - 0.035448, and 0.001231 - 0.014241, respectively.

It has been found that the average normalized values of the C4-P4 channel of theta, alpha and beta activity for healthy humans during S1 were 0.254422, 0.36620 and 0.026485, respectively. The average normalized values of the C4-P4 channel of theta, alpha and beta activity for healthy humans during REM stage were found to be 0.335529, 0.155609 and 0.008987, respectively. While, the average normalized values of the C4-P4 channel of theta, alpha and beta waves for bruxism patients during S1 were found to be 0.15884, 0.488041 and 0.0344, respectively. The average normalized values of the C4-P4 channel of theta, alpha and beta waves for bruxism patients during REM stage were found to be 0.282709, 0.147224 and 0.004477, respectively.

Furthermore, as shown in Table 3, the normalized value of healthy humans and bruxism patients for C4-A1 channels of the theta activity in the S1 sleep stage are in the range of 0.128995 - 0.348288 and 0.139708 - 0.371894, respectively. While, the normalized value of healthy humans and bruxism patients for C4-A1 channels of the theta activity in the REM sleep stage are in the range of 0.202071 - 0.394262, and 0.194454 - 0.356066, respectively. The normalized value of healthy humans and bruxism patients for C4-A1 channels of the alpha activity in the S1 sleep stage are in the range of 0.115432 - 0.302043, and 0.114305 - 0.582068, respectively. While, the normalized value of healthy humans and bruxism patients for C4-A1 channels of the alpha activity in the REM sleep stage are in the range of 0.047994 - 0.326502, and 0.064385 - 0.287076, respectively. The normalized value of healthy humans and bruxism patients for C4-A1 channels of the beta activity in the S1 sleep stage are in the range of 0.001259 - 0.058768, and 0.006976 - 0.035648, respectively. While, the normalized value of healthy humans and bruxism patients for C4-A1 channels of the beta activity in the REM

