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Wavelet Based Sleep EEG Detection Using Fuzzy Logic

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Abstract. The Sleep stage classification has been accomplished using fuzzy inference system, where the prerecorded data of sleep EEG has been processed with the help of wavelet transform. The investigation on sleep stage detection reveals the quantitative presence of three different stages of sleep i.e. Awake, SWS (slow wave sleep) and REM (rapid eye movement). The proposed work approaches to correctly identify the three classes of sleep EEG using fuzzy classification method based on fuzzy rule base. The 3- channel data is preprocessed by wavelet transform via signal processing tools and further processed to identify the stages of sleep EEG. The extracted features from the processed data are EEG sub-band frequencies, standard deviation measures for EMG and EOG and variance measures for EMG and EOG. These features are required to make the fuzzy rules for FIS (Fuzzy inference system) and further used to identify the sleep stages correctly. Performance analysis of the proposed fuzzy model was accurately evaluated in terms of fuzzy variables and the result shows that the proposed approach is able to classify the EEG signals with the average accuracy of 93% in which SWS stage was best detected among other stages of sleep EEG.

Keywords: EEG · EOG · EMG · Fuzzy logic · Wavelet transform
Awake · SWS · REM

1 Introduction

Sleep can change the performance of day- to- day activities in a normal life like productivity, learning, memorization and concentration, which is related to a healthy sleep. Deprived from sleep can lead to the risk of hypertension, diabetes cardiovascular disease, metabolic irregularities, obesity which lowers the immune system [1].

Sleep evaluation is important to diagnose the sleep disorder. The method used to evaluate the sleep is polysomnography (PSG) [2], which is the recording of different physiological signals like EEG (Electrocencephalogram), EMG (Electromyogram), EOG (Electrooculogram), pulse oximetry and respiration. Analysis of sleep can be done when system changes in awake homeostasis. In visual observation of PSG, medical examiner can examine the individual sleep by evaluating the sleep stages [3]. According to Rechtschaffen and Kales, the main stages of vigilance are wakefulness,

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REM (Rapid Eye Movement) and Non REM, where non REM is further divided in to four more stages. In the present work, the sleep stages are divided in to three stages namely: Awake, REM and SWS. EEG, EMG and EOG are the three polysomnographs which have been recorded to determine the vigilance stages of sleep EEG, where EEG signals are used for brain activities and EOG, EMG are used to detect the presence of rapid movement of eye and muscular tone. EEG signals are also used to detect spindles which have frequency of 12–14 Hz. The polygraph method also keeps the record of other signals which are used by the experts to investigate the important information; e.g. ECG used for detection of body movements, abdominal ventilatory movement, body temperatures, and oxymetry [4]. Study of brain activities and with addition to the widespread application in diagnosis of sleep EEG, various developments have been undertaken in the field of signal processing and analysis of bioelectric signals.

The electrical activity of the brain and cerebral cortex is very complicated and produced by different types of neurons, nerves and nerve fibers. This occurs due to large number of neurons, synapses and various properties of synapses, such as inhibition, summation, facilitation etc. which are integrated together to give rise to rhythmic electrical potential changes [5]. EEGs are recording of these minute rhythmic electrical potentials produced by cortical cell discharging of the brain. Cortical dendrites are the sites of forest of dense units placed in the superficial layers of the cerebral cortex and non-propagated hypopolarising local potential changes in the excitatory and inhibitory axo-dendritic synapses [6]. When the excitatory axo-dendritic synapses are activated, current flow in and out in between the cell body and axo-dendritic endings, causing a wave-like potential fluctuation [7].

Intelligent automated sleep scoring systems are needed to support the tedious visual examination of polygraphic recordings. Almost all biomedical systems are required to be analysed for the different electroencephalogram (EEG) waveforms. Many researchers have proposed the different algorithms for classifying the sleep EEG. In the computerized detection of alpha waveforms, amplitude and duration of the signal varies individually [4]. Intelligence of the method can be attributed to the features extracted and the way they are selected. The ranges of the fuzzy rules are determined based on feature statistics in most of the applications.

