Classification of Stress Level using Approximate Entropy Features and Neural Networks

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Abstract

Most studies addressing the effect of chronic stress on health have reported that chronic stress is associated with an increased risk of infectious diseases [1] including HIV [2]. No significant indicator is available to measure the level of stress and it is one of the common research problems. In this paper, to recognize the level of stress, a simple stress level classification system has been proposed using brain wave electroencephalogram (EEG) signals. The proposed stress level classification system records the brain wave signals while listening to the sound clips mixed with noise. The recorded Electroencephalography signals are pre-processed and segmented into four frequency bands. The band frequency signals are used to extract features using band energy and approximate entropy (Apen) algorithm. The extracted features were then associated to the stress levels evaluated by subjective evaluation test. A simple multilayer neural network model has been developed to classify the level of stress. The proposed methods are validated through simulation.

Keywords - Stress, Electroencephalogram (EEG), Approximate Entropy (Apen), Multilayer Neural Network (MLNN).

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I. Introduction

Stress is very common in our daily life. It is induced because of physical and psychological means perceived by us. It is defined as body's reaction with the release of Cortisol (stress hormone) due to physical, mental or emotional pressure [3]. Stress is an undeniable part of human life. It is impossible to live without experiencing some degrees of stress; the effects of stress in people are seen physically, mentally as well as emotionally [4-5]. As a result, there is much loss of work time and increasing medical expenses with huge financial losses for individuals as well as for companies.

There are various types stress inducing elements such as audio and visual noise that can cause distractions subsequently break concentration and increase the stress level. Stress affects health and can cause burnout. The effect of stress hormones when the stressor is repetitive or persistent is detrimental for the body. They may cause irreparable physiological damage of the brain and other effects such as tiredness, lack of concentration, headaches, fever, irritability, muscular tension and short term loss of memory [6]. In recent years, there have been numbers of research on the assessment of stress, practical measures for noise management and prevalence or incidence of stress level. Environmental noise is one of the most pervasive, annoying, and costly residuals of human activity. Minimizing the environmental noise can lead to better concentration, increased productivity and can reduce humans overall stress level [7-9].

In this paper, to evaluate the stress level when six different music clips mixed with noise were played, a simple subjective evaluation test has been conducted [9-11]. A simple experimental protocol has been proposed to play the music mixed with noise for certain period and the EEG brain wave signals are recorded from various subjects. The sound clips were played at three different sound pressure levels and the subjects were requested to listen to the sound clips. The EEG signals are recorded and subsequently four distinct frequency bands namely delta (0-3 Hz), theta (4-7 Hz), alpha (8-13 Hz) and beta [12] are extracted as features.

In this paper, applied entropy features are used as it reflects the nonlinear dynamics of the brain activity [13] and can quantify the regularity of a time series data of physiological signals [14]. The band energy and the applied entropy features are then associated to the stress level obtained by subjective evaluation and the network models are developed. The block diagram of the proposed system is depicted in Figure 1.

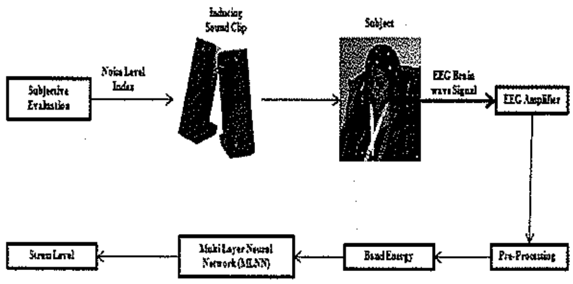

Figure1. Block Diagram of the Proposed System

II. Data Collection

Electroencephalography (EEG) is the most studied potential for non-invasive interface, mainly due to its fine temporal resolution, ease of use, portability and low setup cost. The subjects were induced with different stress levels by exposing them to the sound clips played at different sound pressure levels. The stress signals emanated from the subject were recorded using the EEG electrodes. The recorded EEG brain wave signals were further processed for the classification of the stress level.

A. Subjective Evaluation Test

The level of stress induced in a subject while listening to music mixed with noise depends upon:

1. Types of noise such as pink, white and high pitch noise.

2. The duration of noise added to the music.

3. Total number of noise occurrence in each sound clip.

In this research, six different sound clips mixed with white Gaussian and high pitch noise were used and are played through a 16-bit audio speaker in a sound controlled room. A sound clip containing a base soft music that can be played for 30 seconds is considered. A Gaussian white noise sample with time duration of 3 seconds was selected and recorded separately. This Gaussian white noise was then added to the sound clip at random position so that the resulting sound clip will have three continuous noise level instances and of three seconds duration. By adding different type of Gaussian white noise (3 second duration) to the sound clip six different types of sound clips were generated and their level stress inducement was evaluated using the subjective evaluation test. The subjects are asked to listen and validate the induced stress level while listening to the sound clips. A complete study on the stress induced while hearing the different sound clips were made and the details of the sound clip, type of added noise, the duration of noise and the average subjective evaluation were tabulated and shown in Table I.