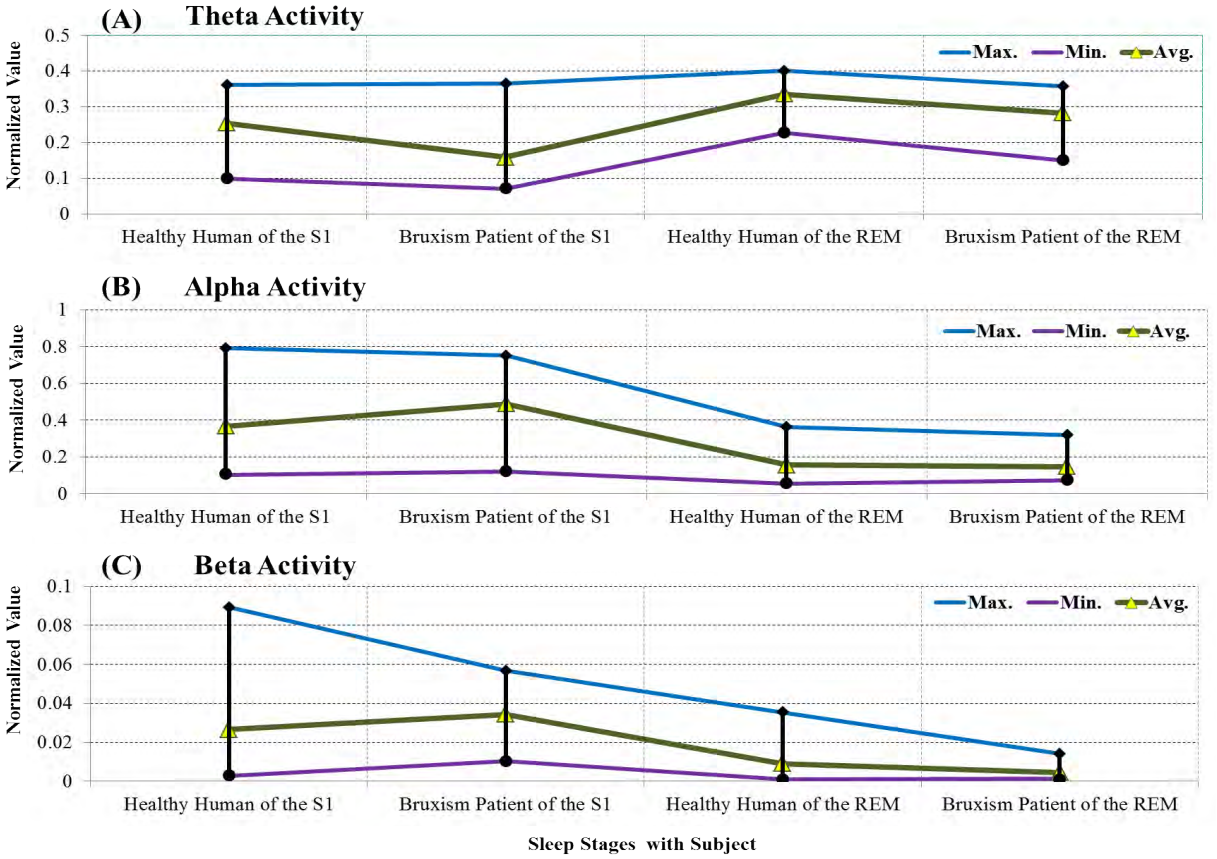

FIGURE 5. perio The comparative chart of normalized value of the healthy humans and bruxism patients for the C4-P4 channel were deduced from Table 2. (A) Theta activity of the EEG signal for the healthy humans and bruxism patients for the C4-P4 Channel. (B) Alpha activity of the EEG signal for the healthy humans and bruxism patients for the C4-P4 Channel. (C) Beta activity of the EEG signal for the healthy humans and bruxism patients for the C4-P4 Channel.

sleep stage are in the range of 0.000793 - 0.027218, and 0.001268 - 0.010795, respectively.

It has been found that the average normalized values of the C4-A1 channel of theta, alpha and beta activity for healthy humans during S1 were 0.266235, 0.195376 and 0.016861, respectively. The average normalized values of the C4-A1 channel of theta, alpha and beta activity for healthy humans during REM stage were found to be 0.320878, 0.129919 and 0.006801, respectively. While, the average normalized values of the C4-A1 channel of theta, alpha and beta waves for bruxism patients during S1 were found to be 0.214213, 0.38938 and 0.022301, respectively. The average normalized values of the C4-A1 channel of theta, alpha and beta waves for bruxism patients during REM stage were found to be 0.284903, 0.124461 and 0.004649, respectively. In brief, the calculated average normalized value for healthy human is smaller than that in bruxism patient of the theta EEG activity in S1 and REM sleep stages (Figs. 5 & 6).

C. EVALUATION OF C4-P4 AND C4-A1 CHANNELS USING DECISION TREE CLASSIFIER

The performance of this work is evaluated with 224 data segments for two channels of C4-P4 and C4-A1. There are 84 EEG recording from healthy humans and 140 EEG recording from bruxism patients for each channel. The evaluation of the classification is process in three conditions such as C4-P4, C4-A1 and combination of C4-P4 and C4-A1 channels. The data segments are dividing into random halves. One part is for training and the other is for testing, and then revises the training data and testing data. The decision tree methods [44], [45] were used for classification of the system. Standard performance measures namely sensitivity, specificity and accuracy are described in equations (8), (9) and (10).

$$Sensivity = \frac{TP}{(TP + FN)} \times 100 \quad (8)$$

$$Specificity = \frac{TN}{(TN + FP)} \times 100 \quad (9)$$

$$Accuracy = \frac{(TN + TP)}{(TN + TP + FP + FN)} \times 100 \quad (10)$$

where, TP is the true positive, TN is the true negative, FP is the false positive and FN is the false negative.

