IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary research
Website: www.ijdacr.com (Volume 3, Issue 3, October 2014)

EEG Signal based Sleep Detection using PCA and Neural Network

Suchi Rawat
M. Tech. Scholar, EC Department
Sanghvi Institute of Management and Science,
Indore (India)

Virendra K. Verma
Asst. Professor, EC Department
Sanghvi Institute of Management and Science,
Indore (India)

Abstract –**The electroencephalogram (EEG) is the most common tool used in sleep research. This unit describes the methods for recording and analyzing the EEG. Detailed protocols describe recorder calibration, electrode application, EEG recording, and computer EEG analysis with power spectral analysis. Computer digitization of an analog EEG signal is discussed, along with EEG filtering and the parameters of fast Fourier transform (FFT) and power spectral analysis. Sample data are provided for a typical night's analysis of EEG during NREM (non-REM) and REM sleep.**

Keywords – **Electroencephalogram (EEG), Fast Fourier Transform (FFT), Power Spectral Analysis, NREM and REM.**

I. Introduction

The importance of sleep research is both in medicine and in theoretical area. There are many sleep disorders, e.g., the most frequent are insomnia, narcolepsy, sleep apnoea; many other disorders manifest themselves through sleep disturbances (e.g. depression, schizophrenia, Alzheimer disease [1], etc.). After the pain, sleep disturbances are the second most frequent indicator of illness. During sleep, human brain goes through several psychophysiological states that are relatively stable. Many nervous centres are inactive, so brain becomes a less complex system and is a suitable object for mathematical modelling.

The beginning of modern sleep research dates back to the 1930s and is closely connected with the invention of the electroencephalography. In 1937, Loomis was the first to observe that sleep is not a homogeneous state during the whole night and described different stages of sleep based on EEG [2]. In 1953, Aserinsky and Kleitman observed a special state of sleep-rapid eye movement (REM) sleep, during which rapid, binocularly symmetrical eye movements occur, EEG pattern is similar to the one observed during wakefulness, and both respiratory and heart rates are increased in contrast to other sleep stages. Their experiments resulted in a relationship between REM sleep and dreaming: majority of people awakened from REM sleep reported dreams, whereas people awakened during nonREM sleep did not recall dreams [3]. From overnight recording of EEG and electrooculogram (EOG), Kleitman with Dement [4] specified the cyclic pattern of REM-nonREM sleep. One cycle of REM-nonREM lasts about 90-100 minutes and during the night, 4-5 cycles occur. Aserinsky and Kleitman also divided nonREM sleep into four stages: 1 through 4, ranging from the lightest sleep in stage 1 to the deepest sleep in stage 4.

II. Sleep Stages and the Rules of Rechtschaffen and Kales

The main states of vigilance are wakefulness, REM sleep and nonREM sleep. NonREM sleep is further divided into four Stages from the lightest Stage 1 to the deepest Stage 4. Stages 3 and 4 are referred to as slow wave sleep (SWS). The frequency of sleep Stages alters during the night - in the early hours of sleep SWS dominates, whereas REM sleep occurs more often in the second part of sleep. The portion of REM sleep during night alters with age – in new-born babies REM sleep lasts for 50%, in adults for 20%.

An essential method in human clinical and basic sleep research is polysomnography. It is composed of measuring electroencephalogram (EEG), electrooculogram (EOG) and electromyogram (EMG). Electroencephalography is the basic method with an excellent temporal resolution and lower spatial resolution of electrical activity of cerebral cortex. The quality of EEG recording depends on some technical parameters, see [5] for details.

Sleep Stages are scored according to "A Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Subject", which was elaborated in 1968 by a committee co-chaired by A. Rechtschaffen and A. Kales [6]. The purpose of these uniform and standard criteria was to increase the comparability and replicability of results from different laboratories. The Manual involves parameters, techniques and wave patterns of polysomnographic recordings. One channel of EEG, two channels of

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EOG and one channel of EMG are recorded. The potentials for eyes movements recording are measured from 1 cm above and slightly lateral to the outer canthus of one eye and 1 cm below and lateral to the outer canthus of the second eye. The reference electrodes for both eyes are placed on the same ear lobe or mastoid. The EMG is recorded beneath the chin (mental, submental).

