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Wavelet Based Performance Analysis of SVM and RBF Kernel for Classifying Stress Conditions of Sleep EEG

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Abstract. The aim of this study is to detect the changes in frequency and power through wavelet transform and assess the effects of externally induced heat stress in the classification of sleep EEG states - Awake, *Slow Wave Sleep* (SWS), and Rapid Eye Movement (REM). *Radial Basis Function Neural Network* (RBFNN) and Support Vector Machine (SVM) algorithms have been successfully applied to classify sleep stages under acute and chronic stress conditions with respect to their controlled Polymosograph. Performance analysis on test data set consists of performance metrics specificity, sensitivity and accuracy. The detection rate of SVM for sleep stage classification has been achieved with an average accuracy of 96.4% under chronic stress and 94.1% for acute stress, whereas an overall accuracy of 87% is achieved using RBFNN in classification of sleep-wake states. The results were also obtained for the identification of types of thermal stress i.e. acute and chronic using SVM approach with 84.4% detection rate. These results demonstrate that RBFNN and SVM models may be successfully employed in clinical studies as a decision support tools to confirm the presence of stress level.

Key-words: Wavelet transform; Heat stress; RBF; SVM; Sleep EEG.

1. Introduction

Stress disturbs many memory functions and mental functioning of the brain causing acute and chronic changes in certain brain areas leading to long-term harm. There are two main reasons which are responsible for the brain harm due to the thermal stress. One is the high temperature environment which leads to hyperthermia and can cause damage to the brain whereas the other is due to the failure of circulating system which results into ischemia [1]. The hypothalamus is the chief centre in the brain having regulatory action over the body temperature as it controls the stress response [2, 3]. It utilizes sensory information from core, muscle, skin and chemoreceptors to control sweating mechanisms, vasomotor changes in blood vessels and motor neurons of the muscles, which in turn affect the temperature in the body itself. Thermal environment serves as an external driver of this regulating system. The hypothalamus is responsible for further heat exchange with the environment by increasing the heart rate in order to increase the blood flow to skin and sweating is initiated in order to enhance evaporative heat loss [4]. The strain of the heat exposure is related to hypothalamus quantitatively in the equilibrium temperature attained and in the increase in thermal conductance and output of sweat for evaporation loss. Reestablishment of body temperature in the face of heat gain depends only to a minor extent on depression of metabolic heat production.

In order to study the effect of acute and chronic stress, the experiments were carried out on rats as subject being exposed under hot environment conditions. The experiment results that the high temperature environment yields the neuronal variations in brain [5-7]. Digital recordings exhibit that the heat exposure may affect the cortical brain activities and can damage the brain due to thermal load and heat exposure, where the heat exposure can be acute or chronic. Researchers reported that the neurons in brain are affected in many ways in thermal loads [1]. Literature also reveals that the EEG observations are very sensitive to the heat environment [8] where results of different algorithms justify that higher frequency components of EEG power spectrum are very profound under thermal stress and change between stressed and control states can be easily observed when exposed to heat [9]. In earlier studies, the effect of acute and chronic heat exposure on frequency of EEG components in different sleep-wake states in young moving rats was investigated in which subjects were kept in certain clinical conditions to observe acute and chronic stresses [5].

Application of wavelet transform is found to be very much useful in automatic recognition of sleep stage [10-18]. Researchers have effectively used time-frequency analysis to address the issues related with sleep EEG. Prediction of the level of drowsiness was examined and delta, theta, alpha, and beta sub-band frequencies of the EEG signals were extracted by using the discrete wavelet transform technique [19] where the wavelet spectrum of the EEG signals were used as an input to a multilayer perceptron neural network. In the analysis of rat electroencephalogram under slow wave sleep using wavelet transform, component powers in different frequency bands were found to be varied with time, and in about a quarter of the delta power percentage was less than 50% [20]. Dynamic state recognition and event-prediction are fundamental tasks in biomedical signal processing. Use of wavelet decomposition enables segmentation of EEG into standard clinical bands [21]. 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 transform, the analysis of the time-frequency structure of *spike-wave discharges* (SWDS) in rats, a model of genetic absence epilepsy [22] was carried out and frequency spectrum of the EEG records was determined within the range from 1 to 20 Hz. The time dynamics of the SWDs was analyzed using fragments of record from several seconds to more than one minute in length. Several studies have been performed using wavelets to analyze EEG signals in an attempts to find a biomarker for Alzheimer's disease, which showed varying degrees of success [23].

Together with EEG spectral analysis, EOG and EMG recordings have also been considered as sleep markers for investigating the stress events of sleep EEG. EEG recording is divided in to various frequency sub-bands, namely, 0.5 - 4 Hz (delta or), 4 - 8 Hz (theta or θ), 8 - 12 Hz (alpha or α) and 12 - 40 Hz (beta or β). EEG responses are comparatively small duration, non-stationary signals produced randomly as a response to stimulus [24, 25]. In identifying epileptic patterns, authors [26] have reported the best results by using Radial Basis Function neural network. Mainly, *artificial neural network* (ANN) with back-propagation algorithm, and *adaptive neuro-fuzzy techniques* (ANFIS) have been applied to accomplish the above addressed objective on similar animal model by few researchers [27, 28].