IV. DISCUSSION

In the present study, 224 data from eight subjects were studied. It has been found that the EEG amplitude for healthy humans and bruxism patients were around -200 to 200 uV and

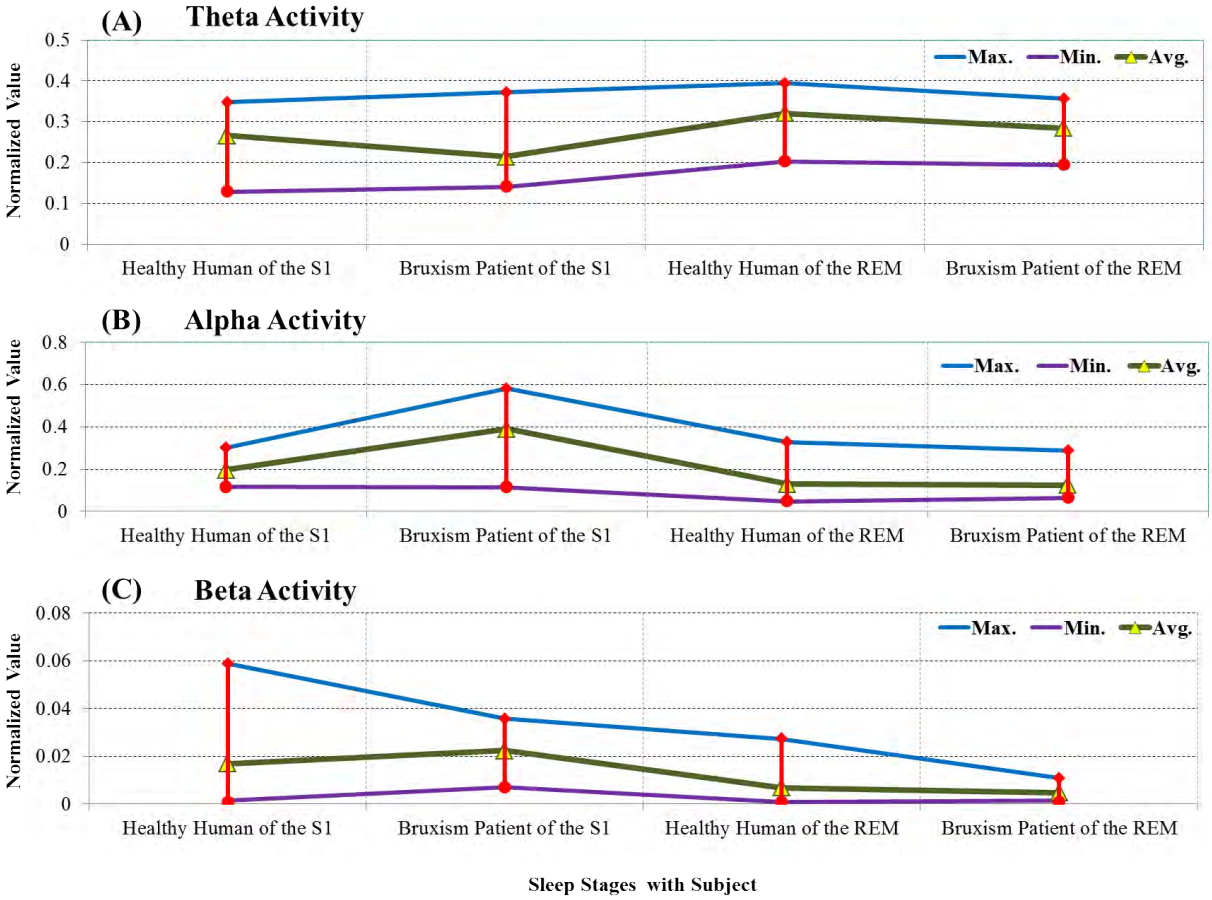

FIGURE 6. perio The comparative chart of normalized value of the healthy humans and bruxism patients for the C4-A1 channel were deduced from Table 3. (A) Theta activity of the EEG signal for the healthy humans and bruxism patients for the C4-A1 Channel. (B) Alpha activity of the EEG signal for the healthy humans and bruxism patients for the C4-A1 Channel. (C) Beta activity of the EEG signal for the healthy humans and bruxism patients for the C4-A1 Channel.

-400 to 400 uV, respectively (Fig. 1). The amplitude of EEG signals of the bruxism patients was higher than those were the healthy humans. Additionally, amplitude of C4-P4 and C4-A1 channels of the bruxism patients were higher than those were the healthy humans. However, in the both two channels, the amplitude of the C4-P4 channel is less as compare to the C4-A1.