Stage 1

Stage 1 is characterized by low voltage, mixed frequency EEG with the highest amplitude in 2-7 Hz range. The vertex sharp waves may occur; their amplitude can reach the value of about 200 µV. In Stage 1 after wakefulness slow eye movements can be present. The EMG level is lower than in the wakefulness. Stage 1 is also scored when the epoch is characterized with alpha activity combined with mixed frequency EEG and the amount of alpha activity is less than 50% of an epoch.

Stage 2

Stage 2 is characterized by wave patterns sleep spindles and K complexes and the absence of slow waves. K complex is a sharp negative wave followed by a slower positive one. Sleep spindles occur in 12-14 Hz frequency range. The duration of these patterns should be 0.5 s at minimum. If the time between two succeeding occurrences of sleep spindles or K complexes is lower than 3 min, this interval is scored as Stage 2, unless there are movement arousals or increased tonic activity. If the time interval is 3 min or more, t is scored as Stage 1.

Stage 3

20%-50% of the epoch of EEG record should contain waves with 2 Hz or slower and with the amplitudes above 75 µV if the epoch is scored as Stage 3. Sleep spindles and K complexes may occur during Stage 3.

III. FUNCTION OF SLEEP

For long time people were interested why sleep is so essential for the life. There are many theories, which try to explain functions and the purpose of sleep. Some of them satisfactorily interpret several facts, but broadly accepted theory that would explain all phenomena and experiments, does not exist till now. Here only the main theories are mentioned:

Conservation of Energy: The main arguments for the purpose of sleep as reservation of energy are that during the sleep deprivation the energy consumption is increased and vice versa during sleep the basal metabolism is decreased about 5-25% [7].

Restoration of Tissues and Growth: During the first hours of sleep growth hormone excretion, cell mitosis and protein synthesis are increased. In the time of growth or after more laboured day the amount of NREM sleep is increased during the night. However J. Horne [8] criticized this theory. According to him cell mitosis occurs a few hours after food intake and has a circadian rhythm, the decreasing metabolic rate is in discrepancy with the protein synthesis that needs higher energy cost and the increased temperature of head after physical activity is the cause of increased rate of SWS.

Thermoregulation: In experiments with rats, long-term sleep deprived rats showed the temperature increased in about 10 degree [9], so sleep probably decreases the temperature.

Regulation of Emotions: In humans the sleep deprivation causes the disturbances of emotional behaviour (such as concentration, interest for distinct goal, etc.), particularly SWS deprivation induces depressive or hypochondriacal states. So NREM sleep is likely to be involved in adjusting and regulating these emotions. This theory is supported by clinical observations that depressed patients show lower duration of NREM sleep as well as that metabolic rates and neuronal discharge are higher in brain regions that take control of emotions (limbic structures) during NREM sleep in contrast with waking state [10].

Neural Maturation: One part of theories about sleep functions is concerned with REM sleep. The percentage of REM sleep of total sleep time decreases with age - in about 6 month of prenatal phase the children spend about 80% of sleep in REM sleep, but young adult people only 25% [7]. So it is assumed that during REM sleep the maturation of brain and myelinization of nerve fibers proceed.

Memory and Learning: Both types of sleep NREM and REM play a key role in memory consolidation and learning. There is an information transfer between cortex and hippocampus during the sleep that realizes the fixation of memory traces or during REM sleep the insignificant bindings are abolished [11]. With this reprocessing of information also the learning process is related. Several papers refer the improvement of performance perceptual or motor task after sleep [12, 13]. The improvement is due to sleep and not due to time interval or circadian factors.

