# Computer Assisted Automatic Sleep Scoring System Using Relative Wavelet Energy Based Neuro Fuzzy Model

GIRISHA GARG[1], VIJANDER SINGH[1], J.R.P GUPTA[1], A.P. MITTAL[1], SUSHIL CHANDRA[5]
[1]Department of Instrumentation & Control Engineering
Netaji Subhas Institute of Technology
University of Delhi, Dwarka, Delhi, India
[5]Department of Biomedical Engineering
INMAS, DRDO, Delhi, India.
girishagarg@gmail.com

*Abstract:* - This paper addresses the automated scoring of sleep stages using Electroencephalograph (EEG). The change in the Sleep Stages is accompanied by changes in the frequency spectrum of the EEG signals. A novel method based on Relative Wavelet Energy based Neuro-fuzzy is proposed to perform automatic sleep stages classification. Features extracted from 30-second epoch of (EEG) using relative wavelet energy are used for representing the EEG signal of different sleep stages. This method gives the best feature vector in terms of specificity and dimension. A neuro-fuzzy based ANFIS model is employed to classify these features to one appropriate stage. The sleep scoring is done for five stages namely, wake, sleep stages: stage1, stage 2, slow wave sleep (stage 3 & 4) and stage 5.The physionet database is used to validate the accuracy of the proposed automatic classification system. The hypnogram generated is compared with the standard hypnogram based on expert rule. The system can be used for real time implementation owing to high classification rate (97.4%), low computational cost, high speed and its feasibility to be implemented on hardware. The result of the study provides a framework of methodology that can be used to design computer assisted sleep scoring systems.

*Key-Words:* - Automated Sleep Scoring, hypnogram, EEG, Relative Wavelet energy, ANFIS, Physionet

## 1. INTRODUCTION

### 1.1 SLEEP SCORING:

Sleep scoring and evaluation is a fundamental tool for sleep research and sleep medicine. The classical method of sleep scoring consists of determining sleep stages through visual inspection of the polysomnograms (PSG) by a sleep specialist. PSG is a test which is conducted by recording many physiological signals such as, Electroencephalograph (EEG) Electromyogram (EMG), Electrooculargram (EOG), pulse oximetry and respiration [4]. The recorded activity is then divided into short periods of time called epochs. According to the Rechtschaffen & Kales (R&K) manual for normal sleep classification [5] these epochs can be scored as waking, Non-Rapid Eye Movement (NREM), Rapid Eye Movement (REM), depending on the behaviour of the recorded brain activity [6]. EEG is the recording of electrical activity of brain and is the most extensively used signal to study human brain. The EEG patterns for all these sleeps are shown in Fig. 1.

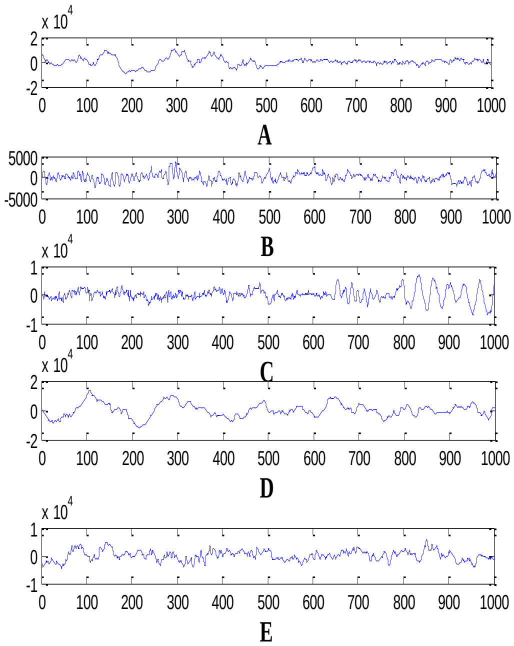


Fig. 1 EEG Sleep Patterns A) Waking stage B) Stage 1 C) Stage 2 D) Slow Sleep E) REM Sleep

The waking stage is referred to as relaxed wakefulness, because this is the stage in which the body prepares for sleep. All people fall asleep with tense muscles and their eyes moving erratically. Then, normally, as a person becomes sleepier, the body begins to slow down. Muscles begin to relax, and eye movement slows to a roll. And gradually the person moves into NREM sleep. The NREM sleep is further divided into four stages namely, stage 1, stage 2, stage 3, stage 4. Stage 3 & 4 are usually pooled due to their similar characteristics. The EEG patterns of the above mentioned sleep stages are shown in Fig. 1.