2. Related Work

The sleep stage classification for stressful events mainly depends on the features and the algorithms, which have been adopted for the investigation and analysis of sleep EEG. Many popular algorithms have been developed so far to classify the sleep EEG under different clinical conditions. The classification methods such as *linear discriminant analysis* (LDA), *neural network* (NN), *fuzzy clustering method* (FCM) [29-31] have been used to study sleep EEG data recorded in various pathological settings. Report suggests that the use of RBF in epileptic and non-epileptic candidate's classification produces a result with an accuracy of 99% [26].

Many research works in the recent past have explored the advantage of using a combination of wavelet technique and SVM in EEG signal classification. In epileptic seizure detection, by using details and approximation coefficients obtained after decomposing the EEG samples into five levels, statistical features were extracted and further used to train the SVM classifier [32]. Similar study on the use of SVM in detecting drowsiness from awake states has been made in which classification accuracy is reported to be very high [33]. Also, performance of the algorithm was reported to have improved by including the sub band features, where large set of SVM classifiers were trained upon a varying number of 1 Hz sub band features. In other reports on sleep stage identification [34, 35] average classification accuracy of the system employing multiclass SVM with linear kernel function has been found to be very high.

However, literature does not reveal the use of classifier such as RBFNN and SVM which predict the changes in sleep wake stages due to exposure of thermal stress. In the present work, time-frequency analysis is applied on raw EEG data to capture the changes in frequency and power and then SVM and RBFNN algorithms have been used for the classification of sleep stages and stressful events. *Polysomnography* (PSG), a type of sleep study based on multi-parametric test is invariably used by the doctors and researchers as a diagnostic tool. The features extracted from PSG data were used as inputs to RBFNN and SVM classifiers. The results are compared with the performance of MLPNN [27]. These classifiers have been leveraged to achieve high accuracy than MLPNN as discussed in the following sections.

3. Preliminaries

3.1. Data Acquisition and Organisation

Present work uses the EEG data acquired from the animal model [27, 28]. EEG recordings of young rats having an age of 12-14 weeks with a weight around 180-200 gms at the staring of the experiment, was accomplished. The rats were kept in cages with drinking water and food at specified clinical conditions. First the subjects were kept in ambient environment temperature of $23 \pm 1°C$ for measurement of control EEG recordings. Rats were chosen as animal model, as they are very well suited for neurophysiological experiments because neurological developments in them are similar to human development [36-37]. The subjects under study were also kept in hot environment causing thermal stress in animals. The different conditions were distinguished as acute heat stress and chronic heat stress. To maintain the high degree of constant temperature, *Bio-Oxygen Demand* (BOD) has been used to maintain the temperature for incubation. In this work, an automatic digital *Biological Oxygen Demand* (BOD) Incubator (Oceania, India) was used for producing acute and chronic heat stress to all groups of animals. The rats were exposed to the BOD incubator at 38$\pm$ 1°C and relative humidity 45-50% for continuous four hours of heat exposure from 8.00 a.m. to 12.00 p.m. for a single day, just before the recording of electrophysiological signals. For the chronic measurements, rats were subjected to the BOD incubator at 38$\pm$ 1°C and relative humidity 45-50% for one hour daily for 21 days of chronic heat exposure from 8.00 a.m to 9.00 a.m and electrophysiological signals were recorded on 22nd day.

Electrodes for the recording of polygraphic electrophysiological signals (EEG, EOG and EMG) were implanted aseptically and chronically on the rat's head under pentobarbital (35 mg/kg, i.p.) anesthesia, with the help of stereotaxic guidance. After shaving the head with scissors, nearly one-inch incision was made on the head of anesthetized rat and the membrane of exposed skull was scrapped to visualize the cranial sutures. The marks for attaching the bipolar, bilateral EEG electrodes were made 2 mm posterior and 4 mm lateral to bregma with the help of stereotaxic apparatus. Another mark was made on the anterior most region of the skull for grounding electrode. Then smooth trephine holes were made on the marked positions by small hand held pen vise drill machine. EEG and grounding screw electrodes were carefully screwed in these trephine holes and the contact pins of these epidural screw electrodes were inserted and fixed in the socket contact. After connecting screw electrodes, both right and left EOG electrodes were sutured with right and left upper outer canthus muscles respectively; and right and left EMG electrodes were sutured with right and left cervical muscles respectively. The whole array of electrodes with their socket contact was fixed on the skull with the help of dental acrylic and then the incision wound was sutured.

3.2. Filtering

Since recorded data may be contaminated due to presence of the environmental and instrumental artefacts, it is always required to minimize the effect of artefacts/noise present in the recorded time domain signal. Having finished the recording with the amplifier settings as mentioned in Table-1, the raw data was band-passed using an infinite impulse response (IIR) Butterworth filter [38 -39] with a lower cut-off of 0.5 Hz and a higher cut-off of 40 Hz. Since EEG and EOG are low frequency signals, 50 Hz filter's setting option is kept ON (represented by In in Table1) to get rid of interference due to A.C power supply. At the same time, for EMG which consists of high frequency components, 50 Hz filter is kept OFF (represented by Out in Table1).