IV. PROPOSED METHODOLOGY

The design of an EEG detection system comprises several tasks; acquisition, pre-processing to obtain a cleaner EEG signal, feature extraction and decision.

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Pre-processing

Removing the artifacts of EEG signal which is acquired from physionet. A fixed notch filter may eliminate the noise when its distribution is centered exactly at the frequency for which the filter was designed [14]. However, the frequency of the power-line noise is not constant at exactly 60 Hz. The importance of the work presented in this paper relies on the fact that there is existence of epileptic form oscillations with frequencies nearby the power line interference frequency which have been ignored because of the lack of an effective notch filter capable of eliminating the noise components without affecting the original electroencephalographic (EEG) signal. Worrell et al. [15] have found that currently available clinical EEG systems and EEG analysis methods utilize a dynamic range (0.1-30 Hz) that discards clinically important information. Their results show that the dynamic range utilized in current clinical practice largely ignores fundamental oscillations that are signatures of an epileptogenic brain. A finer study of high-frequency EEG oscillations may open a new possibility for patients who are poor candidates to epilepsy surgery, allowing seizure prediction and epilepsy treatment through several therapeutic methods. The results presented in [15] suggest the need to design a notch filter with an optimal rejection bandwidth that effectively eliminates the time-varying noise introduced by power transmission lines. The proposed filter should have an optimum speed of convergence and allow the minimization of loss of information and distortion of the signal of interest.