Stage 1 sleep or drowsiness, is often described as first in the sequence. The stage is characterized by slow muscle activity and occasional twitching. Stage 1 may last for 5 to 10 minutes. Next NREM sleep stage is Stage 2 and characterized by sudden bursts of brain activity called sleep spindles and high bandwidth peaks which are followed by negative peaks. In this stage the heart rate slows, and body temperature decreases. At this point, the body prepares to enter deep sleep. Stage 3 and Stage 4 are deep sleep stages, with Stage 4 being more intense than stage 3. These stages are known as slow-wave sleep. Stage 3 represents the transition period from light sleep to deep sleep. And stage 4 occurs when the person is in deep sleep. In deep sleep, there is no eye movement or muscle activity.

REM sleep, also called stage 5, is distinguishable from NREM sleep by changes in physiological states including its characteristic, rapid eye movements. However, PSG shows the wave patterns in REM to be similar to Stage 1 sleep. In normal sleep (in people without disorders of sleep-wake patterns or REM behaviour disorder),the heart rate and respiration speed up and become erratic, while the face, fingers, and legs may twitch.

The distribution of all the stages mentioned above is shown in Fig. 2 in terms of the duration for which they occur in a normal sleep cycle. Sleep does not progress through these stages in sequence, however. Sleep begins with stage 1 and progresses into stages 2, 3 and 4. After stage 4 sleep, stage 3 and stage 2 sleeps are sequentially repeated before entering REM sleep. Once REM sleep is over, the body usually returns to stage 2 sleep. Sleep cycle goes through these stages approximately 4 or 5 times throughout the night.

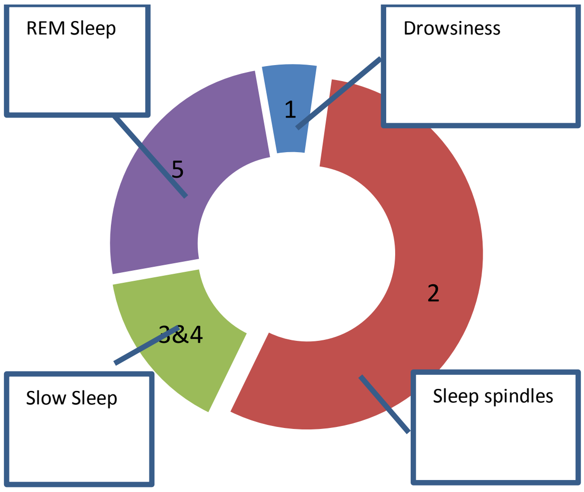


Fig. 2 Sleep Cycle

The process of sleep scoring involves identifying the EEG signal epochs according to the sleep stage which they represent and the result is stored using a graphical plot called hypnogram [7] which represents the sleep profile. There is a high degree of discrepancy involved in the scoring of sleep stages to obtain the hypnogram. Visual analysis of the sleep architecture to obtain the hynogram for diagnosis purposes involves various complexities and variabilities [3]. For these reasons an automatic classification system is indispensable to evaluate the sleep structure with accurate and fast decision making capabilities. Various authors have reported the sleep evaluation for different purposes like vigilance estimation, alertness detection or simply for classification of sleep stages. But most of the approaches are not suitable for implementation on real time systems. Some of the reasons being, low accuracy, infeasibility for hardware implementation, computational complexities, lack of generalization etc. The accuracy of any classification system is dependent on the computational tools that are used to design the system. An objective comparative study of the methods used for sleep classification is presented in section IV along with the comparison of the results obtained. A summary of the computational tools used in few of the relevant work is presented in Table 1.