Table 1. Amplifier settings

Signal	Sensitivity in μV/mm	Low frequency cut-off in Hz	High frequency cut-off in Hz	50 Hz filter
EEG	10	1	70	In
EOG	20	0.3	35	In
EMG	10	5	70	Out

Digitalized data were stored in hard disk in small segments (2 minutes) in separate data files. The three channels recording of EEG, EOG and EMG were visually examined and extracted after adjusting the baseline and removing the artefacts. Visually identified sleep EEG patterns yielded the superior results with filtered data. Further, with the help of wavelet transformation, powers of the four frequency sub-bands - delta band power, theta band power, alpha band power, and beta band power were computed in order to extract the frequency information to classify different stress events. Recordings of EMG and EOG activities at sampling frequency of 256 Hz were used to differentiate the sleep events.

3.3. Features Extraction

EEG data was recorded from 20 subjects where 10 rodents were used for acute stress and respective control group and the remaining 10 rodents for chronic stress and respective control group. Having acquired the digital data for sleep staging from different subjects belonging to acute, chronic, and control groups, continuous wavelet transform, which is based on *multiresolution analysis* (MRA), was applied on each signal. The time varying frequency spectrum of EEG, EOG, EMG have been investigated to extract the features from polymorsographs. By applying wavelet transform to each 2 seconds epoch of EEG signal, wavelet coefficients were calculated for delta, theta, alpha, and beta sub-bands which lie on the scales: 128-46, 46-23, 23-13, and 13-6 respectively. The respective frequency components are 0.5-4 Hz, 4-8 Hz, 8-12 Hz, and 14-40 Hz. Separate coefficients matrices were formed for each of these four bands, which contain coefficients of matrix size [83 x 512], [24 x 512], [11 x 512], and [8 x 512]. Rows and columns of the matrix stand for scales and time (samples). Wavelet coefficients of all sleep EEG signals were calculated and saved in a file.

Further, RBF and SVM have been applied to classify the stressful events of sleep EEG. A total of ten features have been extracted from wavelet processed EEG data where the first four features comprise the relative band power of delta, theta, alpha and beta bands of EEG power spectrum, next four features consist of the total band power of these four frequency sub-bands, and the last two features describe the mean of the absolute values of EOG and EMG for the given time frame. The detailed extracted features were used to train the classifier so as to investigate the three stages of sleep and further perform the stress classification. Feature extraction and classification codes have been written in Matlab R2014b. These extracted feature vectors were further labeled for sleep stage classification into three stages - *Awake* (AWA), *Slow Wave Sleep* (SWS), and Rapid Eye Movement (REM) as 0, 1 & 2 respectively. Similar procedure has been followed for stress classification where class labels 0 and 1 were assigned to acute and chronic state respectively with respect to their control state.

Now, from the available data sets, nearly 70 percent of the data has been used for training and the remaining data for testing and validation of the accuracy of the radial basis function neural network and SVM algorithms. A total of 225 samples were used for training and remaining 100 samples were used for testing for each sleep stage. Total data set consists of 675 samples for three sleep stages (225 samples for each class of Awake, SWS, and REM) used for training where 300 samples (100 samples each) have been considered for the validation of the results. Description of training and test data sets for sleep stage classification has been presented in the Table 2. Six wavelet features have been extracted from the raw EEG data for sleep stage classification and ten wavelet features for stress classification.

Table 2. Description of sleep EEG datasets

Sleep stage classification - 0, 1 and 2 refer to REM, Awake and SWS respectively				
	No. of features	**No. of classes**	**Training data set**	**Test data set**
Class 0 v/s 1	6	2	450	200
Class 1 v/s 2	6	2	450	200
Class 2 v/s 0	6	2	450	200
Stress classification – 0&1 refer to Acute & Chronic				
Acute v/s Chronic	**No. of features**	**No. of classes**	**Training data set**	**Test data set**
Class 0 v/s 1	10	2	450	200

3.4. Methodology

The methodology shown in figure 1 study consists of various steps - (a) pre-processing of recorded data to improve the general signal quality of the EEG in order to get more accurate rhythmic analysis and measurements, (b) extraction of features from wavelet coefficients of EEG signals to compose wavelet feature vectors for further classification, and (c) use of SVM and RBF as classifiers to detect and classify the patterns. Classification accuracies have been used to evaluate the performance of the system.