Three various stages of sleep EEG can be classified without human interpolation automatically with the proposed approched, where the preprocessing has been done through the wavelet transform and the detection is done through fuzzy inference system. As wavelet transform provides better time - frequency resolution, many researchers have exploited this inherent property to analyse such complex and non linear signals. In order to extract the main features, authors have used various approaches based on amplitude, frequency, and entropy [8]. These features which are extracted from multichannel EEG signals are combined using fuzzy algorithms both in feature domain and in spatial domain. One major application of fuzzy logic in the field of biomedical engineering is the analysis of EEG where multistage fuzzy rule-based algorithm were mainly used for epileptic seizure onset detection [9].

Previous classifiers such as back propagation neural network, LDA etc. includes the high mathematical complex calculations for the categorization of the EEG signals, but fuzzy qualitative approach adapts the parameters to achieve the best classification of the signals [10]. This method helps to minimize the effort which is used to refrain the associated parameters of classifier to classify the various stages of sleep.

The three channel data which has been acquired from the recordings are EEG, EMG and EOG, where the sub-band frequencies were extracted with the help of DWT (Discrete wavelet transform) techniques. EEG contains waveforms in a series which are classified into four frequency sub-band that are delta, theta, alpha and beta. Distribution of different frequency sub-bands of the EEG is as shown in Table 1.

Table 1. Different frequency sub-bands of EEG

Different frequency bands of EEG	
0.5–4 Hz	delta or ∂
4–8 Hz	theta or θ
8–12 Hz	alpha or α
12–40 Hz	beta or β

EEG recordings give the information in the form of voltage with respect to time. So, for any time 'T' seconds, the voltage in mV can be measured to read the EEG graphs. For the automated analysis of the EEG, the recording must be converted into the frequency domain by using the discrete values of voltage. Digital signal processing tools are used to acquire the EEG data in the discrete form [6]. EOG keeps the record of eye movements and the technique used for measuring the retinal potential is called Electrooculography. Electric dipoles generate the potential difference due to the positive and negative cornea. Electrodes are placed on the eyes to get the potential difference due to the motion of the eyes balls. This signal has an amplitude ranging from 0.001–0.3 mV and frequency 0.1–100 Hz [11]. EMG keeps the record of electrical activity generated from active muscles. It describes the physiological properties of muscular tissue during rest or activity. These signals are produced due to the activation of muscles of the eye, eye blinks, and head movement. The signal has frequency range of 50–150 Hz [12]. As frequency analysis is not commonly evaluated in EMG, it is used to avoid the unnecessary features like frequency or noise.

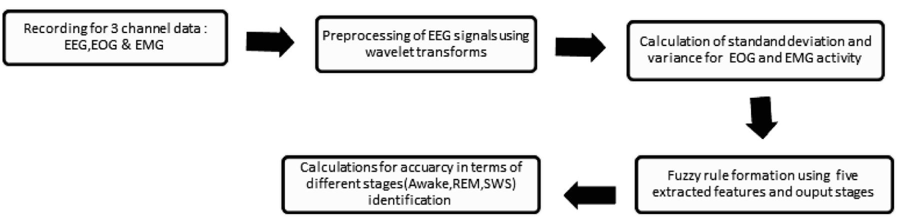

Fig. 1. Block diagram of EEG system

2 Materials and Methods

For the identification of sleep stage, the proposed algorithm is shown in Fig. 1 in which the process starts from the recording of 3 channel data and then preprocessing is done by extracting the wavelet coefficients from raw EEG. DWT has been used to extract the time - frequency signal from the time domain EEG signal. Standard deviation and variance of EMG and EOG have also been calculated to find the sleep awake stages.

2.1 Data Acquisition

In the experiment, 3- channel data was recorded continuously for four hours from normal healthy subjects. The acquired EEG data is preprocessed with DSP (Digital signal processing) techniques i.e. wavelet transforms. The data was recorded at the 256 Hz sampling frequency and features were extracted from the selected data. The recordings represent the three sleep states: Awake, REM and SWS and they were further subdivided into 2 s epoch. Each epoch contains 512 data points as the sampling frequency was selected as 256 Hz.

