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A REVIEW ON SLEEP EEG EVENTS USING NEURO-FUZZY SYSTEM

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ABSTRACT

Brain-Computer interface is used to communicate with the user and the computer through brain signals by extracting the meaningful information from massive data. Electroencephalograph (EEG) is used to read the brain signals and mainly employed in prediction of brain activities. The parameters of the atmosphere are responsible to change the information coming from the brain. The signals are processed using digital processing tools so as to extract the information. Soft computing techniques are used to analyse the signals and take decisions to find the brain disorder. In this paper, sleep disorder issues like sleep snoring, parasomnia, insomnia and apnea are studied and analyzed. In this survey we studied two soft computing techniques such as Artificial Neural Network (ANN), Neuro-Fuzzy logic which provides the knowledge to mainly useful in processing human scalp EEG.

Index Terms—Electroencephalograms (EEG), Magneto Encephalograms (MEG), Functional MRI (fMRI), Artificial Neural Network (ANN). Neuro-Fuzzy Techniques.

I. INTRODUCTION

The human brain is incredibly complex and the task of generating a response to a given stimulus involves several complex interrelated processes that can be delayed for a variety of reasons. For example, temporal variability of the measured EEG signal has been shown to be influenced by endogenous process related to brain state (e.g., fatigue, attention) and exogenous factors such as stimulus properties. Electroencephalograms (EEG), Magneto encephalograms (MEG), and functional MRI (fMRI) are the different methods to capture brain activities which are used to understand the complex inner mechanism by the researchers. Therefore, the analysis of brain waves play an important role in clinical diagnosis as well [1]. Digital signal processing plays important role to find the useful information in huge amount of data gathered from brain signals.

The right path to analyze the depth of sleep is by means of polygraphic recording of electrophysiological signals, which was used by medical EEG laboratories to find useful information but that was not obtainable in wake and inactive states" . The majority of researchers identify sleep stages in animals with the support of EEG, EOG (Electrooculogram), EMG (Electromyogram), ECG (Electrocardiogram) and pneumogram.

However, the sleep classification has continuously been a stimulating way for the clinical electroencephalographers, be it is implemented by paper records analysis or by means of computer systems. Most of the previous attempts to classify the sleep stages were based on threshold measures. To overcome the problems faced by

electroencephalographers in the detection of sleep stages, Artificial Neural Networks (ANNs), Fuzzy Logic and Expert Systems have been used. Recently, ANN has been applied for the classification of sleep stages, where the recognition rate was found to vary from 65% to 94% in comparison with the manual sleep stage scoring .

Study of EEG and analysis of brain includes some of the key points that it must gather the data in form of electrical signals or in graphical form which can be EEG, EMG etc. Data collection from different signal is known as Data Acquisition shown in Fig 1. The gathered data is then subject to preprocessing using the filters. Filters include the band pass filters or band stop filters. Sometime digital filters also used for the spectral analysis e.g. Fast Fourier Transform (FFT). After getting the useful data the processing over it is initiated. The DSP technology or Neural-Fuzzy logics are implemented over the data to get useful information. The information is then used for the diagnosis purpose.

Making the right diagnosis and choosing an appropriate treatment for brain disorders remains a challenging task. Even though recordings are only from a limited number of brain areas, the resulting data sets are often huge, and need to be suitably stored and managed [3][4][5]. The EEG signals provide good signals for the analysis of the brain [6].

EEG recordings hold both electrical signals and unwanted signals that can be [7], [8], [9], [10]:

- Interference from external sources as for example the 50 or 60Hz power supply signals,
- Electromyogram (EMG) signals induced by muscular action,
- Ocular artifacts, due to flashing.

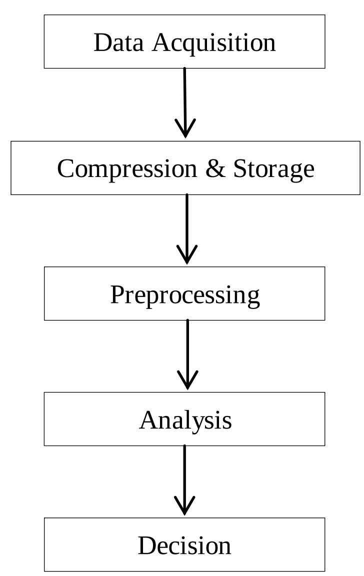

Fig. 1. Decision making in neurology [1].