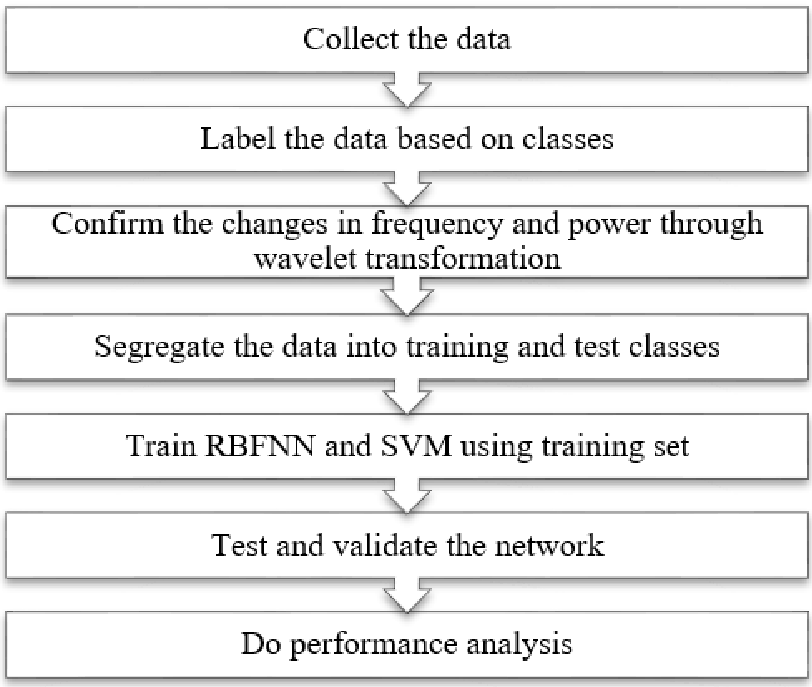

Fig. 1. Methodology.

3.5. Continuous wavelet transform (CWT)

The *continuous wavelet transform* (CWT) is a time-frequency analysis method, which differs from the more traditional *short time Fourier transform* (STFT) by allowing arbitrary high localization in time of high frequency signal features. The CWT does this by having a variable window width, which is related to the scale of observation. Another important distinction from the STFT is that the CWT is not limited to using sinusoidal analyzing functions. Rather, a large selection of localized waveforms can be employed as long as they satisfy predefined mathematical criteria. The wavelet transform of a continuous time signal x(t), is defined as:

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^*\Big(\frac{t-b}{a}\Big)dt \tag{1}$$

where $\psi^*(t)$ is the complex conjugate of the analyzing wavelet function $\psi(t)$, a is the dilation parameter of the wavelet and b is the location parameter of the wavelet. The contribution to the signal energy at the specific a scale and b location is given by the two dimensional wavelet energy density function known as the scalogram E(a, b).

$$E(a,b) = |T(a,b)|^2 \tag{2}$$

The scalogram can be integrated across a and b to recover the total energy in the signal using the admissibility constant, C_g, as follows:

$$E = \frac{1}{C_g} \int_{-\infty}^{\infty} \int_{0}^{\infty} |T(a,b)|^2 \frac{da}{a^2} db \tag{3}$$

The relative contribution to the total energy contained within the signal at a specific a scale is given by the scale-dependent energy distribution.

$$E(a) = \frac{1}{C_g} \int_{-\infty}^{\infty} |T(a,b)|^2 db \tag{4}$$

The spectral components are inversely proportional to the dilation, i.e. f α 1/a, the frequency associated with a wavelet of arbitrary a scale is given by

$$f = \frac{f_c}{a}$$

where, the characteristic frequency of the mother wavelet (the archetypal wavelet at scale a = 1 and location b = 0), f_c, becomes a scaling constant and f is the representative or frequency for the wavelet at arbitrary scale a. The original signal may be reconstructed using an inverse transform:

$$x(t) = \frac{1}{C_g} \int_{-\infty}^{\infty} \int_{0}^{\infty} T(a,b)\psi_{a,b}(t) \frac{da\, db}{a^2} \tag{5}$$

In practice, a fine discretization of the CWT is computed where usually the b location is discretized at sampling interval and the a scale is discretized logarithmically. As the wavelet transform is a convolution of the signal with a wavelet function, convolution theorem can also be used to express the integral as a product in Fourier space, *i.e.*,

$$T(a,b) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{x}(\omega)\hat{\psi}^*_{a,b}(\omega)d\omega \tag{6}$$

$\hat{\psi}^*_{a,b}(\omega) = \sqrt{a}\hat{\psi}^*(a,\omega)e^{i\omega b}$ where, is the Fourier spectrum of the analyzing wavelet at scale a and location b. In this way, a *fast Fourier transform* (FFT) algorithm can be employed in practice to speed up the computation of the wavelet transform. A vast amount of repeated information is contained within this redundant representation of the continuous wavelet transform T(a, b). This can be condensed considerably by considering only local maxima and minima of the transform.

3.6. Radial basis Function model

The RBFNN approach is apparently more spontaneous than the MLPNN [40]. Each neuron in an MLPNN takes the weighted sum of all of its input values where as RBFNN performs classification by measuring the testing input's similarity to the examples from the training input set. Each RBFNN neuron stores a "prototype", which is just one of the examples provided in the training set. When a new input is given to the RBFNN for classification, each neuron computes the Euclidean distance between the given input and its prototype. If the input more closely resembles the class A prototypes than the class B prototypes, it is classified as class A and this resemblance is reflected in the Euclidian distance [41].