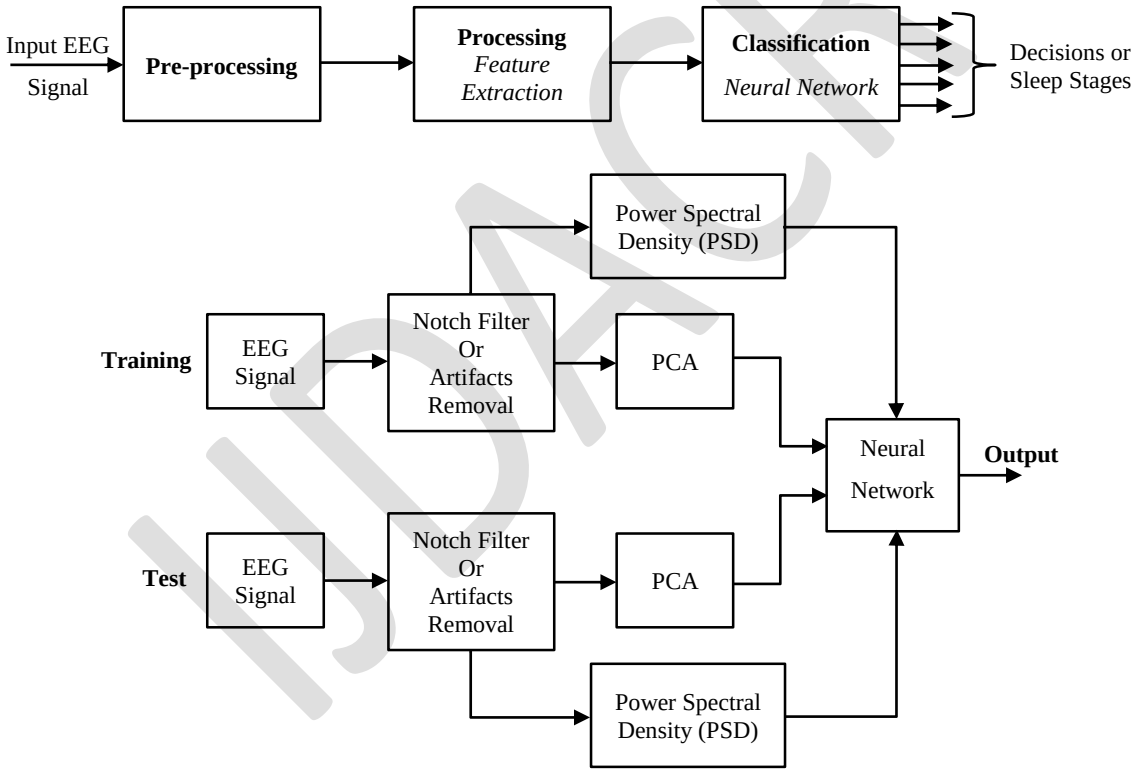

Figure 1: System model for proposed research work

Artifacts Removal by Adaptive Notch Filter

Filtering is a complex and often poorly understood and incorrectly used aspect of EEG and ERP processing, and ERPLAB is designed to make it easy for users to filter their data properly. Filtering is done slightly differently depending on whether you are filtering continuous EEG, epoched EEG, or averaged ERPs.

Conventional Filtering

Conventional filtering is done to restrict the frequency band to the required range. It involves the following:

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- Notch Filter at 50Hz to eliminate the power line interference.
- Butterworth high pass filter at 0.5Hz and low pass filter at 30Hz to restrict to delta (0.5Hz-4Hz), theta (4Hz-8Hz), alpha (8Hz-13Hz) and beta (13Hz-30Hz) frequency range.
- Removing the trend (mean) from the signal.

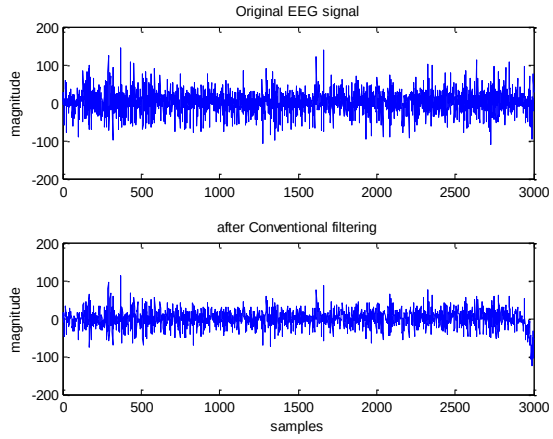

Figure 2: EEG signal after conventional filtering

Processing: Feature extraction

The extraction of relevant information from an EEG signal is related to the information obtained with the MQ sinusoidal model. We propose to use two features based on PSD (Power Spectral Density) and principal component analysis corresponding to non-normal activity.

PSD (Power spectral density)

Linear prediction filters can be used to model the second-order statistical characteristics of a signal. The prediction filter output can be used to model the signal when the input is white noise.

Pyulear estimates the PSD of an input signal vector using the Yule-Walker AR method. This method, also called the autocorrelation or windowed method, fits an autoregressive (AR) linear prediction filter model to the signal by minimizing the forward prediction error (based on all observations of the input sequence) in the least squares sense. This formulation leads to the Yule-Walker equations, which are solved by the Levinson-Durbin recursion. The spectral estimate returned by Pyulear is the squared magnitude of the frequency response of this AR model.

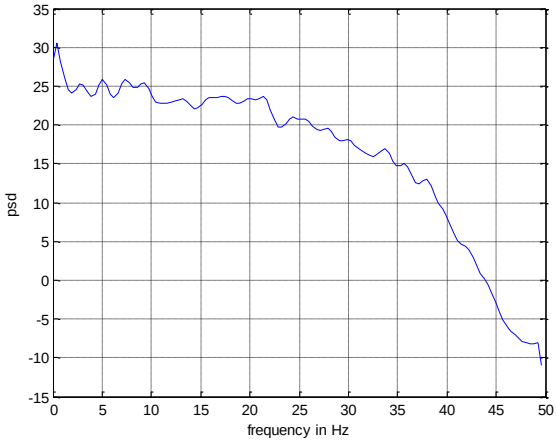

Figure 3: Power spectral density at different frequency spectrum

The Yule-Walker Method block estimates the power spectral density (PSD) of the input using the Yule-Walker AR method. This method, also called the autocorrelation method, fits an autoregressive (AR) model to the windowed input data by minimizing the forward prediction error in the least-squares sense. This formulation leads to the Yule-Walker equations, which are solved by Levinson-Durbin recursion.

