

Chebyshev and Modified Wavelet Algorithm Based Sleep Arousals Detection Using EEG Sensor Database

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Abstract: Electroencephalographic (EEG) arousals are generally observed in EEG recordings as an awakening response of the human brain. Sleep apnea is a major sleep disorder. The patients, with Severe Sleep Apnea (SAS) suffers from frequent interruptions in their sleep which brings about EEG arousals. In this paper, a new method for Segmentation and Filtering process of EEG sensor database signals for finding sleep arousals using Chebyshev and Modified Wavelet Algorithm is proposed. The Segmentation Algorithm appears as various features extracted from EEG Data's and PSG Recordings. The Chebyshev Equiripple Filter is used in Filtering algorithm and then MSVM [M-Support Vector Machine] was utilized as Classification Tool. Algorithms are performed and different features are extracted and the ROC characteristics are performed. The extracted features are Delta, Gama, Beta, Alpha, Sigma of the EEG signal, EEG Signal Mean, EEG Signal Standard Deviation, EEG Signal Peak Signal to Noise Ratio [PSNR], and EEG Signal Normalization. MSVM tool showing EEG signals results.

Keywords: M-wavelet, Chebyshev Equiripple Filter, MW Coefficients, EEG database, MSVM classification tool, CELM, Confusion Matrix.

1. Introduction

Disorders of sleep apnea syndrome (SAS) have several phases such as obstructive sleep apnea syndrome (OSAS), central sleep apnea syndrome (CSAS) and their combination (mixed apnea). The obstructive sleep apnea (OSA) is most major thing in SAS (Chokroverty [1999]). OSAS is the symptom of upper airway closure in patients during sleep, which leads to serious disorders. OSA causes interruption of sleep period frequently during night, so that the patients cannot able to have a good sleep and always feel daytime sleepiness. This interruption of sleep period by OSA can be seen as immediate responses in electroencephalographic (EEG) records, and the response are known as EEG arousals. Usually PSG test is used in hospitals for diagnosing sleep disorders. The

relationship between appearance of arousal responses and sleep apnea is very important function in the diagnosis of SAS. To interpret the EEG arousals from the durable PSG record which is laborious and time consuming task for medical doctors and technologists. Therefore, the computer assisted system for detecting EEG arousals will be the powerful aid in the clinical scene from the efficiency point of view. The studies on automatic analysis for sleep EEG such as automatic sleep staging have been carried by many researchers in the past. Related studies for the automatic detection of EEG arousals have been proposed (Pillar et al. [2002], Pitson et al. [2006]). Even though the clinical PSG consists of various noise components, characteristics of EEG, these physiological data will vary from individual to individual. Thus, an adequate method usable in the clinical diagnosis aid has not yet

been existed. In this paper, the method for automatic detection of sleeping arousals Chebyshev and Modify wavelet Based EEG signals segmentation using EEG dataset. To separate one band of frequencies from another, Chebyshev filters are used. Different band of frequencies are separated using Chebyshev filters. The initial attribute of Chebyshev filters is their speed, typically which is more than an order of magnitude but faster than the windowed-sinc. This is because they are carried out by recursion method rather than convolution. The design of these filters is mainly based on a mathematical technique called the *z-transform*.

2. Sleep Arousal Detection Methodology

2.1. Chebyshev Algorithm

Chebyshev Algorithm methods are evolution of conventional QZ AI [1, 2]. These approaches typically involve multiple Fourier transformations of the data, with the goal of contribute more abstract and ultimately more useful representations [3]. These methods are becoming increasingly popular, often outperforming traditional approaches that include handcrafted features for data representation and Integration methods for polynomials process [4, 5].

One of the advance algorithms in efficient Chebyshev algorithm is used to find Eigen values and Eigen function. In the method of Eigen points, the unknown parameters (of polynomial coefficients) in the model are related to the Eigen points of one or more casual Eigen function, and thus, these unknown parameters can be predicted given the Eigen vectors. The Eigen function is mostly predicted from polynomial coefficients. The input signal is $c[k]$, previous output signal is $y[n - 1]$, the output signal is $[n]$, the polynomial coefficients is c, d .