Table 1 Techniques Used For Sleep Classification

| Author | Year | Feature Extraction | Classification |
|---|---|---|---|
| Schmitt, R.B., et al. | 1998 | FourierTransform | HMM |
| Heiss, J.E., et al. | 2002 | - | NeuroFuzzy |
| Subasi, A., et.al | 2005 | Discrete WT | NeuralNetwork |
| Kerkeni. N. | 2005 | FourierTransform | NeuralNetwork |
| Doroshenkov, L.G., et al. | 2007 | FourierTransform | HMM[1] |
| Tang, W.C., et al. | 2007 | HHT[3] +WT | SVM |
| Ebrahimi, F., et al. | 2008 | Wavelet Packet | NeuralNetwork |
| Liu, H.J., et al. | 2010 | FourierTransform | SVM[2] |
| Vatankhah, M., et al. | 2010 | Discrete WT | SVM+NF[4] |
| Ouyang, T., Lu, H.T. | 2010 | Continuous WT | SVM |
| Liu, Y., et al. | 2010 | HHT[3] | Neural Network |

[1] Hidden Markov Model [2] Support Vector Machines [3]Hilbert Huang Transform [4] NeuroFuzzy

## 1.2 FEATURE EXTRACTION

The variations in the EEG patterns with respect to the sleep stages are very subtle and therefore require advanced signal processing techniques to extract the features for sleep classification. Some of the techniques used for this purpose are Fourier Frequency Transform (FFT) [3,28], autocorrelation function, Hilbert Huang Transform (HHT) [26], Wavelet Transform (WT) [6] etc. It is observed from literature that WT is the most promising technique for feature extraction from the EEG signals for diagnostic classification [12].WT is preferred for feature extraction as, owing to its multiresolution property, it can deal with the non stationary, complex and dynamic nature of the EEG signals. It is noticed that usually only a few bands of the EEG signals are used for feature extraction rather than using the full frequency spectrum. This is done to in order to reduce the dimension of the feature vectors extracted from WT. To solve this problem the concept of relative wavelet energy has been employed to construct the features that correlate with EEG sleep patterns and has the ability to reflect the degree of similarity between different segments of the signal of same sleep stage. The justification for using this approach is that it reduces the computational load of the classification system while optimizing the full EEG frequency spectrum for sleep scoring.

## 1.3 PATTERN CLASSIFICATION

Fuzzy Logic and Neural network have widely been used as pattern classification tools for medical applications. The main difference between the two techniques is that neural network model the classification system in a numerically quantitative way whereas Fuzzy Logic uses the symbolic qualitative approach. Neurofuzzy combines the properties of fuzzy logic (fuzzy reasoning) and neural networks (network calculation) to interpret the relationship between the extracted features. There are many benefits of using neurofuzzy system [8] the most important being automatic tuning and faster speed. This paper presents a robust automated neurofuzzy classifier (NFC) based on ANFIS which is one of the most commonly used neurofuzzy system. ANFIS classifier has been used in various biomedical applications and has demonstrated high accuracy rate [18, 22]. The ANFIS system implemented in the paper takes the RWE feature vector obtained from the EEG signals as the input patterns and classifies them into different sleep stages.

## 2. SLEEPSCORING SYSTEM

An automated Sleep Scoring System consists of the following steps:

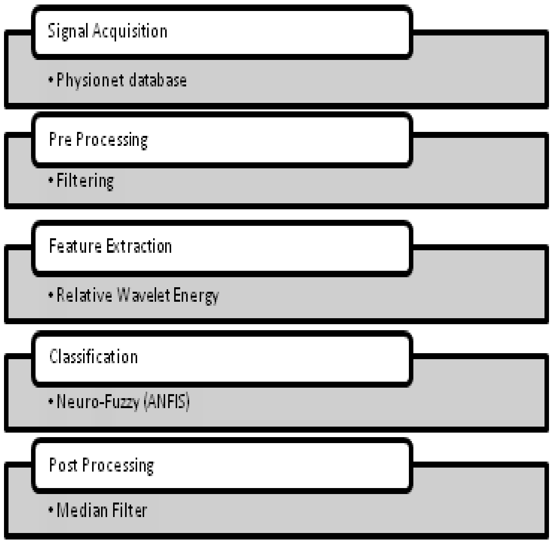


Fig. 3 EEG Processing

- Signal acquisition: The Sleep EEG signals available on the physionet database have been utilized for the study.
- Pre-processing: The data is filtered using FIR filters.
- Feature extraction: The features representing the sleep stage are extracted by applying relative wavelet energy on the filtered EEG epochs.
- Classification: The feature vector for different classes are used as inputs neuro-fuzzy based ANFIS classifier.
- Post-processing: The output obtained from the classification process is further post processed using median filter. The final output is used to generate the hypnogram. The steps are further explained in detail in the following sections.