The brain signals or electroencephalogram (EEG) are the records of a spontaneous electrical activity of cerebral cortex [3]. "It is considered that EEG recordings have wide range of frequencies which are divided into standard bands, i.e., 0.5- 4 Hz (delta or ∂), 4 - 8 Hz (theta or θ), 8 - 13 Hz (alpha or α) and 13 - 35 Hz (beta or β)" [4]. The shapes of complex waves of EEG and responses may depend on the time domain characteristics, phases, and their amplitudes. Hence, examination of analog EEG need physician's expertise and involves much more work. filters are usually not effective to eliminate such artifacts [1]. The spectrum of artifacts is often a priori unknown. Therefore, applying a fixed filter to EEG data would not be effective to remove artifacts. The filter needs to adapt to the spectrum of the recorded EEG: it should attenuate the recorded EEG in frequency ranges that mostly contain artifacts [13], [14], [15].

Sleep is essentially a neurophysiological phenomenon, and EEG remains the best technique for the functional imaging of the brain during sleep [16]-[17] Because of EEG features different stages of the sleep can be investigated. This kind of investigation helps in found the parameters responsible for the sleeping disorders. Sleep Apnea Syndrome (SAS) has been investigated in [18] using wavelet transform (WT) and neural network techniques.

In Section II the Literature survey will be discussed, in this

section many previous works over the EEG signals, processing and analysis have been studied and summarized. The objective of the section is to focus the study on the Sleep study and previous work over it and techniques used by the researchers to find the sleep disorder. Section III provide the study and analysis of the implementation of the Artificial Neural Network (ANN) and Neuro-Fuzzy logic analysis. Section IV has the detailed study of comparison of different previous work and finally in section V conclusion of the whole paper has been discussed.

II. Literature Review

A. Study of Sleep related issues

In the tradition of neuroscience, sleep plays a vital position. Due to familiarity of sleep disorder in universe, this is a very important subject [19]. At least 41% of all considered subjects have one syndrome of disrupted sleep [20]. During daytime sleepiness, one out of 5 adults is distressed as narrated by Young in 2004 [21]. Due to extreme daylight sleep, two problems are Sleep apnea [22] and narcolepsy [22]. Due to these two disorders, confusing or some time vital effect happens on regular activities. Sleep apnea [23], a sleep-related breathing disorder, caused by the disturbances in sleep which causes many concise and long duration dreadful effects. Impaired attention, impact on quality of life, less potency and chances of mishap increasing are the short living effects of sleep disorders and the long-term effects are increment in morbidity and mortality rate from the increasing mishaps, cardiovascular diseases, high blood pressure, bulkiness and learning disability along with discouragement [24]. The physical, psychological, cognitive and motor functioning hampering are caused by sleep disorders. Snoring, sleep apnea, insomnia, parasomnia, are the few disorders that we normally do not give any attention on it. So the main task is to find the sleep disorder. Earlier, the traditional approach used by researchers was in the form of questionnaire for detecting various sleep disorders but this method lacks of accuracy as the whole questionnaire survey depends on total number of participants as well as questions designed for the survey. So, various intelligent approaches have been found out or are in research by researchers to treat this problem.

One of the techniques known as Artificial Intelligence playing important role regarding above. Few intelligent computing techniques such as: ANN, FL, GA, SVM, MLPNN, DM, BN,[Genetic Algorithm(GA), artificial neural network (ANN), support vector machine(SVM), multi-layer perceptron (MLPNN) neural network, Bayesian network (BN), data mining (DM)] all are related to data controlling technique. But researchers are now adopting the various knowledge's, controlling integration applicable in medical domain. RBR and CBR [5] rule based reasoning (RBR), case based reasoning (CBR),] are the few basic problem-solving paradigms in the artificial intelligence field A rigid standard for patient's sleep macrostructure specification had been recommended by Rechtschaffen and Kales (R&K) which is recently mutated by the American Academy of Sleep Medicine [26]. Since, the human scoring is tedious and extravagant, frequent attempts have been done for creating automatic record counting systems [24]. A rule based sleep staging system has been created by the R&K criteria using multi-rule decision tree. To improve the accuracy over a single decision tree, multiple decision tree approach was used, which accounts for more than 7% accuracy over a single model [27]. RBR methods are the time consuming methods, since, they require signal information, specific patterns detection like K-complexes, sleep spindles in EEG and rapid eye movements in EOG. A bio-signals processing algorithms has been used for the detection of sleep disorders breathing from ECG signals with the accuracy of 77% [28]. A huge amount of time is required for creating a system from RBR which extract features from original information for constructing the rules as per human brain [29]. For finding the optimal input features and recognition of network specifications, the chromosomes of variable length structure and fitness function are used (Kim, 2000). But no such human knowledge and rules are required in numerical classification method [29]. For better long-term and home monitoring of snoring, the advanced portable microcontroller based device can be proved useful [30]. They can provide various outputs as: total snoring count, medium number of snores per hour, and the number of irregular snoring with success rate of about 85% in a lab environment and around 70% in a home [31][32]. CBR favours experience learning, as it is easy to learn from an actual problem solving experience [33] [34].