Some examples of two seconds epochs of unprocessed EEG recordings for Awake, SWS sleep and REM conditions have been presented in Figs. 2. It depicts the recordings of unprocessed sleep-EEG with its corresponding EMG and EOG signals with baseline drift unadjusted.

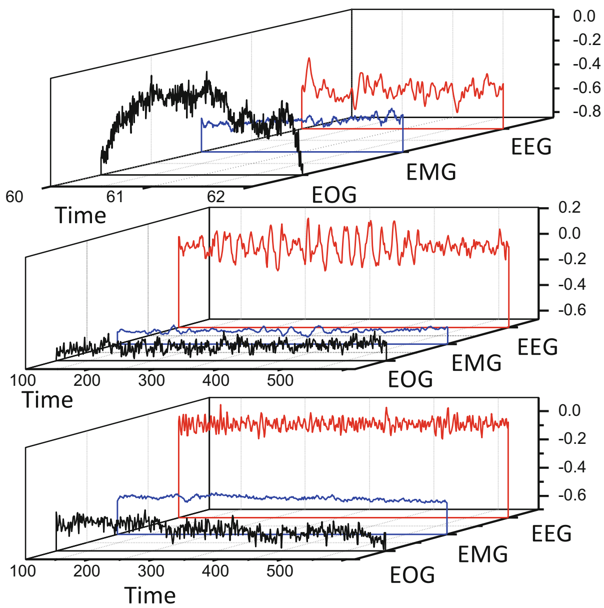

Fig. 2. Two seconds long epoch of recorded unprocessed sleep-EEG (Awake, SWS, REM) with its corresponding EMG and EOG signals

2.2 Data Processing Using Wavelet Transform

Use of wavelet decomposition enables segmentation of EEG into standard clinical bands [13]. The entropy of the wavelet coefficients in each level of decomposition reflects the underlying statistics and the degree of bursting activity associated with the recovery phenomena. With the help of wavelet analysis, changes in frequency for each signal (MAT files) were visually examined and analyzed. In the orthogonal wavelet decomposition procedure, the signal is decomposed into a vector of approximation coefficients and detail coefficients and new approximation coefficient vector is further split without considering the succeeding particulars. The analysis of the signal starts from a scale-oriented decomposition and examines the different frequency bands for EEG signal. With these four frequency bands of EEG and the other features (EMG, EOG), different stages i.e. Awake, REM, and SWS signals were clearly indentified.

Calculation of wavelet co-efficients has been done in MATLAB. Continuous wavelet transform using Daubechies order-4 wavelet was applied to Awake, REM, and SWS sleep EEG data of size [512, 1] over scales 1:128, which gives coefficients as a function of time and scale (translation vector and scale). With the ease of wavelet processing, recorded signals for all three states were split into an epoch of two seconds length. Two seconds long processed EEG signals for the three sleep states - Awake, SWS and REM have been shown in Fig. 3.

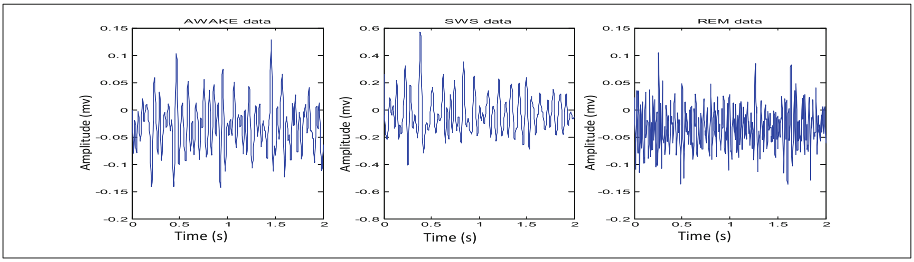

Fig. 3. Processed EEG signals of Awake, SWS and REM states

2.3 Features Selection

In this study, feature vectors of sub-band frequency have been calculated to implement the sleep stage classification. Other features namely standard deviation and variance of EMG and EOG were calculated from Eqs. (1) and (2). Wavelet transform has been applied to represent the EEG signals in time - frequency domain. Total five features were selected to frame the rules for fuzzy rule base engine in the proposed work, whereas various features like energy entropy, Shannon's entropy, amplitude, R.M.S value and mean value have been taken to determine the activity feature vectors of the EOG in [14]. Since, frequency domain analysis is not required, these features can suitably represent the changes that can distinguish various sleep stages. Various deep sleep stages lead to muscular relaxation and change the EMG values. These changes can help classify sleep stages and also help in reinforcing the sleep stages result achieved using EEG [14].