Previously, sleep disorder from healthy and affected person using time frequency analysis of power spectral density approach applied on EEG signals using right of central – left of central 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]. A further clarification and comparative analysis between healthy humans and bruxism patients are required for better analysis. In the present work, healthy humans and bruxism patients were analyzed and presented. We have calculated normalized value of both subjects for the C4-P4 and C4A1 channels for the S1 and REM sleep stages. It is easy to analyze and compare the bruxism patients using present approaches.

A. PERFORMANCE OF THE C4-P4 AND C4-A1 CHANNEL OF THE EEG SIGNAL

The performances of the proposed work were mention in Table 4, 5 and 6. In the table 4, the sensitivity of the C4-P4 channel in the S1, REM and combined both stages (S1 and REM) are 95.99, 94.94 and 96.93%, respectively. The specificity of the C4-P4 channel in the S1, REM and combined both stages are 96.43, 82.15 and 77.07%, respectively. While, the accuracy of the C4-P4 channel in the S1, REM and combined both stages are 84.78, 79.55 and 81.70%, respectively. Importantly, the S1 stage is more accurate than REM and combines both stages. In the table 5, the sensitivity of the C4-A1 channel in the S1, REM and combined both stages (S1 and REM) are 86.96, 94.05 and 93.29%, respectively. The specificity of the C4-A1 channel in the S1, REM and combined both stages are 91.30, 88.13 and 93.29%, respectively. While, the accuracy of the C4-A1 channel in the S1, REM and combined both stages are 89.13, 83.33 and 74.11%, respectively. Importantly, the S1 stage is more accurate than REM and combines (S1 and REM) stages.

In the table 6, the sensitivity of the combination of both channels such as C4-P4 and C4-A1 in the S1, REM and

TABLE 4. Performance of the C4-P4 channel.

Testing Fold	S1 Stage			REM Stage			Combination of the both S1 and REM stage		
	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy
1	96.15%	100%	91.30%	95.00%	92.31%	75.76%	97.14%	85.71%	87.50%
2	95.83%	92.86%	78.26%	94.87%	72.00%	83.33%	96.72%	68.42%	75.89%
Mean	95.99%	96.43%	84.78%	94.94%	82.15%	79.55%	96.93%	77.07%	81.70%

TABLE 5. Performance of the C4-A1 channel.

Testing Fold	S1 Stage			REM Stage			Combination of the both S1 and REM stage		
	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy
1	93.55%	90.91%	92.23%	100%	81.82%	84.85%	94.12%	79.31%	77.68%
2	84.62%	91.67%	88.14%	88.10%	94.44%	81.82%	92.45%	75.00%	70.54%
Mean	86.96%	91.30%	89.13%	94.05%	88.13%	83.33%	93.29%	77.16%	74.11%

TABLE 6. Performance for the combination of C4-P4 and C4-A1 channels.

Testing Fold	S1 Stage			REM Stage			Combination of the both S1 and REM stage		
	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy
1	96.55%	100%	86.96%	97.30%	85.71%	81.82%	90.48%	75.00%	80.36%
2	86.96%	86.36%	84.78%	97.30%	88.89%	78.79%	88.41%	81.58%	82.14%
Mean	**91.75%**	**93.18%**	**85.87%**	**97.30%**	**87.30%**	**80.30%**	**89.44%**	**78.29%**	**81.25%**

TABLE 7. Comparison of classification results between proposed work and previous works.

Authors	Year	Detection	Major	Name of the Classifier	Accuracy
Christodoulou et al. [47]	2012	Neuromuscular Disorder	EMG	Self-Organizing Map (SOM)	60.00%
Castroflorio et al. [48]	2015	Sleep Bruxism	EMG and ECG	-	62.20%
Tushar et al. [49]	2018	Sleep Disorder	EEG	K-Nearest Neighbors (KNN)	71.75%
Proposed work	**Present**	**Sleep Bruxism**	**Combination of C4-P4 and C4-A1 Channels of the Scalp EEG**	**Decision Tree (DT)**	**81.25%**

combined both stages (S1 and REM) are 91.75, 97.30 and 89.44%, respectively. The specificity of the combination of both channels such as C4-P4 and C4-A1 in the S1, REM and combined both stages are 93.18, 87.30 and 78.29%, respectively. While, the accuracy of the combination of both channels such as C4-P4 and C4-A1 in the S1, REM and combined both stages are 85.87, 80.30 and 81.25%, respectively. Importantly, the S1 stage is more accurate than REM and combines both stages. It has found the accuracy of S1 stage in all channels (C4-P4, C4-A1 and combine of C4-P4 and C4-A1) is better than REM and combination of S1 and REM sleeps stages. As shows in table 7, the performance of the proposed method is more accurate than that of other methods [47]–[49].