Chebyshev Nodes:

$$X_k = \cos\left(2k - \frac{1}{2n} - \pi\right) \quad (1)$$

$$k = 1, \dots, n$$

Chebyshev Polynomials:

$$U_0(x) = 1;$$

$$U_1(x) = 2x;$$

$$U_{n+1}(x) = 2xU_n(x) - U_{n-1}(x) \quad (2)$$

2.1.1. Method of Polynomial Analysis

We assume throughout this paper that, the desired Eigen values are smallest ones. The well-known Chebyshev polynomial to accelerated (fixed dimension) subspace iteration algorithm [5 - 7].

Polynomial Algorithm:

Filter x by an m degree Chebyshev polynomial that dampens on $[a, b]$.

Input: Vector x , degree m and interval and points a, b .

Output: filtered polynomial y

$$\text{Step 1. } e = \frac{b-a}{2}; \quad (3)$$

$$\text{Step 2. } c = \frac{b+a}{2} \quad (4)$$

$$\text{Step 3. } \sigma = \frac{e}{(a-c)} \quad (5)$$

$$\text{Step 4. } \sigma_1 = \sigma \quad (6)$$

$$\text{Step 5. } y = \frac{(Ax-cx)\sigma_1}{e} \quad (7)$$

$$\text{Step 6. } i = 2:m \quad (8)$$

$$\text{Step 7. } \sigma_{new} = \frac{1}{\left(\frac{2}{\sigma_1} - \sigma\right)} \quad (9)$$

$$\text{Step 8. } x = y \quad (10)$$

$$\text{Step 9. } y = y_{new} \quad (11)$$

$$\text{Step 10. } \sigma = \sigma_{new} \quad (12)$$

2.1.2. Filtering Techniques

$$Ch = \cos * \frac{\pi i}{8 * ch} + \cos * \frac{\pi i}{2 * ch} + \sin \frac{3 * \pi i}{4 + ch} \quad (13)$$

Ch ---channels

2.1.3. Trigonometric Techniques

$$Ch_{trio} = \cos \frac{\pi i}{8 * ch1} + \cos \frac{\pi i}{2 * ch1} + \sin \frac{3 * \pi i}{4 + ch1} \quad (14)$$

2.1.4. Equiripple Techniques

Equal ripples in both the passband & stopband, denotes the signal distortion which happens at the edge of passband due to presence of a large ripple is avoided in Equiripple design whereas the Equiripple design [8, 9] has a large transition band, where the total passband width will be limited.

$$Eq = \cos \left(2 * i - \frac{1}{2} * 7 - \pi\right) \quad (15)$$

2.2. Segmentation Process

In this section we have Segmentation process for EEG Data base using M-Wavelet Transform Algorithm Development. The Modules have various parameters, and also two main segment, they are arousals and valance frames. They parameters act as a coefficient matrix from M-wavelet. This algorithm first stage is decomposing the coefficients and then the decomposed elements are reconstructed and then various features are extracted from this module [10, 11].

Wavelet function is

$$\int_{-\infty}^{\infty} \varphi(t) dt = 0 \quad (16)$$

M-Wavelet function is

$$MW_{\varphi}x(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \varphi * \frac{t-b}{a} dt, \quad (17)$$

where a is the Decomposed data's, b is the Decomposed vector's

The wavelet coefficients are deals with soft thresholding. The various steps of the M-DWT method are detailed below:

- 1) Apply Modified discrete wavelet transform to the signal;
- 2) Compute the hierarchical correlations of the detailed coefficients between level 1 and level 2 for three different (horizontal, vertical and diagonal) directions;
- 3) Select relevant threshold values based on the achieved hierarchical correlation values.
- 4) Apply the selected threshold values to the coefficients of level 1 for removing of noise, and can obtain the modified detailed coefficients for level 1;
- 5) Apply inverse wavelet transform to the modified wavelet coefficients;
- 6) Repeat steps 1-5 again, leading to obtain a final value.

2.3 Features Extraction Process

The Features are Power spectrum, Normalization, Entropy, Mean, Standard Deviation, Variance, Dynamic Range, Relative Power Energy, Logarithmic Relative Power Energy, and Absolute Logarithmic Relative Power Energy.

2.3.1 Mean

The probability distribution of random signals X the mean is equal to sum over every possible signal values.

$$\mu = \sum xP(x), \quad (19)$$

where x denoted to total number of signals values of EEG.

An analogous formula applies to the case of a 2D EEG Database probability distribution.