Following are the standard deviation and variance calculations of the EOG and EMG activities.

2.3.1 Standard Deviation

It is the measure of dispersion of a set of data points from its mean value. It is calculated as the radical of variance by determining the variation between each data point relative to the mean [15].

$$\mathrm{S.D}\,(\sigma) = \sqrt{\frac{\sum (x-\mu)^2}{N}} \tag{1}$$

where,

σ = standard deviation
μ = mean of all data values in the data set
N = total number of values
x = each value in the data set.

2.3.2 Variance

It is defined as the square of standard deviation [16] which is a measure of the amount of alteration in probable values and its probability of the variable.

$$\text{variance}\,(\sigma^2) = \mathrm{SD}^2 = \frac{\sum (\mathrm{x}-\mu)^2}{\mathrm{N}} \tag{2}$$

3 Fuzzy Logic Implementation

Fuzzy logic approach is mainly used in computing words or linguistics which depends on granularity and imprecision. In human brain, the perceptive organs interpret the complex and incomplete sensor informations. Similarly, the fuzzy theory also provides the same approach to deal these linguistic information with words. It uses the membership functions to perform computations.

Fuzzy rule system, fuzzy models, fuzzy associative memories and fuzzy controllers are different terms known for Fuzzy inference systems. Fuzzy logic implementation involves the following steps.

- Preprocessing
- Fuzzification
- Rule base engine/Knowledge base engine
- Defuzzification
- Post processing

Fuzzy logic is widely used in different fields e.g. robotics, data classification, expert system, automation, time series analysis decision making,, pattern and signal classification, system identification etc. [17]. FIS depends on three components i.e. a rule base which consists of fuzzy rules, a database having membership functions and a mechanism which is used in fuzzy inference to generate output.

Fuzzification: In this module, the crisp inputs are transformed in to fuzzy sets. Fuzzy operator is used to find the if-then rule of the antecedent and consequent. Fuzzy membership values can be described by antecedent and consequent. The linguistic variables are used to define the degree of association with given membership functions [18]. The method used for evaluation of degree of association to the crisp input in given fuzzy set is called the fuzzification. Membership functions which are used in fuzzy sets can be trapezoidal, triangular, gaussian or bell shape etc. In fuzzification, there is a loss of information due to degree of the membership which is just because of nonlinear transformation of the inputs [18, 19].

When membership functions of trapezoidal or triangular are used, there is loss of information where the slope is zero and resultant membership also becomes zero. Thus, the problems in these functions occur due to learning from data. There are some smoother membership functions such as Gaussian or Gaussian bell functions which are used to overcome the above problem.

Fuzzy Inference System (FIS): Implementation of fuzzy if-then rules are used to define input–output relationships and model the qualitative inputs and reasoning process for creating the output. The fuzzy inference systems incorporate a set of antecedent and consequent fuzzy membership functions as well as a set of fuzzy IF–THEN rules which are considered to form a firm basis for developing the core of any system which might be used for making decisions in vague and inaccurate situations.

Aggregation: In this module, aggregation of all outputs for each rule is done in fuzzy set. Three methods of aggregations can be applied: maximum, probabilistic OR, or simply the sum of each rule's output set.

Logical operators OR and AND are used in the method of aggregation [19]. The conjunction of linguistic statements can be applied by using logical t-conorm and the t-norm operator. Classification of task uses the Min and Max operators. In Identification and approximation process, the product operators are used for the smoothness and differentiability. It has many advantages in Neuro-fuzzy schemes.

Defuzzification: In order to get the crisp output of the given system, defuzzification is needed at the final fuzzy output. For the conversion of fuzzy sets to crisp sets, different defuzzification methods such as bisector of area, smallest (absolute) of maximum (som), mean of maximum (mom), largest (absolute) of maximum (lom) and center of gravity are used.