A pattern recognition approach has been explicitly followed for EEG analysis which plays an important tool for the study of brain computer interface (BCI) [34, 35] [36, 37,38], epilepsy research [39], sleep studies [40–42], psychotropic drug research [43, 44]. But the main challenge is the computerized study of EEG data. The challenge in brain signals has been further amplified by high density EEG nets consists of huge number of 300 channels [45][46] with consistently increasing sampling frequency (1K Hz or more) by advanced digital processing technologies.

B. EEG's Cortical Source

The principal source of EEG is Excitatory postsynaptic potential (EPSP) which is at the apical dendritic trees of pyramidal neurons [47, 48]. On receiving inputs from neurons, apical dendrites EPSPs are generated into apical dendrites trees. The apical dendritic membrane becomes transiently depolarized and consequently extracellular electronegative with respect to the cell soma and the basal dendrites [47]. This is responsible for the potential difference and cause to flow the current through the volume conductors by means of non-excited membrane of soma and basal dendrites to the apical dendritic tree sustaining the EPSPs [48, 49]. The shortest path is taken by the current between source and sink through dendritic trunk.

Primary currents are those currents which are between Intracellular current flows while extracellular currents are known as Secondary current .Simultaneous initiation of a huge population of cell with the spatial arrangement contributes to the spatio-temporal superposition of the elemental activity of every cell, resulting in a current flow that generates detectable scalp EEG signals [51].

C. Dimensionality reduction

The collected data is huge collected from EEG signals as we can calculate it by number of channels × number of trials. For huge array EEG consisting of hundreds of channel and hundreds of trials is needed for recording. And for such case each spanning for seconds, minutes, and hours with a sampling frequency of 1000Hz the 10s or even 100s of gigabytes of data collected. Because of this without data reduction the EEG signal will be difficult to handle. It will also be hard to store the data in main memory without reduction in data. Reduction in the data could be achieved by selecting the appropriate channel [52, 53]. Dimension of EEG at the post processing stage is calculated usually in terms of the feature's proportions. Feature extraction is attained either by making to a lower dimensional space or by choosing a part of the original space [54, 55]. After converting EEG from all channels into a single channel the dimensionality reduction is achieved in [55].

Analysis over the different sleep stages can be done using the relevant EEG features for the investigation of different sleep events. Wavelet transforms (WT) and Neural Network Techniques are used to analyze the effect of heat stress on EEG [56]. In [56], the EEG signals are segregated into alpha, beta, delta, theta by using multi-resolution wavelet transforms before feeding to classifier. In [57], the correlation dimension is evaluated of a male subject over polysomnography. The correlation dimension decreased from 'awake' stage to sleep stages 1–3 (stage1:6 Hz–8 Hz, stage2: 4 Hz–7 Hz Stage3: 1Hz to 3Hz and during rapid eye movement (REM) it was increasing. Then, the study of heat stress classification accomplished by ANN has been introduced which makes ANN an appealing approach for the researchers. In [58], after feature extraction in terms of wavelet coefficient, Multilayer perceptron neural network has been used to detect the different sleep stages.