The input is a sample-based vector (row, column, or 1-D) or frame-based vector (column only) representing a frame of consecutive time samples from a single-channel signal. The block's output (a column vector) is the estimate of the signal's power spectral density at N_{fft} equally spaced frequency points in the range $[0, F_s]$, where F_s is the signal's sample frequency.

When Inherit estimation order from input dimensions is selected, the order of the all-pole model is one less that the input frame size. Otherwise, the order is the value specified by the Estimation order parameter. The spectrum is computed from the FFT of the estimated AR model parameters.

When Inherit FFT length from input dimensions is selected, N_{fft} is specified by the frame size of the input, which must be a power of 2. When Inherit FFT length from input dimensions is not selected, N_{fft} is specified as a power of 2 by the FFT length parameter, and the block zero pads or truncates the input to N_{fft} before computing the FFT. The output is always sample-based.

In parametric spectral estimation, one assumes that the signal is modeled by a stationary process which has a spectral density function (SDF) $S(f; a_1, \ldots, a_p)$ that is a function of the frequency f and p parameters $a_1, \ldots, a_p$. The

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ISSN: 2319-4863

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estimation problem then becomes one of estimating these parameters.

The most common form of parametric SDF estimate uses as a model an autoregressive model $AR(p)$ of order p. A signal sequence $\{Y_t\}$ obeying a zero mean $AR(p)$ process satisfies the equation:

$$Y_t = \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + \epsilon_t \quad (1)$$

Where $\emptyset_1, \ldots . \emptyset_p$ are fixed coefficients and ϵ_t is a white noise process with zero mean and innovation variance σ_p^2. The SDF for this process is

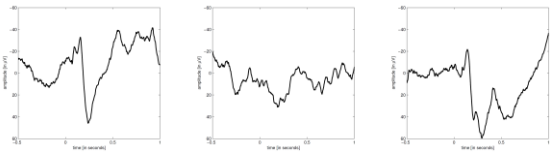
$$S(f; \emptyset_1, \ldots, \emptyset_p, \sigma_p^2) = \frac{\sigma_p^2 \Delta t}{|1 - \sum_{k=1}^{P} \emptyset_k e^{-2i\pi f k \Delta t}|^2} \quad (2)$$

$$|f| < f_N$$

With Δt the sampling time interval and f_N the Nyquist frequency. There are a number of approaches to estimating the parameters $\emptyset_1, \ldots, \emptyset_p, \sigma_p^2$ of the $AR(p)$ process and this the spectral density. The Yule-Walker estimators are found by recursively solving the Yule-Walker equations for a $AR(p)$ process.

Principal Components Analysis (PCA)

Interpreting EEG data can sometimes be difficult. Figure 4 shows raw EEG traces recorded at the central electrode CP_z during stimulation of infants' heels. Each of the measured signal is not only determined by electrical activity due to the stimulation, but also by other processes in the brain and measurement noise. Determining whether a specific stimulation has a measurable effect is not trivial. Mathematical tools for the processing, analysis, and presentation of large data sets can be very helpful in this endeavour. On a computer, each of the traces in Figure 4 is represented as a vector with 3001 dimensions; each time point being encoded by one dimension. However, this representation is neither very well suited for humans to visualize and understand, nor to mathematically find common patterns or differences between different trials.



(a) (b) (c)

Figure 4: Standard raw EEG data traces recorded at electrode CP_z at the centre of the infants' heads. At time 0 the infants were stimulated by a touch at the heel (a and b) or by a medically necessary heel lance, respectively (c).

Principal components analysis (PCA) is a widely used mathematical technique to find patterns in data and to represent the data in a way that is more suitable for highlighting the differences between different trials. PCA can be pictured as a rotation of the coordinate axes so that the axes are not along single time points, but along linear combinations of sets of time points which collectively represent a pattern within the signal. PCA rotates the axes in a way that maximizes the variance within the data along the first axis, maintaining the orthogonality of the axes.