This method is used to generate a single number from above step of aggregation. In this, centroid calculation method is popularly used which gives the center of area under the aggregated output curve. Other methods like bisector and average of certain range of aggregated output curve are also used for defuzzification.

3.1 Fuzzy Rule Based Model

FIS (Fuzzy Inference System) model is based on various concepts such as fuzzy sets, fuzzy rule base engine and fuzzy logic reasoning. Formation of fuzzy rules is an essential component of Fuzzy model. The basic structure of a FIS (shown in Fig. 4) includes three main components viz. a rule base engine which consists of the stipulated fuzzy rules, knowledge based engine i.e. database which defines the membership functions for the entire fuzzy rule formation, and the reasoning mechanism, required to execute a inference model with the framed rules to achieve a reasonable output or conclusion.

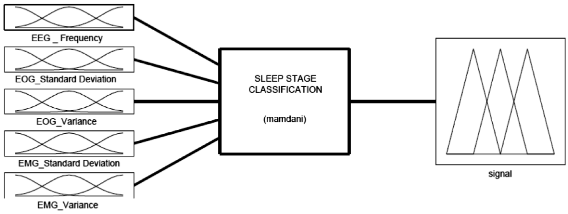

Fig. 4. Fuzzy inference system

Following rules are framed for the classification of sleep stages as shown in Table 2.

Table 2. Rules for the classification of sleep stages

EEG frequency	EMG		EOG		EEG stage
	Standard deviation	Variance	Standard deviation	Variance	
Low	Low	Low	High	High	REM
High	Medium	Medium	Low	Low	SWS
Medium	High	High	Medium	Medium	Awake

The extracted parameters such as frequencies, standard deviation and variance are taken as input variables to the Fuzzy inference system subjected to selection process block. The fuzzy rules have been framed after extracting the features to classify the EEG in to three classes: Awake, REM and SWS stages. Mapping was done between input feature vectors and output classes by an inference system using FL [20]. The processed EEG signals for Awake, REM and SWS are shown in Fig. 3.

4 Result

4.1 Membership Function for Input and Output Variables

A Membership function is a curve that defines how each point in the input space is mapped to a membership value or degree of membership between 0 and 1. The membership function associated with each input is described in Fig. 5. Triangular membership function has been taken for each linguistic variable (low, medium and high). The range of the input has been decided on the basis of EEG frequency sub-bands and mean of EOG and EMG. The study of the frequency sub-bands of the EEG reflects changes which are further reinforced by the sleep stages rules as discussed in Table 3.

Table 3. Identification of different stages based on features

EEG	EOG		EMG		Output	
Frequency	Standard deviation	Variance	Standard deviation	Variance	Fuzzy score	Sleep stage
9.26	4.92	7.2	5.49	6.38	4.47	Probably Awake
9.26	9.21	10	1.98	1.9	2.57	Marginally Awake
31.6	9.21	8.54	10	8.84	5.35	Definitely REM
7.1	0.263	6.16	10	8.69	6.62	Probably REM
3.01	9.72	8.99	0	0	8.25	SWS

The output will be in the form of fuzzy score. Fuzzy score is the value that is calculated by FIS considering all input values, constraints and membership functions. Table 3 shows the fuzzy score of all inputs and outputs which is decided by the fuzzy rules. As shown in Table 3, the system is able to find the different sleep stages accurately which may be further used for the purpose of clinical diagnosis. Five