2.3.2. Power Spectrum

The power spectrum of a signal is the power or more simply energy of the signal at each frequency that contains. It can also be considered as the range or signal of energy or power of the given signal derived from the signals range of frequencies.

$$P = \frac{1}{2T} \int_{-T}^T x(t)^2 dt \quad (20)$$

Above process are stationary process, for instance, may have a finite power but an infinite energy. The

energy is the integral of power, and the stationary signal continues over an infinite time.

The content of signal $x(t)$, we can compute the Fourier transform $\hat{x}(\omega)$.

The truncated Fourier transform $\widehat{x}_T(\omega)$, where the signal is integrated only over a finite interval $[0, T]$.

$$x_T(\omega) = \frac{1}{\sqrt{T}} \int_0^T x(t) e^{-i\omega t} dt \quad (21)$$

2.3.3. Normalization

The Landolt concludes that forced normalization (FN) is the phenomenon characterized by the fact that, with the occurrence of psychotic states, the electroencephalography become more normal or entirely normal, as compared with previous and subsequent EEG signals.

$$d = P(:) \quad (22)$$

$$N_{(d,dn)} = \frac{d}{\text{sum}(d+1e-12)}, \quad (23)$$

where d is the normalization of signals. This signal converts into single column. $N_{(d,dn)}$ is the total number of EEG signals. This represents as based on EEG band's.

2.3.4. Entropy

The Anesthetic and arousal detection and analysis based on entropy parameter's, from EEG bands. Entropy used to find to EEG activity from electromyogram.

$$\text{Log} = \log_2(d + 1e - 12) \quad (24)$$

$$\text{Entropy} = \frac{-\text{sum}(d.*\log)}{\log_2(\text{length}(d))} \quad (25)$$

2.3.5. Standard Deviation

For continuous EEG signal

$$\sigma = \sqrt{\int_{-\infty}^{\infty} p(x) dx} \quad (26)$$

where x is the EEG Band data.

For a discrete EEG signal

$$\sigma = \sqrt{\int_{-\infty}^{\infty} p_i x_i} \quad (27)$$

Relative power energy can be given by the following equation:

$$R_p = \frac{\text{norm}(y)^2}{\text{length}(y)} \quad (28)$$

Logarithmic RPE:

$$\log_{rpe} = \log(R_p) \quad (29)$$

Absolute RPE:

$$Abs_{RPE} = abs(RPF) \quad (30)$$

2.4. Fusing and CELM Process

2.4.1. Fusing Process

$$Features_{(x,y,...,n)} = Concat^{all\ features} \quad (31)$$

2.4.2. CELM Process

Step 1.

Present samples X_t, C_t

$$C_{xy} = sum(fea) * l, \quad (32)$$

where x,y are the total samples, l is the dynamic range of signals

Step 2.

Apply compute process by features by Entropy parameters.

Step 3.

Conjugate Process of EEG data's.

Extracting real and complex parameters of EEG data's

Step 4.

Apply FFT Process.

2.4.2. Proposed Multi Support Vector Machine (MSVM) Process

The SVM has been studied extensively for classification, regression, and density estimation. Fig. 1 represents the proposed block diagram of SVM. It maps the input patterns into a higher-dimensional-feature space through some nonlinear mapping which is chosen by priority. A linear decision surface is then constructed in this high-dimensional-feature space. Hence the SVM is a linear classifier in the parameter space, where it develops into a nonlinear classifier as a result of nonlinear mapping of the space of the input patterns to the high-dimensional feature space. Training the SVM will be a quadratic-optimization problem. The construction of a hyper plane $wT x + b = 0$ (w is the vector of hyper plane coefficients, b is a bias term) creates the maximum margin between the hyper plane and the nearest point which can be posed as the quadratic-optimization problem. SVM has been shown to provide high-

generalization ability. A proper kernel function is always dependent on the specific data for any problem and till now there is no proper way for how to select a kernel function. In this paper, the selection of the kernel functions was studied experimentally and optimal results were achieved using radial-basis function (RBF) kernel function.