TABLE I

Noise Level Evaluation

Noise	Type of Noise	Stress level 60 dB, 70 dB & 80 dB
SC1	White Gaussians Noise	Very Low
SC2	White Gaussians Noise	Low
SC3	White Gaussians Noise	Very Moderate
SC4	White Gaussians Noise	Moderate
SC5	High Dog Pitch Wiesel	Very High
SC6	High Dog Pitch Wiesel	High

B. EEG Data Collection

A 19 channel Mindset-24 Topographic Neuro-Mapping Instrument with electrode cap arrangement whose band pass analog filters were set at 0.5 to 34 Hz has been used to record the EEG signal emanated from the brain scalp [12]. The subjects are seated in a comfortable chair and in a sound controlled air-conditioned room. The EEG brain wave signals are collected from the subject while remaining in a totally passive state. No overt movements were made during the performance of the tasks. The protocol starts with an introduction screen for 30 seconds which explains the subject to take a deep breath and allowing a relaxation time for five seconds. Then the first sound clip at 60 dB played for 30 seconds. A blank screen with no sound clip played for 10 seconds. The process is repeated for all the remaining five sound clips. Once after playing all the six sound clips, the subjects were asked to do a breathing exercise for 15 seconds. The above procedure is repeated by playing all the six sound clips at different sound pressure level such as 70 dB and 80 dB. The experiment protocol for the proposed system is depicted in Figure 2.

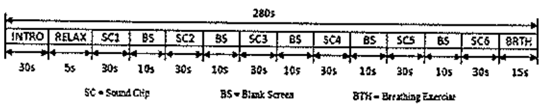

Figure 2. The Experimental Protocol for the Proposed System

Sixteen healthy volunteered subjects (eight males and eight females) aged between 18 and 24 years were considered for the study and analysis. Most of the subjects are students from Polytechnic Tuanku Syed Sirajuddin, Perlis state of Malaysia. The EEG brain wave signals were recorded from Occipital (O), Parietal (P), Temporal (T), Central (C), Frontal (F), Frontal Pole (FP) and ground electrode locations of 10-20 system.

The subjects were requested to feel the noise level while the sound clip is played at 60 dB, 70 dB and 80 dB sound pressure levels. A time break of 10-20 minutes has been given for a subject to make them comfortable after each sound clip is played. The experiment was conducted for two subjects per day in two sessions. The sampling frequency was chosen as 250 Hz.

III. Feature Extraction

The EEG signals recorded from eight differential electrodes such as F3, F7, F4, F8, T3, T4, T5, and T6 are processed using a band pass filter to remove all signals below 0.5 Hz and above 34 Hz [15], The 30 seconds of the EEG signal is passed to cut the five second of EEG signal in front and end point of the EEG signal. The remaining 20 second of the EEG signal is segmented into number of frames.

Frame Blocking, is a common method for pre-processing of non stationary and complex signals. To analyze the EEG stress signal, a window is slid over the EEG stress signal and the features (energy features and applied entropy features) over each frame are extracted. Overlapping windows offer better time resolution and can produce shorter delays in the detection, in order not to miss any possible stress events happening at the end of each frame and prolonging to the next one. A frame length of one second having 256 samples per frame has been chosen with an overlap of 0.5 sec. The frame signal is filtered using a Chebyshev band pass filter and band width signals are extracted for frequency bands 0.5-3Hz, 4-8Hz, 8-13Hz, and 13- 30Hz. The band energy features for different frequency bands under different stress levels are depicted in Figure 3 and 4.

The EEG signal obtained from each channel is divided into 38 frames such that each frame has 256 samples. The four spectral band filters are applied to each frame and the energy features and approximate entropy features are extracted. Therefore for both energy features and approximate entropy features will have 32 (8 x 4) features vector from the recorded EEG channels.