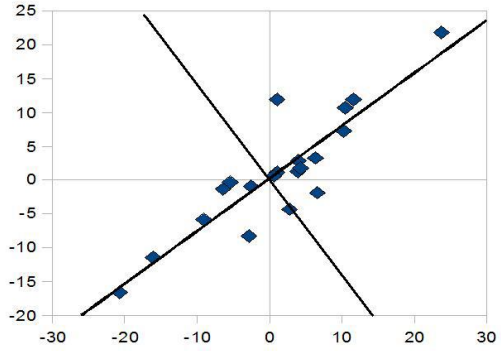


Figure 5: Example for rotation of the coordinate axes

Figure 5 shows a simple example of this idea in two dimensions. Considering only one of the dimensions while disregarding the other would lead to a considerable loss of information within the data. However, there is a high correlation between the two dimensions. Therefore, if we rotate the axis as depicted in Figure 5, then nearly 95% of the variance within the data could be explained by the first axis alone, leaving only little more than 5% to be explained by the second axis. In other words, in the rotated coordinate system the first axis would represent the important features within the data set, whereas the second axis would merely encode how much the two variables of a data point deviate from their average relation within the whole data set

Mathematically, we represent the data as a matrix X with each column of X being one trial. The task is then to find an orthonormal matrix P such that Y = P X and the covariance matrix for Y is diagonal. The rows of P are then the principal components, i.e. an alternative basis for the data, and Y is the data expressed in terms of the alternative basis. If the covariance matrix for Y is diagonal, that means that there is no redundancy between the different dimensions of Y and therefore, one dimension explains as much of the variance in the data as possible; otherwise it would covary with at least one other dimension. The same is true for the second most explanatory dimension, it must explain as much of the leftover variance as possible because otherwise it would covary with one of the remaining dimensions. And so forth for all new dimensions.

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Conveniently, the amount of variance explained by the i^{th} principal component is equal to the i^{th} diagonal entry of the covariance matrix of Y. Ordering the principal components by the amount of variance they explain provides a way to rank them according to their importance. Finding such a matrix P that satisfies the constraints is not too difficult.

Neural Network

The general Neural Network approach contains following steps:

- Neural network creation
- Configuration
- Training
- Simulation

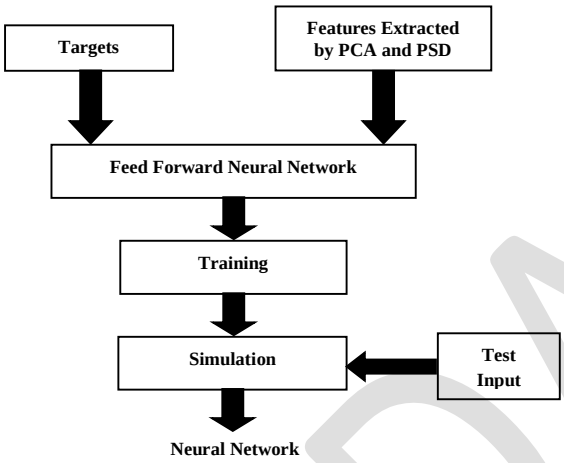

Figure 6: Flow diagram for Neural Network method

Figure 6 depicts the functionality of Neural Network in our project, which accept the features of training images and test image as an input a predefined target value has been set to perform feed forward neural network with gradient descent back propagation neural network algorithm in the presence of supervise learning, this algorithm is used to reduce the overhead and increase the accuracy of network and we use sigmoid transfer function to perform calculation at output layers. With the help of these all function desired output is generated.

Feed-forward ANNs (Figure 7) as the name implies allow signals to travel in one way only; from input to output layer. There is no feedback loops or recurrent loops i.e. the output of any layer will not affect that output of the same layer. Feed-forward ANNs is also tend to be a straight forward networks that is associated with inputs outputs. They are highly used in pattern recognition and classification.