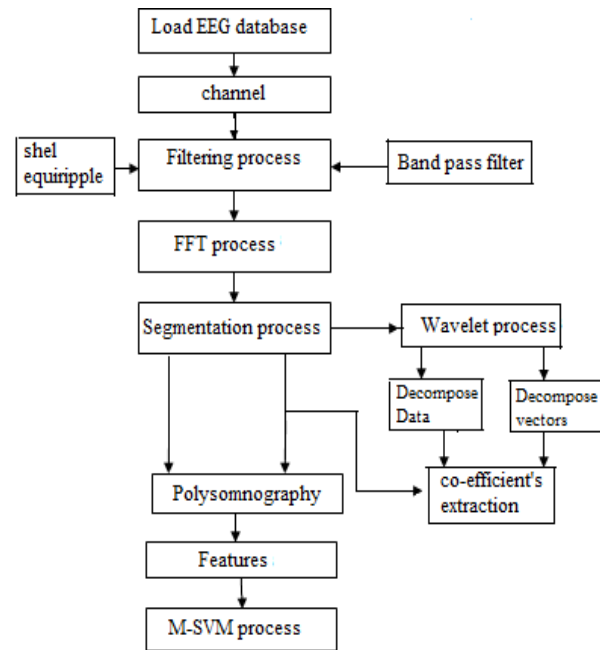


Fig. 1. Proposed Block Diagram.

Generally SVM is a binary classifier, which can be extended by fusing several of its kind into a multiclass classifier. In this paper, we fuse SVM decisions using the ECOC approach, adopted from the digital communication theory. In the ECOC approach, up to $(2n-1) - 1$ (where n is the number of classes) SVMs are trained, each of them aimed at separating a different combination of classes. For three classes (A, B, and C) we need three classifiers; one SVM classifies A from B and C, a second SVM classifies B from A and C, and a third SVM classifies C from A and B. The multiclass classifier output code for a pattern is the combination of targets of all separate SVMs. In our example, vectors from classes A, B, and C have codes $(1,-1,-1)$, $(-1,1,-1)$, and $(-1,-1,1)$, respectively. If each of the separate SVMs classifies the pattern correctly, then the multi class classifier-target code is met and the ECOC approach reports no error for that pattern. However, if one of the SVMs disagrees the pattern, the class selected for this pattern is the one its target code closest in the Hamming distance senses to the actual output code and this may be an erroneous decision.

Algorithm steps:

Step 1:

$$G = length(EEG), \quad (33)$$

where G is the group of MSVM.

Step 2:
Apply MSVM Training Process

$$MSVM_{(d,g)} = \int_{-\infty}^{\infty} f_{(x,y)} dx \quad (34)$$

where d is the total features data, g is the total number of groups.

Step 3:
Classification process

$$MSVM_{structs,class} = \int_{-\infty}^{\infty} p_{xyz} dx \quad (34)$$

where x is the kernel function of MSVM, y is the class, z is the MSVM Vector.

ROC Curve performance:

The roc curve plotting performance is shown in Fig. 2. This figure represents the MSVM algorithm performance based in Bundle of features.

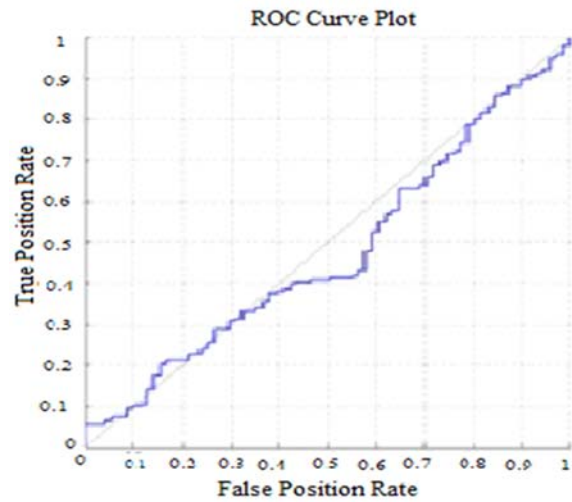
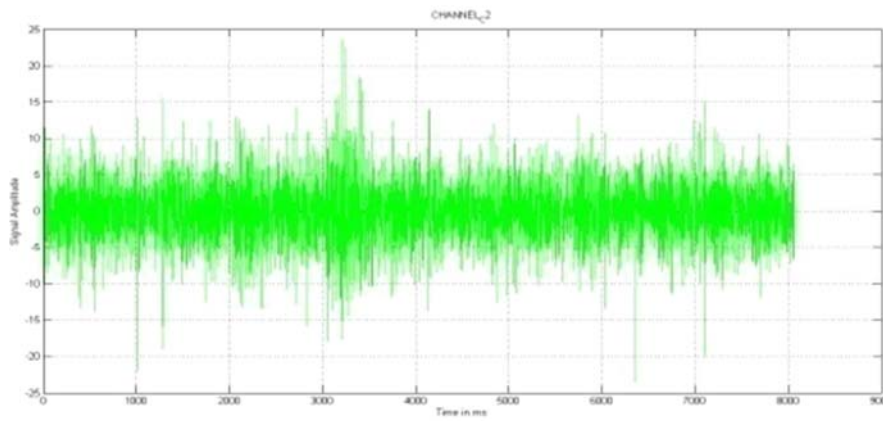