Further, for each sound clip we have 38 feature samples and each feature samples has 32 features. For sixteen subjects 608 (38 x 16) x 32 feature samples have been formed for one sound clip and are associated to one of the stress level. This process is repeated for seven different sound clips and thus we have 4256 x 7 feature vectors. These feature vectors are then used to model the MLNN for 60 dB, 70 dB and 80 dB sound pressure level. This process is repeated for both energy features and approximate entropy features.

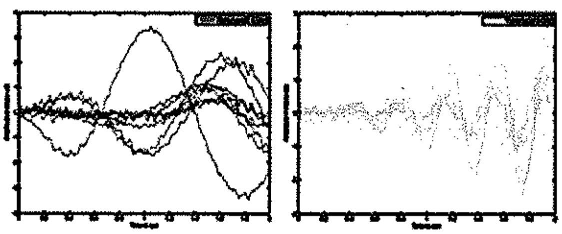

Figure 3. Delta Band and Theta Band signal for low stress at 60 dB (channel1-8)

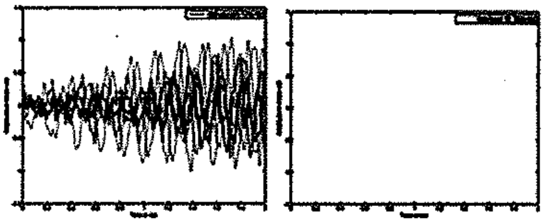

Figure 4. Alpha Band and Beta band signal for low stress at 60 dB (channel 1-8)

IV. Multilayer Neural Network Model (MLNN)

The feature vectors formed for the 60 dB sound pressure level using band energy features are partitioned into training set, and testing set. The training set has 2724 samples and the testing set has 3405 samples. The neural network model is developed with two hidden layers and three neurons in the output layer. The hidden and the output neurons are activated using binary and bipolar sigmoid activation function as shown in equation 1 and 2.

$$f(x) = \frac{1}{(1+e^{-x})-1} \tag{1}$$

$$f(x) = \frac{2}{(1+e^{-x})-1} \tag{2}$$

where, x is the net input to the neuron. The initial weights for the above networks are randomized; the input and output data are normalized using the following equation.

$$x_n = \left(\frac{0.8(x - x_{min})}{x_{max} - x_{max}}\right) + 0.1 \tag{3}$$

$$x_n = \left(\frac{1.8(x - x_{min})}{x_{max} - x_{max}}\right) - 0.1 \tag{4}$$

where, x_n is the normalized data, x_{max} and x_{min} are the maximum and minimum value of the data respectively. While training the neural network, a Mean Squared Error (MSE) tolerance of 0.1 is used.

$$MSE = \sum_{p=1}^{P} \sum_{k=1}^{m} (t_{k,p} - o_{k,p})^2 \quad (5)$$

where, P is the total number of patterns in data set, k is the output units, $t_{(k,p)}$ is the target value at the k^{th} utput neuron for the p^{th} sample. The learning rate and momentum factor for the three models are chosen as 0.5 and 0.8 respectively.

The values for learning rate, momentum factor and number of neurons in the hidden layers are chosen by experimental observations in order to get better classification accuracy. The neural network models are also developed for the 70 dB and 80 dB sound pressure levels with two hidden layers having 20 neurons in the first hidden layer and 20 neurons in the second hidden layer and three neurons in the output layer for the binary sigmoid activation and for the bipolar sigmoid activation function 20 neurons in the first hidden layer and 20 neurons in the second hidden layer and three neurons in the output layer are set. The three network models are trained with 25 such trial weights and the number of epoch, network training parameters and the mean classification rate are shown in Table 2 and Table 3.

TABLE 2
Classification of Stress Level Index using Binary Sigmoidal Activation Function (Energy features)

Binary Sigmoid Activation Function			
No of Input Neurons	32	Training Tolerance	0.01
No of output Neurons	3	Testing Tolerance	0.1
No of hidden Neurons		25	25
Sound Pressure Level	No. of. Epochs	Training Time (seconds)	Classification Rate (percentage)
60 dB	632	1192	83.79
70 dB	636	1139.3	86.89
80 dB	697	1149.4	87.09

TABLE 3.
Classification of Stress Level Index using Bipolar Sigmoid Activation Function (Energy features)

Bipolar Sigmoid Activation Function			
No of Input Neurons	32	Training Tolerance	0.009
No of output Neurons	3	Testing Tolerance	0.1
No of hidden Neurons		17	17
Sound Pressure Level	No. of. Epochs	Training Time (seconds)	Classification Rate (percentage)
60 dB	363	480	85.7
70 dB	412	532	86.51
80 dB	434	578	89.76