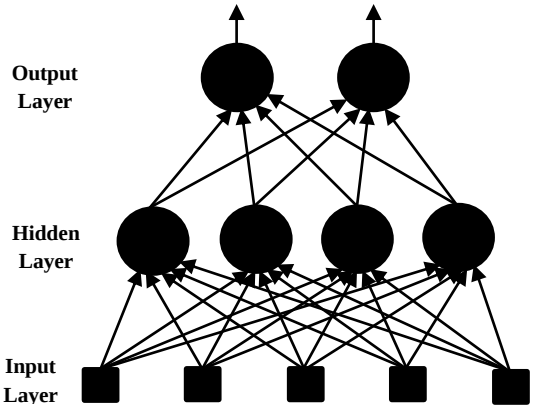

Figure 7: An example of a simple feed forward network [16]

Figure 7 depicts the functionality of feed forward neural network.

The Network layers

The general type of neural network consists of three groups of layers, or three groups of units: first one is a layer of "input" units which is always is connected to a second layer i.e. layer of "hidden" units, which is finally connected to a layer of "output" units. Figure 7 shows the representation of all layers of neural network.

The Learning Process

There are basically two major categories of learning methods used for neural networks Supervise learning methods and unsupervised learning method in our project we work or perform simulation of neural network under supervised learning mechanism Supervised learning which work as an external teacher or guide, so that each output unit is told to perform what should be desired response to the respected input signals. Global information may be required during learning process. Error convergence is the main concern issue of supervise learning, i.e. the minimization of error between the desired and computed unit values of network. Here the main aim is to find a set of weights which minimizes or reduce the error up to precise level. The least mean square (LMS) convergence is well known method for many learning paradigm.

Transfer Function

The whole behavior of our Neural Network totally depends on both the weights and the input-output function i.e. transfers function that is specified in the all units. There are basically three categories of Transfer Functions:

- Linear (or ramp)
- Threshold

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- Sigmoid

For linear units or for the linear transfer function, the output activity is directly proportional to the total weighted output units. For threshold units or for threshold transfer function, the output unit outputs are set at one of two levels, which totally depending on whether the total input of output unit is greater than or less than some predefined threshold value. For sigmoid units or for sigmoid transfer function, the output varies or changes continuously but not linearly as the inputs of input unit changes.

V. Simulation And Results

The performance of proposed research work has been studied by means of MATLAB simulation.

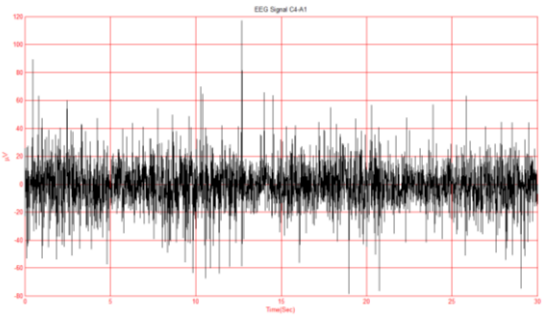

Figure 8:

Table 1: Comparative Analysis of Accuracy and Reliability of sleep stages

Reference	Signal	Method	Classifier	% Accuracy
[Chin, 2005]	EEG, ECG, EOG	FFT	Linear Regression Model 2 Class	85
[Rakesh, 2008]	EEG, EOG, EMG	FFT	BPNN 3 Classes	95
[Mehmet, 2008]	EEG, EMG	WT	BPNN 3 Classes	98.5
[Hong, 2010]	EEG	WT	Sparse Representation Method 3 Classes	94.2
[Wali, 2013]	EEG	WT+ FFT	Fuzzy 4 Classes	84.41
Proposed	EEG	PCA+ PSD	BPNN	100

VI. Conclusion

This paper proposes an improved technique for EEG signal based sleep detection using Principal Components Analysis, Power Spectral Density and Neural Networks. On observing Table 1, it was found that the proposed method gives higher accuracy than previous research works.

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