B. APPLICATONS AND LIMITATIONS OF THE PROPOSED WORK

The present work showed potential applications in the detection of bruxism by using the C4-P4 and C4-A1 channels of the EEG signal. The research work would provide a fast and effective detection system of the 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 detect the psychological patients in short time with high accuracy. The big data techniques play main role in sleep research. It has important role in the sleep such as performance, prediction of the effect and risk, signal detection and detection of sleep disorders for scrutiny purposes [50]. It is also used in medical polysomnography, wearable sensors, self-quantification systems, and longitudinal studies.

It 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 the C4-P4 and C4-A1 channels of the EEG signal were not be able to record the all channels of the neuron. Additionally, the third limitations are related to filter used in this work.

The low pass finite impulse response filters were used for finite range. In order to design a better filter, both the finite impulse response and the infinite impulse response in the same time should be implemented in both continuous and discrete time signals. In future we will use the proper channels such as A1-T3 and A2-T4 because now it's not available in present data base.

V. CONCLUSION

Bruxism is a sleep disorder, in which individual involuntarily crushing and clenching the teeth. In the present work, we have developed a detection system of the bruxism using C4-P4 and C4-A1 channels of EEG signal. The results obtained from the theta activity have consistency, while alpha and beta showed slightly variations. Additionally, the accuracy of S1 stage is better than REM in the C4-P4, C4-A1 and combination of C4-P4 and C4-A1 channels. We summarized that the theta activity of the S1 stage can be utilized in the detection of bruxism. This will ease the detection of bruxism. The future prospects of the research to easily detect the neurological disorder with high accuracy.

ABBREVIATIONS

Continuous Positive Airway Pressure (CPAP); Decision Tree Method (DT); Electroencephalogram (EEG); Electrocardiogram (ECG); Finite Impulse Response (FIR); K-Nearest Neighbors (KNN); Low Pass Finite Impulse Response Filter (LPFIRF); Non Rapid Eye Movement (NREM); Nocturnal Frontal Lobe Epilepsy (NFLE); Proton Pump Inhibitor (PPI); Power Spectral Density (PSD); Rapid Eye Movement (REM); Rapid eye movement Behavioral Disorder (RBD); Sleep Bruxism (SB); Spatial Temporal Electroencephalogram and Functional magnetic resonance imaging Fusion (STEFF); Self-Organizing Map (SOM).

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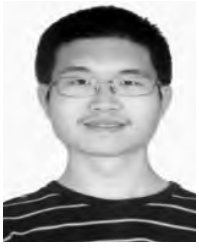
MD BELAL BIN HEYAT received the B.Tech. degree in electronics and instrumentation (EI) and the M.Tech. degree in electronics circuit and system (ECS) from Integral University (IU), Lucknow, India, in 2014 and 2016, respectively. He is currently pursuing the Ph.D. degree with the University of Electronic Science and Technology of China (UESTC). He has published several research papers in reputed international journals and conferences. His current research interests include developing diagnosis system of the neurological disorder and sleep disorders.

DAKUN LAI (M'11) received the Ph.D. degree in biomedical engineering from Fudan University, Shanghai, China, in 2008. He completed his three-year postdoctoral fellowship in biomedical engineering with 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 an Associate Professor of electrical engineering and biomedical engineering. He is currently the Director of the Biomedical Imaging and Electrophysiology Laboratory (BMI-EP), UESTC. He is currently working in the field of cardiac arrhythmia, neurological disorder, and sleep disorders. He has published over 40 peer-reviewed papers in these areas and also serves as a reviewer for several international journals. His major 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.

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 of the University of Electronic Science and Technology of China (UESTC) and focuses on atrial fibrillation and other heart-related diseases using both experimental and computational techniques.



YIFEI ZHANG received the bachelor'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 arrhythmias using machine learning.