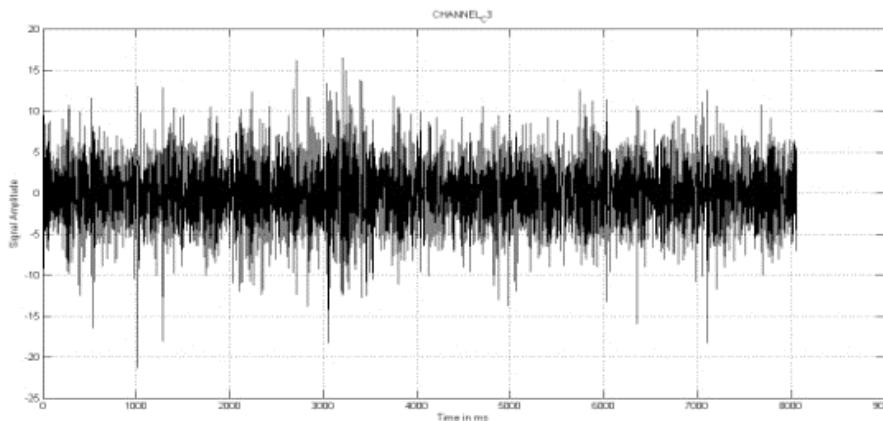
Fig. 2. ROC Characteristics

3. Experimental Results

The experimental results are shown in Fig. 3-12.



(a)



(b)

Fig. 3. (a) EEG signal of channel 1, (b) EEG signal of channel 2.

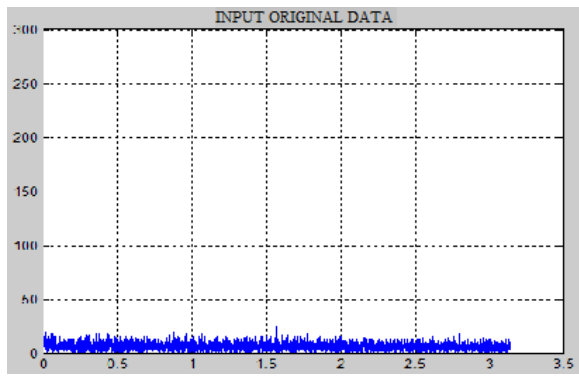


Fig. 4. Input original data.

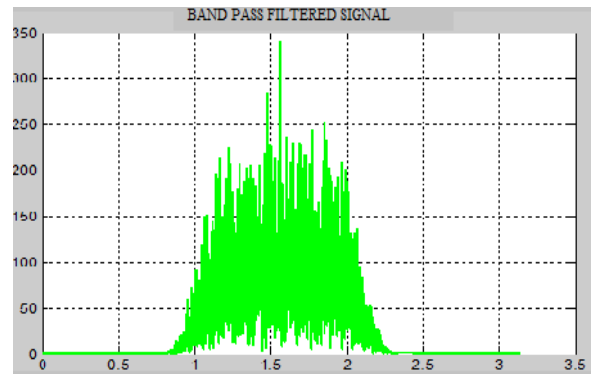


Fig. 5. Band pass filtered signal.