Meanwhile for the approximate entropy feature, the feature vectors of 60 dB sound pressure level are partitioned into two parts that is training set, and testing set. The training set has 2724 samples and the testing set has 3405 samples. The model was developed with two hidden layers and three neurons in the output layer. Both the hidden and the output layers are activated using binary and bipolar sigmoid activation function which same activation function that being use for the band energy feature. The activation function is shown in equation 6 & 7.

$$f(x) = \frac{1}{(1+e^{-x})-1} \quad (6)$$

$$f(x) = \frac{2}{(1+e^{-x})-1} \quad (7)$$

where, x is the net input to the neuron. The initial weights are randomized between -0.5 and 0.5. Both of the input and output data are normalized using the following equation.

$$x_n = \left(\frac{0.8(x - x_{min})}{x_{max} - x_{max}}\right) + 0.1 \quad (8)$$

$$x_n = \left(\frac{1.8(x - x_{min})}{x_{max} - x_{max}}\right) - 0.1 \quad (9)$$

where, x_n is the normalized data, x_{max} and x_{min} are the maximum and minimum value of the data respectively. For the neural network training, a Mean Squared Error (MSE) tolerance of 0.1 is used.

$$MSE = \sum_{p=1}^{P} \sum_{k=1}^{m} (t_{k,p} - o_{k,p})^2 \quad (10)$$

where, P is the total number of patterns in data set, k is the output units, $t_{(k,p)}$ is the target value at the k^{th} output neuron for the p^{th} sample. The learning rate and momentum factor for the three models are chosen as 0.5 and 0.8 respectively.

In order to get better classification accuracy, the values for learning rate, momentum factor and number of neurons in the hidden layers are chosen by experimental observations. The neural network models are also developed for the 70 dB and 80 dB sound pressure levels. For binary sigmoid activation, the developed neural network model has two hidden layers with 20 neurons in the first hidden layer and 20 neurons in the second hidden layer; three neurons in the output layer. Meanwhile for the bipolar sigmoid activation function, the developed neural network model has 20 neurons in the first hidden layer and 20 neurons in the second hidden layer; three neurons in the output layer. The three network models are trained with 25 such trial weights and the number of epoch, network training parameters and the mean classification rate for all the six models are shown in Table 4 and Table 5.

TABLE 4.
Classification of Stress Level Index using Binary Sigmoid Activation Function (Approximate Entropy features)

Binary Sigmoid Activation Function			
No of Input Neurons	32	Training Tolerance	0.01
No of output Neurons	3	Testing Tolerance	0.1
No of hidden Neurons		25	25
Sound Pressure Level	No. of. Epochs	Training Time (seconds)	Classification Rate (percentage)
60 dB	135.9	241	**89.21**
70 dB	118.9	201.3	**89.50**
80 dB	97.9	184.6	**90.26**

TABLE 5.
Classification of Stress Level Index using Bipolar Sigmoid Activation Function (Approximate Entropy features)

Bipolar Sigmoid Activation Function			
No of Input Neurons	32	Training Tolerance	0.009
No of output Neurons	3	Testing Tolerance	0.1
No of hidden Neurons		17	17
Sound Pressure Level	No. of. Epochs	Training Time (seconds)	Classification Rate (percentage)
60 dB	96.2	199.1	**90.13**
70 dB	108.5	210.7	**90.48**
80 dB	94.7	172.9	**90.99**

V. Results and Discussion

The EEG signals are divided into number of frames and the frequency band power features namely Delta, Theta, Alpha, and Beta are extracted. In order to extract energy features and applied entropy features a simple feature extraction algorithm has been used. Both of the extracted features also associated with the subjective evaluation of stress level. Three multi layer neural network models (60 dB, 70 dB and 80 dB sound pressure levels) have been developed in both the binary and bipolar sigmoid activation function to classify the type of stress level. For energy features, the result from Table II and Table III shows that the network models have classification accuracy in the range of 83.79% to 87.09% for the binary sigmoid activation function and 85.7% to 89.76% for the bipolar sigmoid activation function.

Meanwhile for approximate entropy features, Table IV and Table V show that the network models have classification accuracy in the range of 89.21% to 90.26% for the binary sigmoid activation function and 90.13% to 90.99% for the bipolar sigmoid activation function. This shows that for both energy and approximate entropy features bipolar sigmoid activation function give higher accuracy. Besides that it can also be observed that the 80 dB neural network model has the highest classification accuracy for both energy and applied entropy feature that is 89.76 % using bipolar sigmoid activation function for energy features and 90.99% using bipolar sigmoid activation function for applied entropy features. Further, the developed network models were analyzed to identify the actual and predicted classifications by developing a confusion matrix and shown in Table VI, Table VII, Table VIII and Table IX.