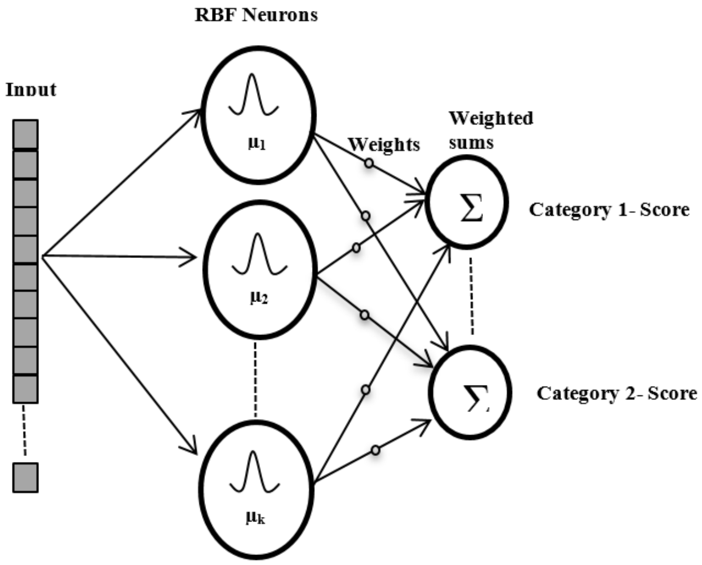

Fig. 2. RBFN layered structure.

Figure 2 shows the typical architecture of an RBF network which consists of an input layer, a layer of RBF neurons also known as pattern layer, summation layer and an output layer with one node per category or class of data. Each of the RBF neuron computes a measure of the similarity between the test input and its prototype vector (taken from the training set). Test input vectors which are more similar to the prototype or training inputs return a result closer to 1. There are different kinds of similarity functions, but the most popular is based on the Gaussian curve. Given below is the equation for a Gaussian function with one-dimensional input.

$$f(x) = \frac{1}{\sqrt{2\pi}}e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{7}$$

where, x is the input, μ is the mean, and σ is the standard deviation. Also, each RBF neuron produces its largest response *i.e.*, 1 when the input is equal to the prototype vector. This allows taking it as a measure of similarity, and summing the results from all the RBF neurons. As we move away from the prototype vector, the response falls off exponentially. The exponential fall-off of the activation function means that the neurons whose prototypes are far away from the input vector will actually contribute very little to the result.

3.7. Support Vector machine

SVM, as proposed by Vapnik in 1995, is a supervised learning based algorithm for solving binary (two class) classification problems. It has been widely applied in diverse fields of machine learning and pattern recognition problems. In the present work, the SVM classifier has been applied to separate extracted features into the two categories of stress - chronic and acute. Ideally, an SVM can identify a hyper-plane that separates stress and control feature vectors of EEG signal in its high-dimensional feature space [42, 43]. SVM performs the classification task by constructing a set of hyperplanes in a high dimensional space. This is achieved by mapping n-dimensional feature vector to a higher dimensional space using a function $y = f(x)$. The function aims at maximizing the margin of separability between the classes. For the simplest case, where the classification can be performed using a linear function, the hyperplane equation is given by

$$y =< w.x > +b;\ b; \varphi = sign(y) \tag{8}$$

where $< w.x >$ represents the dot product of the weight vector w and feature vector x and b represents the bias weight.

However, for many-features dataset, the classes may not be separable using a linear hyperplane because the feature versus class relationship may be nonlinear. For such cases, the SVM solves the nonlinear classification problem using kernel functions. For classification, each sample in a set of training vectors is matched with two categories before being reflected into a high dimensional space using the appropriate Kernel function. Further, the SVM creates a model and uses it to group the samples to a definite class. The nonlinear kernel used for mapping the input patterns into a higher dimensional feature space is chosen a priori. Based on the mapping, the model constructs a linear separating hyperplane in the high dimensional space. The hyperplane on both sides is covered by parallel hyperplanes, which groups the data points into two categories between the two hyperplanes as shown in figure 3.

The hyperplanes are shown separating the data points in two groups. A greater distance or difference between parallel hyperplanes indicates a smaller total SVM error rate. Although no proper method exists for the selection of Kernel function, we have considered the widely used Gaussian *radial basis function* (RBF) in the present work. The function is given as:

$$\varphi(x_i) = exp\left(\frac{-||x_i - x_j||^2}{2\sigma^2}\right) \tag{9}$$

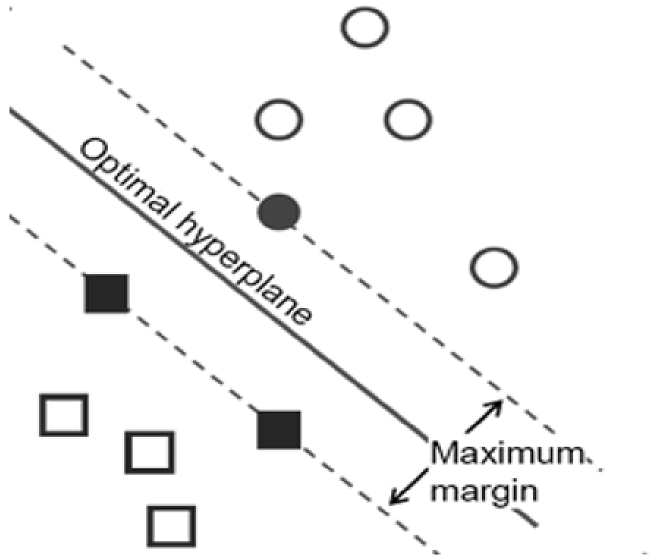

Fig. 3. It represents the optimal separating hyperplane along with parallel hyperplanes on both sides.