### 2.1 SIGNAL ACQUISITION

In sleep literature various signals like EEG, EMG, EOG, heart rate variability (HRV), Electrocardiogram (ECG) [6,9,10]etc have been used for sleep evaluation. For this study EEG signals have been taken into consideration. The correlation between EEG signals and sleep stages is shown in Table 2 and Fig. 1

Table 2 Correlation between Sleep stages and EEG bands

| EEG Feature | Frequency | Amplitude | Temporal |
|---|---|---|---|
| Alpha activity | 8-13 Hz | 20 – 60 uV | Awake, stage 1, and REM |
| Beta activity | 13 Hz | 2-20uV | awake |
| Theta | 4-8Hz | 50-75 uV | 1 2 3 4 |
| Delta | 0-4Hz | 75 uV | 3 4 |
| Sleep spindles | 12-14Hz | | 2 |

The dataset provided by the PhysioBank [11] was used for this study. The recordings contain horizontal EOG, Fpz - Cz and Pz Oz EEG, each sampled at 100 Hz. Hypnograms are manually scored according to R&K scale based on Fpz-Cz /& Pz-Oz EEG.

The EEG signals used from the database are first divided into 30 sec epochs. The epochs are pre-processed by filtering the whole data. This filtering step removes the unwanted artifacts from the EEG data and improves the accuracy.

## 2.2 WAVELET TRANSFORMS

A crucial part of the EEG processing consists of transforming the information acquired from the signals into a small number of components which represent the brain activity.

Traditional Fourier transform methods (Fast Fourier transform and Short time Fourier Transform) have proved to be extremely insightful over the years as a feature extraction technique. There are various limitations while applying these techniques like they are not suitable to extract features localized simultaneously in time and frequency domain. Due to this reason they cannot be used to analyse transient signals especially when it is required to generate features for detection and discrimination for critical applications. Over the past several years, the methods based on wavelet (Stationary WT, Discrete WT, Wavelet Packet) have received a great deal of attention for extracting information from the EEG signals. This can be accounted to the Multi resolution analysis (MRA) which makes WT the most suitable candidate for analysis of frequency content of non stationary events which is a prerequisite for EEG signals.

WT decomposes a signal into small waves with energy concentrated in time called wavelets. Wavelets are the scaled and shifted copies of the main pattern, so-called the "mother wavelet" The mother wavelet function is defined by equation (1), where b is translation parameter and, a as scale parameter [14]

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad \ldots (1)$$

DWT analyses the signal using MRA by decomposing the signal into approximations and detail information by employing two functions: scaling and wavelet function as shown in equation 1 The approximation coefficient is subsequently divided into new approximation and detailed coefficients which are shown in equation (2) given below. This process is shown in Fig. 4 which is carried out iteratively producing a set of approximation coefficients (CA) and detailed coefficients (CD) at different levels (N) of decomposition.
For a given signal x(t) the DWT decomposition can be represented by equation (2).

$$x(t) = \sum_{k=-\infty}^{k=+\infty} C_{N,k}\emptyset(2^{-N}t-k) + \sum_{j=1}^{N}\sum_{k=-\infty}^{k=+\infty} d_{j,k}2^{-j/2}\psi(2^{-j}t-k) \quad \ldots (2)$$

Where $C_{N,\ k}$ represents approximation coefficients at level N, while dj, k (j = 1 to N) represents detailed coefficients or wavelet coefficients at level j. ψ(t) is the wavelet function, while φ(t) is a companion function, named as scaling function.

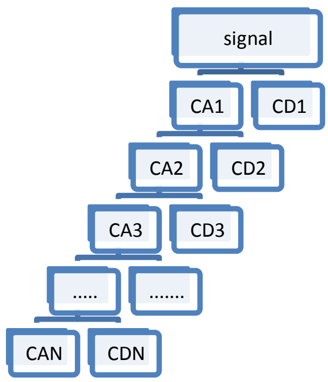


Fig. 4 Decomposition of a signal into approximation and detailed components

## 2.3 RELATIVE WAVELET ENERGY

If the scaling functions and wavelets form an orthogonal basis, Parseval's theorem relates the energy of the signal x(t) to the energy in each of the components and their wavelet coefficients. The energy $E_j$ of the detailed signal at each resolution level j , is given by:

$$E_j = \sum_k |d_{j,k}|^2 \quad j = 1 \text{ to } N \quad \ldots (3)$$

And the total energy for all the levels is given by:

$$E_{total} = \sum_{j=1}^{N+1} E_j \quad \ldots (4)$$

The wavelet energy can be used to extract only the useful information from the signal about the process under study. For this work the concept of relative energy has been used. RWE gives information about relative energy with associated frequency bands and can detect the degree of similarity between segments of a signal. RWE is defined by the ratio of detail energy at the specific decomposition level to the total energy. Thus the relative energy is given by:

$$RWE = \frac{E_j}{E_{total}} \quad \ldots(5)$$

RWE resolves the wavelet representation of the signal in one wavelet decomposition level corresponding to the representative signal frequency. Thus this method accurately detects and characterizes the specific phenomenon related to the different frequency bands of the EEG signal. RWE gains an advantage over DWT based feature extraction in terms of speed, computation efficiency and classification rate.

## 2.4 NEURO FUZZY APPROACH

Fuzzy logic and neural networks are two complementary soft computing technologies. Each method has its merits and demerits [17]. Neuro fuzzy systems harness the power of both of these paradigms by using the learning capabilities of the neural networks to automatically tune the membership functions and the fuzzy rules of the fuzzy systems. This enables the system to discover the rules that may explain how the classification process should be performed and to find the parameters that define the degree of presence or absence for each pattern [18]. In this work ANFIS approach proposed by Jang [19] has been used.

ANFIS: Adaptive neurofuzzy inference system is an approach in which a fuzzy inference system is constructed using a given set of input and output. The membership functions and rules of these systems are adjusted using various computational algorithms to make them learn from the data they are modelling

ANFIS architecture: To present the ANFIS architecture, let us consider two-fuzzy rules based on a first-order Sugeno model.

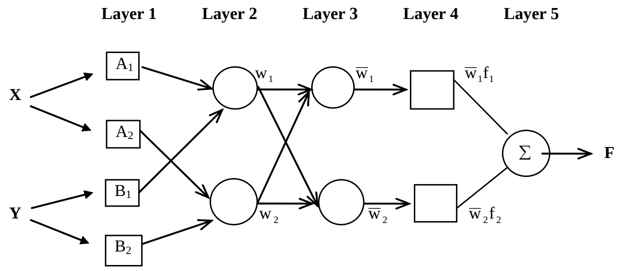


Fig. 5 ANFIS Layers

Rule 1:
*If* $x$ *is* $A_1$ *and* $y$ *is* $B_1$ *THEN* $f_1 = p_1 x + q_1 y + r_1$
Rule 2:
*If* $x$ *is* $A_2$ *and* $y$ *is* $B_2$ *THEN* $f_2 = p_2 x + q_2 y + r_2$

One possible ANFIS architecture to implement these two rules is shown in Fig. 5. Note that a circle indicates a fixed node whereas a square indicates an adaptive node (the parameters are changed during training).

Layer 1: All the nodes in this layer are adaptive nodes. i is the degree of the membership of the input to the fuzzy membership function (MF) represented by the node. The output of each node is given by

$$O_{1,i} = \mu_{A_i}(x) \qquad for\ i = 1,2 \quad \ldots(6)$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \qquad for\ i = 3,4 \quad \ldots(7)$$

where, O1,i(x) is essentially the membership grade for x and y. Ai and Bi can be any appropriate fuzzy sets in parameter form. For example, if bell MF is used then

$$\mu_A(x) = \frac{1}{1 + \left| \frac{x - c_i}{a_i} \right|^{2b_i}} \quad \ldots(8)$$

Where ai, bi and ci are the parameters for the MF.

Layer 2: The nodes in this layer are fixed (not adaptive). They play the role of a simple multiplier. The outputs of these nodes are given by

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2 \qquad ...(9)$$

Layer 3: Nodes in this layer are also fixed. They perform a normalization of the firing strength from previous layer. The output of each node in this layer is given by

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad ...(10)$$

Layer 4: All the nodes in this layer are adaptive nodes. The output of each node is simply the product of the normalized firing strength and a first-order polynomial

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \qquad ...(11)$$

Where pi, qi and ri are design parameters.

Layer 5: This is a single node layer which performs the function of a simple summer. The output of this single node is given by

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad ... (12)$$

The ANFIS architecture is not unique. Some layers can be combined and still produce the same output. In this ANFIS architecture, there are two adaptive layers (1 and 4). Layer 1 has three modifiable parameters ($a_i$, $b_i$ and $c_i$) pertaining to the input MFs. These parameters are called premise parameters. Layer 4 has also three modifiable parameters ($p_i$, $q_i$ and $r_i$) pertaining to the first-order polynomial. These parameters are called consequent parameters.