A. Confusion Matrix

A confusion matrix is a visualization tool which contains information about actual and predicted classifications done by a classification system. The confusion matrices for the developed 80 dB neural network models using binary and bipolar sigmoid activation function are depicted in Table VI and Table VII. The confusion matrix for 80 dB is shown since the classification is higher when compared with the 60 dB and 70 dB sound pressure levels.

TABLE 6.

Confusion matrix for 80 dB sound pressure level neural network model using Binary Sigmoid Activation Function (Energy features)

EEG Sample	Relax	Very Low	Low	Very Moderate	Moderate	Very High	High
Relax	93	3	6	0	3	2	0
Very low	1	86	9	0	2	10	0
Low	2	2	93	1	0	4	6
Very Moderate	2	1	2	99	3	1	1
Moderate	1	2	1	6	96	2	0
Very High	2	1	3	1	4	98	1
High	2	1	3	5	6	4	86

From Table 6, it is observed that the very moderate stress level has the highest classification accuracy when compared to other stress levels. Further, it can also be observed that the very low stress level has more number of misclassifications as compared to the other stress levels.

TABLE 7.

Confusion matrix for 80 dB sound pressure level neural network model using Bipolar Sigmoid Activation Function (Energy features)

EEG Sample	Relax	Very Low	Low	Very Moderate	Moderate	Very High	High
Relax	96	3	4	1	2	2	0
Very low	0	89	6	3	3	7	0
Low	1	3	91	1	0	4	8
Very Moderate	0	3	0	102	1	1	1
Moderate	0	2	0	2	100	4	0
Very High	3	1	1	1	4	98	0
High	0	2	2	4	7	3	90

Table 7 shows that the very moderate stress level has the highest classification accuracy when compared to other stress levels. Besides that, the very low stress level has more number of misclassifications as compared to the other stress levels.

TABLE 8.

Confusion matrix for 80 dB sound pressure level neural network model using Binary Sigmoid Activation Function (Apen features)

EEG Sample	Relax	Very Low	Low	Very Moderate	Moderate	Very High	High
Relax	92	6	2	3	3	2	0
Very low	0	95	1	2	4	4	2
Low	8	2	99	3	3	1	0
Very Moderate	0	4	1	95	2	3	3
Moderate	0	1	2	0	100	2	3
Very High	0	4	1	3	0	99	0
High	1	4	0	0	1	3	98

From Table 8, the moderate stress level has the highest classification accuracy when compared to other stress levels. Further, it can also be observed that the relax level has more number of misclassifications as compared to the other stress levels.

TABLE 9.

Confusion matrix for 80 dB sound pressure level neural network model using Bipolar Sigmoid Activation Function (Apen features)

EEG Sample	Relax	Very Low	Low	Very Moderate	Moderate	Very High	High
Relax	98	0	1	5	2	2	0
Very low	2	92	2	3	1	0	5
Low	0	0	100	2	4	0	2
Very Moderate	2	1	1	99	2	1	1
Moderate	0	1	3	1	97	1	4
Very High	1	2	2	4	1	97	0
High	1	0	1	0	3	3	100

From Table 9 the moderate stress level has the highest classification accuracy when compared to other stress levels. Further, it can also be observed that the very low stress has more number of misclassifications as compared to the other stress levels.

Referring to the Table II and Table III for Energy features, the bipolar sigmoid activation function give better classification accuracy which 89.76% at 80 dB sound pressure level with a training time of 578 seconds in 434 epochs. Meanwhile according to Table IV and Table V for Applied Entropy features, the bipolar sigmoida activation function also give better classification accuracy which 90.99% at 80dB sound pressure level with a training time of 172.9 seconds in 94.7 epochs. The more number of correct classifications is at 80 dB sound pressure level for very moderate stress level in bipolar sigmoid activation function.

VI. Conclusion

In this paper EEG has been use for the source of stress level index classification. The proposed classification of mental stress level from EEG signals using MLNN is simple and the proposed feature extraction algorithm based on frequency band energy features and applied entropy features shown that the features are distinguished easily. The extracted band energy features and applied entropy features are used as a feature set and six different neural network models were developed and the test results obtained from this study open many possible areas of applications and improvements. Further, it is propitious to explore useful characteristics from EEG signals based on effective feature extraction and classification methods.

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