Section III

A. Artificial Neural Network(ANN)

Artificial Neural network (ANN) can be used to process Low signal to noise ratio (SNR) [61] in case of scalp EEG. ANN can be applied over the EEG signals. But before this some of the important issues are targeted in the coming discussion.

a. Removal of Artifact

Artifacts are undesirable electrical potentials which introduce from other causes not from brain. Because EEG signals are very sensitive to artifacts so external signals need to be controlled and rejected. The types of signals are electro galvanic signals and frequency artifacts. The artifacts are detected and erased to improve the EEG signals. In [62], an improved Kalman filter approach and a Neural Network instead of AR model are used for detection of artifacts. This algorithm was able to detect around 90% of artifacts and having the sensitivity of 65%. The artifacts could be detected automatically and an efficient parametric system is studied in [63]. In [64], singular value decomposition to separate multichannel EEG signals into optimized component Signal to Noise (SNR) has been discussed and analyzed. These components were used to detect the artifacts.

b. Sleep studies

In the tradition of neuroscience, sleep plays a vital role. Due to familiarity of sleep disorder in universe, this is a very important subject [65]. At least 41% of all considered subjects have one syndrome of disrupted sleep [66]. During daytime sleepiness, one out of 5 adults are distressed as narrated by Young in 2004 [67]. Due to extreme daylight sleep, the two problems are sleep apnea [66] and narcolepsy. Due to these two disorders, sometimes vital effect happens on regular activities. Sleep apnea [68], a sleep-related breathing disorder caused by the disturbances in sleep gives rise to many concise and long duration dreadful effects. Impaired attention, impact on quality of life, less potency and chances of mishap increasing are the short living effects of sleep disorders and the long-term effects are increment in morbidity and mortality rate from the increasing mishaps, cardiovascular diseases, high blood pressure, bulkiness and learning disability along with discouragement [69]. The physical, psychological, cognitive and motor functioning hampering are caused by sleep disorders. Snoring, sleep apnea, insomnia, parasomnia are the few disorders that we normally do not give any attention to them. Thus, the main task is to find the sleep disorder. Earlier, the traditional approach used by researchers was in the form of questionnaire for detecting various sleep disorders but this method lacks of accuracy as the whole questionnaire survey depends on total number of participants as well as questions designed for the survey. So, various intelligent approaches have been researched to treat this problem.

"For the improvement of epoch-based methodologies which depends on low temporal resolution, the automatic study of the sleep macrostructure in continuum approach has been introduced by Diego Álvarez-Estévez, José M. Fernández-Pastoriza in 2013. Classifications based on categorisation can be removed and soft transitions can be exploited by using neuro fuzzy systems as these properties permit us to approximate the constant growth to investigate the sleep EEG with its various states." [67]. Genetic algorithm was introduced in 2013 and used to examine for the weight alteration for both "sensitivity and specificity" [67] in order to improve the diagnostic rate from 85.99 to 94.2% [67].

Alterations in sleep EEG Signal for hypononea, which is cessation of breath during sleep was detected by ANFIS and wavelet coefficient in 2009 by Elif Derya Ubeli . By the end of 2010, seasonal time-series approach was introduced for the robust long-time predictions [14], which are very useful for the sleep stage detection. However, frequency analysis is the best method to analyze the frequency alterations in different bands (alpha, beta, gamma, theta) of EEG. The same approach was also used to detect a novel sleep apnea in 2011 by Hilbert – Huang transformation mechanism. Its main advantage is the free tuning of time scale to find system with fast response [65]. Epileptic EEG was diagnosed by extracting entropies with 98.1% accuracy.

c. Classification Algorithms

Many Algorithms have been proposed by researchers for the feature extraction and classification of vigilance states for EEG which was based on pattern recognition system. In 2007 'L&A, Wang & He' introduced the comparison of those algorithms and divided them into different classes i.e., linear classifiers (proposed by "*Müller et al., 2004"*)[70] non-Bayesian classifiers (*Tavakolian & Rezaei.,2004*)[71] nearest neighbor classifiers (proposed by *blakertz in 2002)*[72] , decision tree by Duman et al in 2009, combination of classifiers (proposed by *Übeyli, 2008*). For the experimental purpose, rat has been used as specimen because it is a very difficult task for human beings to be exposed at high environmental heat for long time during clinical EEG recording as to classify the effect of thermal stress and its consequences[73]. The R&K strategies for visual study and carrying out the classification of sleep-wake stages were published in 1968 and acknowledged as a standard reference. Sleep EEG is still one of the open ended focus for researchers where tremendous work can be done by understanding the vigilance states of brain because brain regulates the alterations of sleep awake vigilance stages.