Learning algorithm: The learning algorithm is used to update the parameters associated with the membership function. The updating of these parameters is facilitated by a gradient vector which provides a measure of how well the fuzzy inference system is modelling the input/output data for a given set of parameters. Further the parameters are adjusted using any of approach mentioned below to some error measure. There are several other learning algorithms proposed by researchers to obtain an optimal set of rules [21]. In this paper the hybrid algorithm is used for its non complexity and high efficiency in training.

A hybrid algorithm adjusts the consequent parameter $p_i$, $q_i$ and $r_i$ in a forward pass and the premise parameters $a_i$, $b_i$ and $c_i$ in a backward pass. In the forward pass the network inputs propagate forward until layer 4, where the consequent parameters are identified by the least-squares method. Once the optimal consequent parameters are found, the backward pass starts immediately. In the backward pass, the error signals propagate backwards and the gradient descent method is used to update the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back propagation algorithm [22]. A summary of the hybrid algorithm is presented in Table 3.

Table 3 Hybrid Learning Algorithm

| | Forward pass | Backward pass |
|---|---|---|
| Premise parameters | fixed | Gradient descent |
| Consequent parameters | Least square method | fixed |
| Signals | Node outputs | Error signals |

## 3. METHOD DESCRIPTION

The automated sleep scoring system presented is designed using the relative wavelet energy based neuro-fuzzy classifier which uses the aforementioned computational tools, Relative wavelet energy and Neuro-Fuzzy classifier.

### 3.1 WAVELET TRANSFORM

WT is exploited in this study to decompose the EEG signal into several frequency bands. One of the most important issues while addressing DWT for signal analysis is choosing the appropriate wavelet and decomposition level. After performing several tests db2 wavelet and 6 decomposition levels were chosen for this study. Thus using DWT 30 second epochs of EEG signals were decomposed in 6 levels giving A6, and d6 to d1. Frequency bands corresponding to the six decomposition levels for db2 wavelet are shown in Table 4. It is to be noted here that as mentioned in section 2.1, the sampling frequency of the EEG signals is 100 Hz.

Table 4 DWT Decomposition

| Decomposition level | Frequency Range (Hz) |
|---|---|
| D1 | 50-100 |
| D2 | 25-50 |
| D3 | 12.5-25 |
| D4 | 6.25-12.5 |
| D5 | 3.12-6.25 |
| A6 | 1-1.15 |

Generally the DWT coefficients are used as feature space for classification [24]. But since the classifier here used is ANFIS, the feature space was required to be compact because the ANFIS classifier suffers from the curse of dimensionality which refers to a situation in which the number of fuzzy rules increases exponentially with the number of input variables [25]. It works well with the small feature vectors. Therefore when the proposed ANFIS classifier was deployed with the DWT coefficients the system crashed before the rule set could be designed.

### 3.2 RELATIVE WAVELET ENERGY

To overcome these entire problems the concept of RWE is introduced to implement the NFC classifier. RWE has the capability to automatically select the features that are highly correlated with the variations in the EEG patterns if different sleep stages. The relative wavelet energy is calculated from the coefficients obtained from the DWT decomposition using equation (2) and gave a feature vector of 6 features. This helped in obtaining lesser computational load for the system. The wavelet energy patterns for different sleep stages are shown in Fig. 6 .

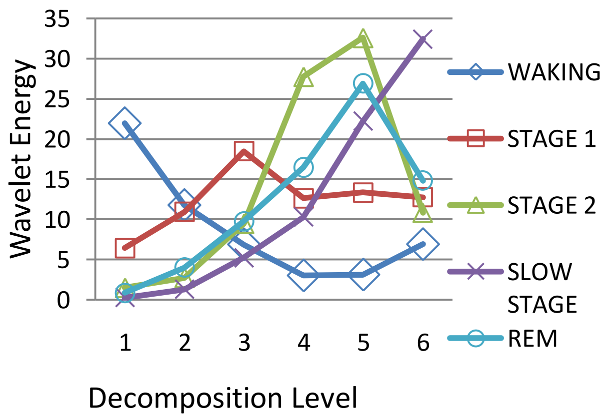


Fig. 6 Wavelet Energy versus Decomposition Level

### 3.3 ANFIS

The normalized RWE feature vectors representing EEG signals were used to create the training and test dataset for the ANFIS classifier. Five set of RWE vectors with targeted outputs corresponding to 5 stages namely waking, stage 1, stage 2, slow sleep and REM were constructed for training purposes. Stage 3 and 4 were pooled together as slow sleep. The training input set was formed by taking 15 patterns of 6 RWE features each where each pattern represented 1epoch i.e. 30sec of EEG recording. This gave a total of 90 inputs per sleep stage to the ANFIS classifier as training data with targeted output. Each training pattern consisted of a vector $X_{ij}$:

$X_{ij} = [x_1\ x_2.....\ x_n]$

Where i is number of training patterns used for a representing a sleep stage, j is the number of sleep stages and n is the number of decomposition levels. For the NFC implemented in this study i=15,j=5, and N=6. Corresponding to the training patterns desired output vector is provided to the NFC which can be represented by D:

$D = [d_1\ d_2\ d_3\ .......d_k]$

Where k is total number of training patterns and can represented as k=i×j .For this study the value of k=75.

### 3.3.1 ANFIS ARCHITECTURE

The ANFIS architecture explained in section III.D is implemented. Two membership functions are used for designing the architecture and same number of membership functions is associated with each input. Since there are 6 features for each input pattern, all possible combination of inputs result in 64 rules. The generalized bell-shaped function is used as the input function and linear function is used as the output function. To train the parameters associated with the membership functions of the fuzzy system the hybrid algorithm is used as the learning process, which is a combination of least square and back propagation method. The architecture of the ANFIS classifier can be summarized as follows:

Number of inputs for one pattern = 6

Number of membership function for each input = 2

Total number of fuzzy rules = 64

Input membership function = Generalized bell shaped function

Output membership function = Linear function

Learning algorithm = Hybrid of least square and back propagation method

Number of epochs = 70

Table 5 depicts the features of the ANFIS classifier for different decomposition levels of db2 wavelet. This step was important to decide the optimal number of decomposition levels at the feature extraction stage.

Table 5 Comparison of Decomposition levels

| | N=5 | N=6 | N=7 |
|---|---|---|---|
| Number of nodes | 92 | 161 | 294 |
| Linear parameters | 192 | 448 | 1024 |
| Non linear parameters | 30 | 36 | 42 |
| Fuzzy rules | 32 | 64 | 128 |

$^N$ Decomposition level

The ANFIS classifier designed using the mentioned architecture details is then tested using a total of 600 patterns of 6 RWE features each, which corresponds to approximately 5 hours of EEG recording. The sleep stage outputs obtained from the ANFIS classifier were post-processed using median filter. The final outputs were then used to generate the hypnogram shown in Fig. 7. Fig. 7 shows the hypnogram depicting the variation in the sleep stages obtained from the EEG of a normal person using the presented automated sleep scoring system. Whereas Fig. 8 shows the hypnogram obtained from the same EEG signal, but by manual R&K sleep scoring system. It can be verified by comparing the two hypnogram that the presented sleep scoring system is able to generate the same hypnogram depicting high accuracy of the system.

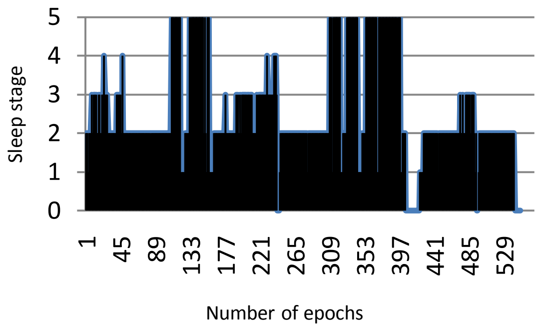


Fig. 7 Hypnogram from Proposed Classifier

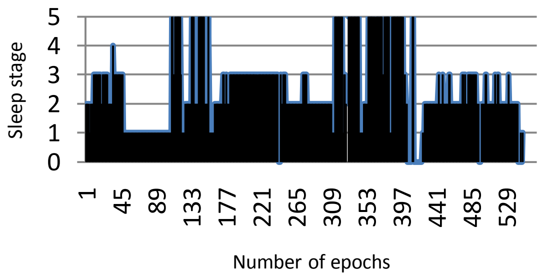


Fig. 8 Hypnogram from R& K rule

## 4. RESULTS and DISCUSSIONS

The paper demonstrates the implementation of wavelet energy based neuro-fuzzy classifier. The features based on RWE are extracted from DWT decomposition of db2 wavelet and classified using ANFIS classifier. To find the optimal DWT decomposition level of db2 wavelet different ANFIS parameters and features are tested. Table 5 depicts the reason for selecting the decomposition level to be 6. In order to achieve good generalization capability, it is important to have the number of training data points several times larger than the number parameters being estimated. This limitation impeded the decomposition level to be increased beyond 6 and for lesser decomposition levels there is insufficient detailing in terms of frequency bandwidth preventing the model from giving accurate results.