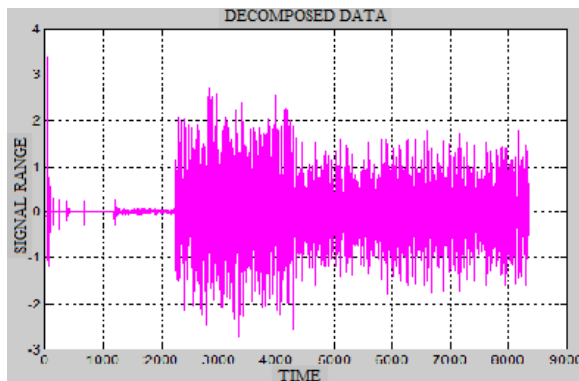


Fig. 6. Decomposed signal.

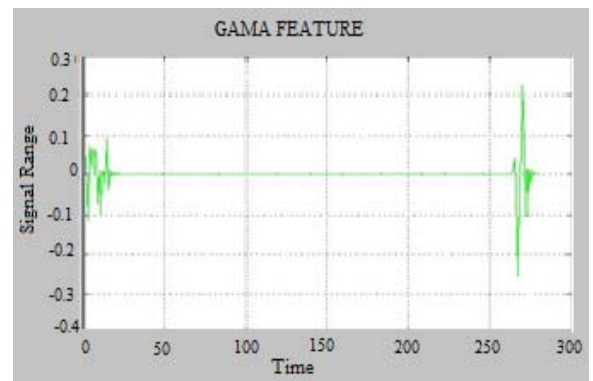


Fig. 7. Gamma Feature.

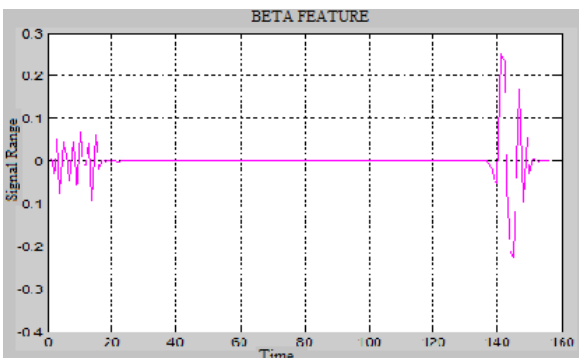


Fig. 8. Beta Feature.

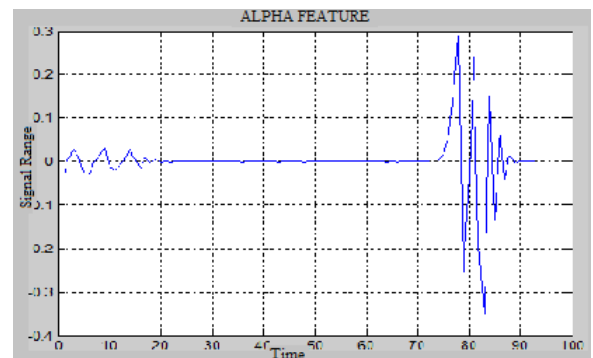


Fig. 9. Alpha Feature.

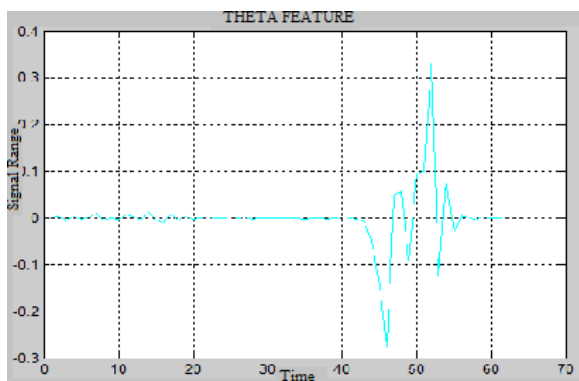


Fig. 10. Theta Feature.

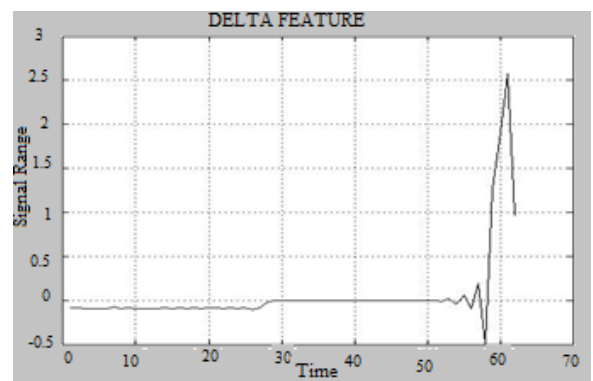


Fig. 11. Delta Feature.