Adaptive Neuro fuzzy inference system (ANFIS) is a type of neural network based on Takagi–Sugeno fuzzy inference system. It has potential to capture the benefits of both the neural network and fuzzy logic in a single framework. Its inference system looks up to a set of fuzzy IF–THEN rules that have learning capability to approximate all non-linear functions. Hence, ANFIS is considered to be a universal estimator [74-77]. More over there is lot of has been done artificial neural network applied over the EEG signal.

Real Time Automated System has been implanted by Clabian M, Nussbaum. LVQ, PNN and FFNN are the three methods which have been implemented [78]. There is a single hidden layer was selected in all techniques, 4 neurons in input layer and one neuron in output layer, tansig + purelin and logsig + purelin used as activation functions. In this leave one out cross-validation technique. The Accuracy of such system is as LVQ-70%, pNN-79%, FF-NN-85%. It is used for the classification of sleep.

One Automated system implemented in which Feedback MLPANN is analyzed, discussed and implemented, the output is coming in the form of Transient waveforms, and specificity was calculated for the three groups: SS, Mild Cognitive Impairment (MCI) and Alzheimer disease (AD). In this the sensitivity is 81.4 % for SS-62.2% for MCI and 83.3% for AD [79]. The application used for Detection of sleep spindles. In the extension of the work the same author in provide an Automated system i.e. FFMLPANN of 3 layers with 64, 30 and 2 neurons in the input, some hidden and output layer respectively[80]. The features were extracted and time-domain representation of EEG signals provided in this work. Error back-propagation training algorithm and log sigmoid transfer function for neurons was implemented to accurate the results the Accuracy for this system were 92%. The application was detection of sleep spindles.

An automated classifier implemented using ANN where single neuron with hyperbolic tangent activation functions at output layer and LM algorithm to train network implemented by the author[81]. The author provided a Novel pattern recognition algorithm where Fourier Transformation has been used. Author also implemented the south-well relaxation technique for adjustment of parameters and suggested and designed multiple additive regression trees to benchmark ANN. The Sensitivity is 96.1% for sleep, 95.25% for wake. The classification of sleep versus wake stage is the main application of work.

PCA was introduced to reduce dimensions of the data is used by the author, FFMLPNN with BP learning algorithm, one hidden layer and 5 nodes were implemented and analyzed, and LDA based classification models used by the author to classify the signals for sleepiness. The application of the proposed work targeted to detection of sleepiness[82].

Bio sleep Tm ANN were design and implemented, in this work cohen's kappa coefficient for various combinations of sleep stages were implemented. The application of the work is detection of SS[83].

ANN of ART2 implemented, ART2 is used for the reduction of communication cost, fourier or wavelet transformation were the technology implemented on the data of EEG signal. The Accuracy is 91% of the proposed work. The application of the work is detection of OSA and narcolepsy[84].

one automated system using BPNN has been implemented; 89% and 70.6% sensitivity detected in training and test set of ANN respectively. The application is detection of sleep disordered breathing [85].

A vector based NN has been analyzed and implemented [86]. The techniques used for the classification of the spectral density were LVQ, self-organizing feature map and growing cells structure. The Accuracy of the system is 80% but less on high dimensions data. The application is used for recognition of beginning micro sleep.

analysis of comparison of linear and quadratic classifiers and implementation k-NN, Parzen kernels and neural networks on the data of automatic sleep stage classification, MLPNN trained with 8 neurons in the input layer (hyperbolic tangent transfer function) 6 neurons in the hidden layer for linear transfer function and 6 in the output layer for logarithmic siginoid transfer function trained by with FFBP gradient algorithm implemented by the author. The application is analysis of SS[87].

Bispectral ANN implemented by the author, the techniques used were QPC, to reduce the variance of the bispectrum 2-D window function is used and implemented, For bispectral calculation hanning window is used. One of the neural network techniques is also used [88]. The NN used with one input layer, two hidden layers, and one output layer. The accuracy is measured as 96.15%. The application of the work done is estimation of OSA

The multivariate adaptive regression splines (MARS) and support vector machine (SVM) are used for classification of sleep EEG signals [89]. The author found that using acoustic features for categorization of simple snores and such patients were suffered from OSA. The application of work is to diagnosis of snoring sound.