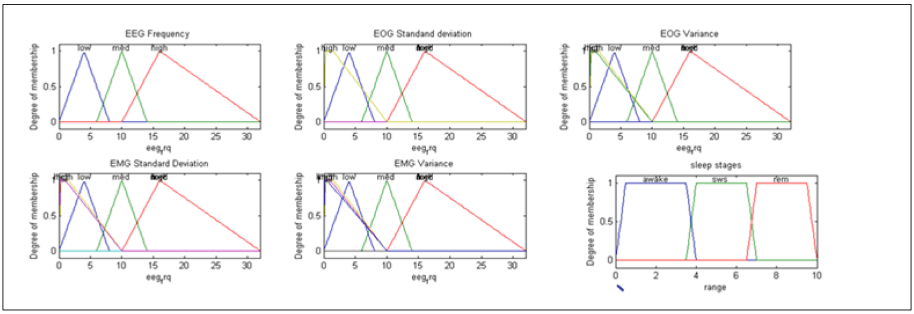

Fig. 5. Membership function for input and output

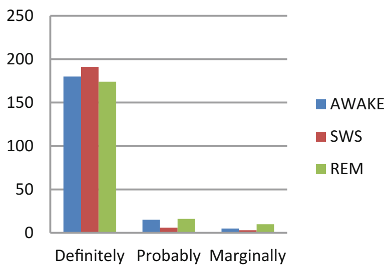

Fig. 6. Identification of correct sleep stages

Table 4. Accuracy breakdown of different stages of sleep

Different stages of sleep	Definitely	Probably	Marginally	Accuracy
Awake	180	15	5	91%
SWS	191	6	3	95%
REM	174	16	10	89%

features namely frequency, standard deviation and variance of EOG and EMG have been fed to the FIS. Once the corresponding input is presented, the corresponding rule gets fired and estimates the stage of sleep EEG.

Each membership function of all five features has been described with three linguistic variables (Low, Medium and High) which represent the particular range of each input. For the output stages three trapezoidal memberships have been chosen for the entire range as specified in Fig. 4, where each membership function defines the stage of sleep EEG as Awake, REM or SWS. For the precise identification of all stages, they are further classified as probable, marginal and definite. Fuzzy score is evaluated on the basis of five features and further the stage is identified on the basis of the rule base engine which is fed in to the fuzzy inference system. The fuzzy rule base engine generates the fuzzy score after evaluation of all fuzzy rules and its constraints. The output obtained from the fuzzy score lies between 0 and 10. The range of fuzzy score is classified in to nine categories i.e. definitely awake (0–2.5), marginally awake (2.5–3.5), probably awake (3.5–4.5), definitely SWS (4.5–5.5), marginally SWS (5.5–6.5) probably SWS (6.5–7), definitely REM (7–8.5), marginally SWS (8.5–9.5) and probably REM (9.5–10). Table 3 shows the detailed overview of fuzzy score for the sample identification of sleep EEG.

Performance of the fuzzy system for sleep stage classification has been assessed and experimental results have been plotted as shown in Fig. 5. Table 3 confirmed that the proposed model has potential in classifying the EEG signals with the average accuracy of 93%. The accuracy of each stage is 91% for Awake, 95% for SWS and 89% for REM stage (Fig. 6 and Table 4).

5 Discussion

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 [21]. Review of literature reveals that neural network along with the various transforms (such as Fourier transform, wavelet transform) has been applied for finding the solution of complex problems associated with human brain [22]. Many researchers have reported on the automated sleep scoring techniques using wavelet transform as a pre-processor. Applications like event related potentials, sleep spindles detection, spike detection, epileptic seizures have also been discussed in past years with different supervised and unsupervised classifier techniques [23, 24], but very less works have been reported till now which investigate the frequency and powers changes for different stages of EEG with the help of fuzzy logic.

6 Conclusion

The soft-computing tools are very effective tools for automatic identification of small changes occuring in EEG signals associated with various stress stimuli [16]. Therefore, the proposed research work will help the neurologists and doctors to find the sleep-awake correlation. By means of Fuzzy logic approach, sleep stage classification on the subject's polygraphs under consideration have been studied. EEG, EOG and EMG have been used in this study where the range of EEG sub-band frequencies are catagorised into 4 frequency bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–40 Hz). The proposed work approaches the classification of the sleep stages through the use and attributes of fuzzy logic and fuzzy inference system accompanied by wavelet transform. The sleep stage identification has been done with an accuracy of 91% (Awake), 95% (REM) and 88% (REM) with the help of proposed algorithm with an accuracy. The goal of this study is to improve an available computerized diagnostic system to investigate the abnormalities in sleep EEG signals for normal and abnormal conditions.

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