4. Results

After the subjects were exposed to heat stress, the effect caused significant change in the powers of some frequency bands, whereas insignificant change in powers of other frequency bands was observed. Reports on the variation of powers of frequency components of delta, theta, alpha and beta sub-bands in Awake, SWS and REM states have been studied for acute and chronic cases.

4.1. Detection of changes in frequency and power

Changes in frequency and power were investigated for all the epochs pertaining to control and stress subjects of 30 seconds epoch through the use and attributes of wavelet transform. In order to make minute changes in power and frequency visible, graphs containing signals of 2 s length has been presented as depicted in figure 4. Powers of higher frequencies of delta band among all the bands were found to be the largest at time 50 *i.e.*, at the start of the epoch, which further showed decreasing tendency over all the scales till the end of the epoch. Between time 300-512, it had drastically reduced but at the same time faster waves reported their existence with small powers. Next dominant frequency components belonged to theta band for which the highest component of the band held largest power. Theta too, did not show noticeable power during time 300-500. The plot of alpha implies that lower frequencies of alpha, which lies on scale 16-22 (8.3 Hz – 11.4 Hz) seemed to have more power and it slightly decreases for the higher frequencies of the same band. Between 220-340, many lower frequencies reported their presence with reduced power. After time 340, powers of all frequency components were not worth mentioning. In beta band, two peaks were observed on scale 7 (26.1 Hz) during 150-170 with equal power, which was quarter of delta power on scale 44.

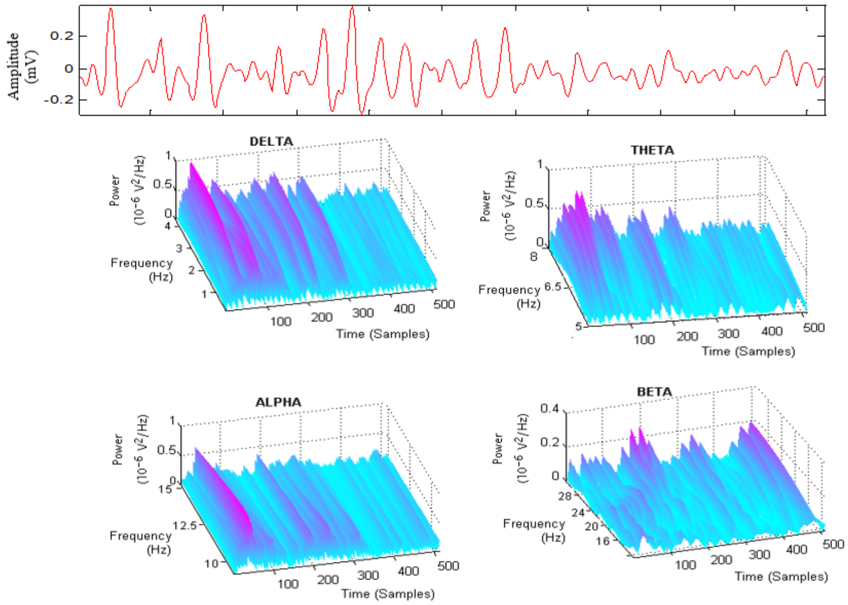

Fig. 4. EEG signal of 2-s duration. Power versus time and frequency of delta, theta, alpha and beta bands of SWS signals for control group.

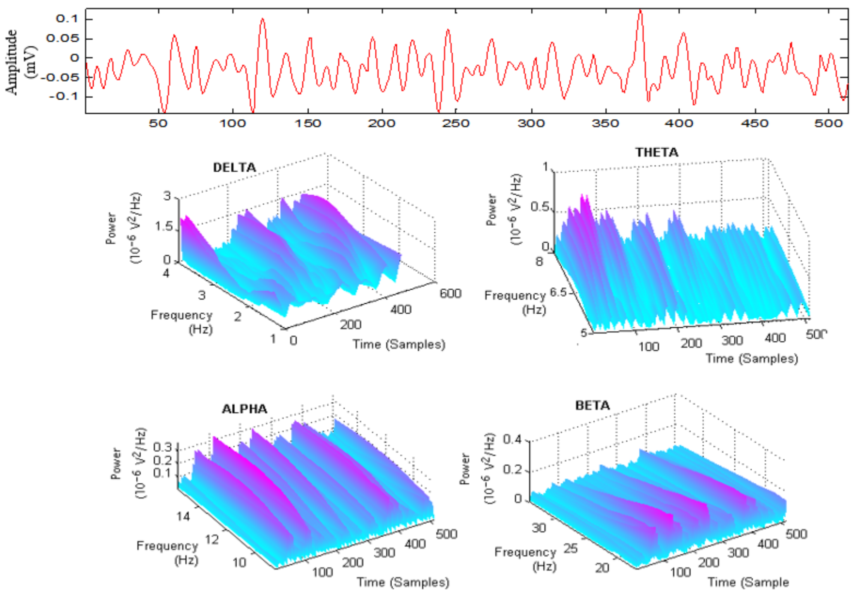

Fig. 5. Power versus time and frequency of delta, theta, alpha and beta bands of SWS signals under exposure of acute heat stress.