To verify the accuracy of the trained ANFIS model a hypnogram is constructed from the scoring output of the test dataset corresponding to 5 hours of EEG recording. This automatically generated hypnogram is then compared with the hypnogram scored manually using R& K scale. In the hypnogram the sleep stage scoring is found for every epoch (30 sec) of the EEG signal for a recording of 5 hours.

It was observed from the results that 97.4% of agreement is achieved between the hypnogram generated by the R& K rule scoring and the proposed automatic classifier. The comparison of different approaches used for sleep evaluation is presented in Table 6. It is clearly evident that the proposed approach provides a much higher accuracy as compared to other approaches.

Table 6 Comparison of Different approaches

| Approach | Accuracy |
|---|---|
| RWE+ANFIS | 97.4% |
| DWT+ANN | 94% |
| WP+ANN | 93% |
| FFT+SVM | 90% |

The approach presented in this paper is represented by RWE + ANFIS. The other approaches mentioned in the comparison table are briefed as follows:

Also it is observed that the other approaches mentioned in the Table 6 were not able to classify all the sleep stages precisely, whereas the approach presented in the paper could identify all the steep stages with nearly same classification accuracy. An exception being stage 2 for which the accuracy was slightly lesser then the other 4 stages.

The approaches presented in [28] and [3] are represented as FFT+SVM and FFT+ANN. Both approaches are based on applying Fourier transforms for feature extraction which are more suitable for analysis of stationary signals and hence are not very suitable to be applied on non stationary EEG signals. The classifiers used in these approaches are Artificial Neural Networks (ANN) and Support Vector Machines (SVM). The approaches mentioned in [3,6, 26 and 13] are represented by FFT+ANN, WP+ANN, HHT+ANN, DWT+ANN respectively. All these approaches use ANN for classification system which lacks the capability of modelling the system on logical reasoning and also require hit and trial method to select the number of hidden layers and the associated neurons. The approach represented by ANFIS is presented in [18]. The classification is based on the neuro-fuzzy approach. There is no feature extraction technique described and the accuracy achieved is 88.2%.

Accuracy achieved in the approach DWT +SVM+ ANFIS presented in [4] is slightly higher than the accuracy achieved with the proposed RWE+ANFIS classifier. The reason being that the approach DWT+SVM+ANFIS involves high computational complexities resulting in heavy computational load. Moreover the feature extraction technique mentioned in this approach makes use of statistical features which cannot be easily generalized for EEG signal classification.

It is noticed that the results obtained from the ANFIS classifier gave satisfactory results (97.4%). The time taken by the classifier for automatic generation of a hypnogram from 5 hours of Sleep recording was very less as compared to the other classifiers. Also the results are clearly discriminative, precise and interpretable which is not the case with other normally used classifiers like Neural Networks , Support vector machines etc. That means, the ANFIS classification system is an efficient system for predicting and classifying different EEG patterns.

# 5. CONCLUSION

In this paper DWT based feature extraction is incorporated to classify the sleep stages using neuro-fuzzy based ANFIS classifier. The RWE of different EEG signals were obtained which provided a compact and accurate feature space to achieve better classification rate and reduced computational load. Due to its memory efficient capability this concept can generalize the EEG processing to much larger datasets. The ANFIS classifier presented has a good performance in classifying the 5 stages of sleep architecture and can be easily implemented on hardware for real time response. The most redeeming feature of proposed system is its capability to achieve excellent computational efficiency without any loss of information. This sets apart the system from the other automatic classifiers falling in the same levels of accuracy without any requirement of top-notch PCs. Owing to the suitably high accuracy achieved using the synergy of neuro-fuzzy and RWE technique, the methodology presented in this paper can be utilized for designing automatic sleep classifiers which can be used by the neurologists for detecting various sleep disorders.

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