Support Vector Machine has been used for the analysis. To check the snoring level (heavy and light) SVM was applied[90]. This was from heart rate variability features, PCA was used to enhance the accuracy of classification, and Snoring Density was analyzed and computed. Comparative study between SVM and statistical analysis has been done. The accuracy was 75.82% of the system and the application is for Snoring Classifier.

An approach of FFNN, BP algorithm is implemented to train the network [91]. The EEG signals passed as input to ANN. The accuracy calculated as 93.3%, the sensitivity is 87.5%, and specificity is 100%. The application of the work is OSA

Implementation of the Kohonen self-organizing ANN to analyze the EEG signals for indication of dynamics in sleep application [92]. The approach focused on Kalman filter for the analysis of EEG signals and ANN for clustering in high dimensional space with accuracy of 80% .

A hybrid approach of wavelet transform (WT) and ANN has been used for the decomposition of EEG signals into delta, theta, alpha, and beta spectral components[93-94]. ANN was used for the Wavelet coefficients for training purpose, 12 neurons in Input layer, 32 neurons in hidden layer and 3 neurons in output layer, sigmoid function for the restriction of output values. The specificity is 44.44 %. The sensitivity is

69.64%, and used for the Identification of SA application.

IV. Motivation

Since EEG signal are highly complex and nonlinear in nature, study of analog records need physician's expertise and needs much work.

Digital signal processing tools are used to diagnose the Sleep EEG as conventional approaches of paper recordings were confined to diagnose the stress events of EEG signals. To quantify the vigilance stages and variations in sleep wake states of EEG under acute and chronic stress conditions, soft computing techniques have been introduced for three channels i.e., EEG, EOG (Electrooculogram) and EMG (Electromyogram) recordings. Neural networks architectures were designed to analyze three channel recordings, which reduce the labor of neurologists.

As the applications of soft-computing and digital signal processing tools in solving brain electrophysiological problems and systems modeling of various brain functions have great clinical and pathophysiological importance, the design of such types of systems with development of a clinical software package, after some training to the clinical and research persons definitely will reduce the labor involved in clinical diagnosis.

IV. Conclusions

As per the earlier work done in EEG signal processing, we have a clear idea of use of digital signal processing for reading and decoding brain signals with a high level of precise-ness. Fuzzy and Neuro-fuzzy logic acts as a new base to analyze these signals with a variety of human brain states like sleep, mid-sleep, awake, thinking, etc. Filtering of special frequency bands is an important step to remove all the unwanted interfering signals. Filter should attenuate the recorded EEG in frequency ranges that mostly contain artifacts. Human scalp EEG signals has been further augmented by high density EEG nets introduction consisting of more than 300 channels and with ever increasing sampling frequency (1000 Hz or more) of digitization by advanced technologies means. This is a huge data and by projecting EEG from all channels into a single channel the dimensionality reduction is achieved. The EEG signals are segregated into alpha, beta, delta, theta spectral components by using multi-resolution wavelet transforms before feeding to classifier. Sleep Apnea Syndrome using EEG signals is analyzed and optimized using Recurrence Qualification Analysis (RQA) [95]. For getting analyzable artifacts out of the EEG signal, we require dimensionality reduction, artifact removal, and finally source localization. ANFIS classifiers were used on features extracted from EEG by wavelet transformations (WTs) for classification pertaining to five different classes with a total accuracy of 98.68%. WT on EEG followed by ANFIS could classify normal subjects from epileptic patients with 93.7% and 94.3% respectively [96]. For a comprehensive treatment of the subject, combining adapted resonance theory (ART) NN with fuzzy logic, fuzzy ARTMAP NN was created which has found several applications in human EEG processing often with classification success rate of 90% or above. We are using the above technique to get the best analysis of sleep patterns. A lot of past experiments were made using this technique with slight tweaks in the gathering/processing/analyzing/reducing methods. The applicability of the method is subject to the availability of the quality EEG signals captured for the analysis, so to maximize its success rate. Review of literature reveals that neural network along with the wavelet transform are of significant clinical importance for solving complex problems related with brain electrophysiology. The soft-computing tools have proved to be an important tool for automatic and real-time identification of even minor alterations in EEG signals occurring due to variety of stress stimuli. Therefore, the proposed research work will be helpful for the neurologists to analyze the sleep-awake correlation.

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