Figure 5 shows the power spectrum of respective stressed subjects. When subject undergoes exposure of acute heat stress, change in power over all scales was investigated for the sub-bands – delta, theta, alpha, and beta. Increase in the powers of delta components were noticed at many places in the epoch but on the other hand, powers of alpha and beta components went down, indicating reciprocal relationship between changes in the powers of slow and fast waves. Similar analyses have been carried out on awake and REM signals for acute and chronic states with respect to their control groups. The alpha components witnessed a normal increase in the amount of power; meanwhile powers of beta components were significantly enhanced. Delta and theta components seemed to have nearly no change in their powers. For awake signals, some change in the powers of delta and beta components have been observed, however no change in powers of theta and beta was noted. Powers of the frequency components of delta band appeared to have decreased, whereas it has increased for beta band. In the similar way, the changes in frequency and powers due to heat exposure have been examined and confirmed through time-frequency analysis for all the epochs under consideration. Further, classification of sleep EEG and stressful events were carried out through RBFN and SVM.

4.2. Radial Basis Network for sleep stage classification and stress classification

Since it is easier to assess the performance of the algorithm for two classes separately, Awake, SWS and REM have been classified in binary mode such as REM versus Awake, Awake versus SWS and REM versus SWS. Number of feature sets used for training was kept equal to avoid the weight vectors getting more adapted towards the dominant class, which may increase the inaccuracy of the algorithm.

Table 3. Classification accuracy for RBF

Classification	**Classification accuracy**	**No. of epoch to reach goal**
Class 0 vs. Class 1	88.5%	150
Class 1 vs. Class 2	86%	200
Class 2 vs. Class 0	86.7	200

The overall accuracy was found to be 87% for sleep stage classification using RBFNN as shown in Table 3.

The accuracy for stress classification has been reported as 90.5% for both classes.

4.3. Performance of SVM for sleep stage and stress classification

Table 4 shows the classification accuracy of sleep stages under chronic and acute exposure of heat with the number of correctly identified and incorrectly identified samples after testing.

True positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) were obtained from the results and the performance of the kernel SVM classifier has been evaluated using equations (10-12).

Table 4. Accuracy breakdown for sleep stage classification under the exposure of chronic stress and acute stress

Sleep stage classification under exposure to chronic stress					
Sleep Stage	**Testing data set**	**incorrectly identified**	**correctly identified**	**Accuracy**	**Average accuracy**
REM v/s Awake	200	14	188	94%	96.5%
Awake v/s SWS	200	4	196	68	
REM v/s SWS	200	5	195	98\98	
Sleep stage classification under the exposure of acute stress					
Sleep Stage	**Testing data set**	**incorrectly identified**	**correctly identified**	**Accuracy**	**Average accuracy**
REM v/s Awake	200	13	187	94%	94.1%
Awake v/s SWS	200	8	192	96%	
REM v/s SWS	200	14	186	93%	

$$Specificity = TNR = \frac{TN}{FP + TN} * 100 \tag{10}$$

$$Sensitivity = TPR = \frac{TP}{TP + FN} * 100 \tag{11}$$

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} * 100 \tag{12}$$

Sensitivity, specificity and accuracy, being the statistical measures in the analysis of sleep stage classification, have been calculated for each class as shown in Table 5, 6 and 7. Same performance measures were obtained in stress identification as presented in Table 8 where SVM is able to achieve 84.2% accuracy with ten features taken as input vectors.

Table 5. Calculation of TPR, TNR for AWAKE v/s SWS

AWAKE v/s SWS	**Sleep stage classification**			
AWAKE=100	TP	97	FP	2
SWS=100	FN	3	TN	98
Sensitivity	**Specificity**		**Accuracy**	
97%	98%		97.5%	

Table 6. Calculation of TPR, TNR for REM v/s AWAKE

REM v\s AWAKE	**Sleep stage classification**			
REM=100	TP	93	FP	8
AWAKE	FN	7	TN	92
Sensitivity	**Specificity**		**Accuracy**	
93%	92%		92.5%	

Table 7. Calculation of TPR, TNR for REM v/s SWS

REM v/s SWS	Sleep stage classification			
REM= 100	TP	95	FP	8
SWS= 100	FN	5	TN	97
Sensitivity	**Specificity**		**Accuracy**	
95%	97%		96%	

Table 8. Calculation of TPR, TNR for Acute v/s Chronic

Stres Conditions	Acute		Chronic	
Acute	TP	75	FP	20
Chronic	FN	10	TN	85
Sensitivity	**Specificity**		**Accuracy**	
88.2%	80.9%		84.2%	

5. Performance comparison

Performance of SVM in the classification of stress has been compared with the previous work on similar animal model which employed three-layered back-propagation neural network [27] as shown in Table 9. Results demonstrate that SVM based approach is found to be superior to the MLPNN when the subject is exposed to thermal stress. Percentage recognition of SWS and REM under exposure to chronic state is observed to be 98% with SVM approach whereas MLPNN resulted with 95.5% and 93.8% respectively for SWS and REM. However, recognition rate was witnessed to be reduced by 4.5% for awake state. On the other hand, under acute exposure of heat, SVM turns out to be a better classifier for all three sleep stages. Average accuracy obtained in this case is 94.7% for SVM which is 4.67% more than what was obtained in case of MLPNN.