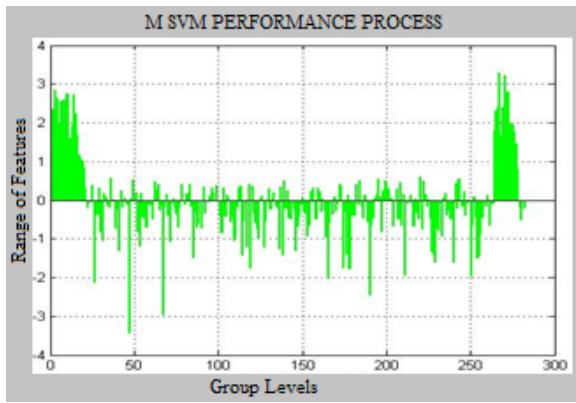


Fig. 12. MSVM Performance.

4. Confusion Matrix Performance

The confusion matrix describes the performance of MSVM performance based on features. It is represented as performance of MSVM Classification algorithm. This technique expose as accuracy (ACC), specificity (SPC), sensitivity (TPR), false positive (FPR), false negative (FNR), true positive (TPR), true negative (TPN). The Confusion Matrix is shown in Fig.13.

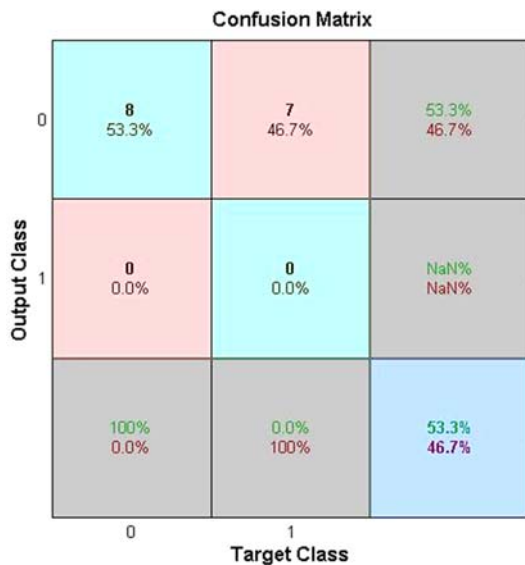


Fig. 13. Confusion Matrix performance.

$$TPR = \frac{TP}{P} \quad (36)$$

$$P = TP + FN$$

$$SPC = \frac{TN}{N} \quad (37)$$

$$N = FP + TN$$

$$PPV = \frac{TP}{TP + FP} \quad (38)$$

$$NPV = \frac{TN}{TN + FN} \quad (39)$$

$$ACC = \frac{TP + TN}{P + N} \quad (40)$$

Comparison performance of existing system and proposed system are shown in the Table 1.

Table 1. Comparison Features Performance.

Features	Existing system	Proposed system
Entropy	0.9624	0.9441
Mean	3.314	2.056
Variance	1.193	3.36
STD	1.0365	0.0174
SNR	3.1975	0.0118
LRPE	30.1205	3.0137

This table briefly explained about arousal detection of EEG and PSG data base. This performance analysis is briefly explained Brain signal analysis and also arousal and valance detection. This tabulation mentioned as different features by EEG DB. The features are Entropy, Mean, Standard Deviation, Signal to Noise Ratio, Logarithmic Relative Power Energy. These features are peacefully extracted from EEG and PSG using MSVM Proposed system. This implementation are developed by MATLAB 2013a Software , Memory 2 GB RAM, 3.40 GHz processor are we have used. This processor has only able to performing and speed result by using our MAT files DATA BASE.

5. Conclusion

In this paper, the Arousal band detection approach is performed by Chebyshev with MSVM segmentation & Classification algorithms. The segmentation algorithm mainly to segment EEG and PSG Database, and then extracting bands from EEG based in frequency range. The algorithm result shows that the various features from various algorithms and its all are parameters are evaluated. Mainly compared features by segmentation level algorithm.

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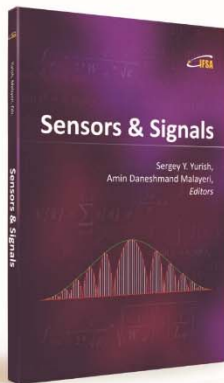
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Sensors & Signals

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