Table 9. Comparison between two algorithms: MLPNN and SVM

Comparison of MLPNN with SVM under the exposure of chronic stress						
SVM				**MLPNN**		
Sleep Stage	**no. of samples**	**Accuracy**	**Average accuracy**	**no. of samples**	**Accuracy**	**Average accuracy**
Awake	200	94%	96.50%	50	98.5	95.9%
SWS	200	98%		50	95.5	
REM	200	98%		50	93.8	
Comparison of MLPNN with SVM under the exposure of chronic stress						
SVM				**MLPNN**		
Sleep Stage	**no. of samples**	**Accuracy**	**Average accuracy**	**no. of samples**	**Accuracy**	**Average accurac**
Awake	200	94%	94.17%	50	91	89.5%
SWS	200	96%		50	92.0	
REM	200	93%		50	85.5	

6. Discussion

Past research works on sleep EEG analysis under the exposure of environmental heat have shown that if subjects are exposed to high environmental heat of 38±10°C for four hours (acute exposure), there will be severe changes in brain pathophysiology, which may resume back to its original state after few hours when thermal stress is withdrawn [1, 44]. However, in case of chronic stress, the changes in physiological parameters are not reversible, rather they acquire a new set point [7,45].The results obtained from the previous study have suggested that the exposure to high environmental heat has significant effects on brain signal. Literature reports that only multilayer perceptron neural network as a classifier with backpropagation algorithm has been employed to detect the changes in sleep wake states [27], where an average recognition rate was reported to be 95.35% for all the three sleep wake states. In order to overcome the inherent limitations offered by back propagation algorithm such as problem of local minima and overtraining of the patterns, authors in the present work have tried to present RBFNN and SVM as better alternative with good recognition rate. To the knowledge of authors, no such computational classifiers in the past have been used to identify efficiently the changes in brain signals due the stressful events. This can further be used to develop an automated detection system for psychophysiological analysis. In order to develop a robust system, we must have to include biochemical, metabolic as well as autonomic variations along with the EEG signals and the system has to be tested with real time application on human subjects.

Results from the observations of stress markers following heat stress, either acute or chronic, provide evidences of the stressful conditions of rats. Stress is characterized by some physiological stress markers such as body temperature and body weight. Previous reports suggest that body temperature increases if subject is induced with acute exposure of the high environmental heat [46]. Significant rise in body temperature of rats as compared to the respective control groups in case of acute heat stress has been reported unanimously by all the authors [46-48]. Previous reports also suggest that stimulation of the mechanisms requires heat dissipation and owing to which the body temperature rises following acute heat stress. However, physiological behavior of animals in case of chronic exposure of heat gives rise to the body temperature which is set at the higher temperature similar to the findings of past report [6-7].

SVM detection rate for sleep states is found to be superior for chronic stressed data with an average accuracy of 96.4% as compared to acute stressed cases where it appears to be 94.1%. Under the exposure of chronic stress, Awake and SWS are best detected with 98% average accuracy. However, when subjects were exposed to acute high environmental heat the detection rates of SVM decreases slightly for Awake and SWS. Similar results have been obtained for REM and SWS. These results are suggestive of the fact that a permanent shift in the physiological behavior of mammals under chronic heat stress is observed relative to the mammals which were under acute exposure of high heat. For the detection of sleep and awake stage, SVM has been applied to distinguish the two clusters of different stages where feature extraction has been accomplished by maximum overlap discrete wavelet transform with the success rate of 95% [43]. Author has applied this approach on 14 sleep EEG records to detect the sleep apnea [49]. Based on physical activities and lifestyle data sets, stress classification was reported by the researchers using deep belief network [50]. Deep learning models achieved an accuracy and a specificity of 66.23% and 75.32%, respectively. The authors [51] have presented an automatic sleep stage classification method by using sparse deep belief net for extracting feature vectors and combination of classifiers to classify sleep stages. Total accuracy of the classifier was reported as 91.31%. In another work, convolutional neural networks based automatic sleep stage classification method was suggested by the authors [52]. Awake, SWS and REM stages were detected with an average accuracy of 84.5%.

7. Conclusion

Physical or natural stress is a creature's response to a stressor which reacts to a challenge. It is an anxiety syndrome which can lead to acute or chronic stress disorders. The correct diagnosis of a patient's stress simplifies the choice of drug treatment and also allows an accurate assessment of prognosis in many cases. A method has been presented for an effective use of RBFNN, SVM algorithms in establishment of EEG power spectra, EOG and EMG activity as an index of stress in hot environment. The results obtained after simulation of real EEG data set have been found to be interestingly encouraging for SVM over RBFNN and MLPNN. This high level of accuracy ensures the development of medical diagnosis tool for automated detection of stress level of human being.

Ethics statement The authors declare that all procedures in this study have been conducted in compliance with 'committee for purpose of control and supervision of experiments on animals (CPCSEA)', India as well as with internal institutional policies and guidelines. All the authors also declare that there are no conflicts of interest to disclose.

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