EEG based Emotion Recognition using SVM and PSO

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***Abstract*— Machine learning has fueled real breakthroughs in affective computing in making the machines more emphatic to the user. This emotion recognition capability of machines enables them to act according to the observed mental state. Human feelings and emotions are triggered by stimuli which are external or internal and manifest themselves in the form of pulse rate, tone, facial expressions and many more. In this paper we classify human emotions using EEG signals into four discrete states, namely happy, sad, angry and relaxed. The preprocessed signals from the DEAP database is used and spectral and statistical features are extracted by discrete wavelet transform. These features are classified using a SVM classifier and the performance of the classifier is optimized using the PSO algorithm. An overall emotional accuracy of 80.625% was obtained for a combination of 32 electrodes with a valence and arousal accuracy of 86.25% and 88.125%.**

***Keywords*— EEG, Wavelet transform, Emotion recognition, SVM, PSO.**

I. Introduction

Emotions play a key role in understanding human behavior. They are believed to be extremely potential for analyzing the condition of the human mind and hence this area of recognizing emotions is of interest to both psychologists and engineers. Today different forms of human-centric and human-driven interactions with digital media have revolutionized entertainment, cyber worlds, learning, neuro-cognitive sciences and many more areas. The demand for computer applications to detect the current emotional state of the user is ever growing. Emotion recognition is popularly done using text, speech, facial expressions or gestures. But emotions are not always what they are displayed as. There is an explicit separation between the physiological arousal, the behavioral expression (affect), and the conscious expression of an emotion (feeling). Automatic emotion recognition using EEG signals is now the most preferred technique. This is because facial expressions and gestures being a behavioral expression can always be controlled by voluntary actions while EEG signals concentrate on the inner emotions of a person. Emotional markers are present in EEG signals and it is a relatively easy and cheap method to measure the brain activity. In the current century scientists are diligently trying to make computer interaction more natural. This can be applied in designing wearable gadgets to detect real time human emotions, it helps psychiatrists in treating psychological disorders like autism spectrum disorders (ASD), attention deficit hyperactivity disorder (ADHD) and anxiety disorders.

In our paper, we classify the EEG signals into four discrete emotional states namely, “happy”, “sad”, “angry” and “relaxed” using Russell’s Circumplex model. Spectral features like power spectral density and coherence and wavelet features including energy and entropy are extracted and fed to an SVM classifier. We have also tried reducing the number of electrodes such that there is no substantial decrease in the accuracy. The paper can be summarized as Section II deals with Literature Survey, Section III dealing with Dataset Description, Section IV with Feature Extraction and Classification, Section V explains the Methodology, Section VI contains Results and Discussion, Section VII deals with the Conclusion.

II. Literature Survey

Emotions are known to have a prominent role in analyzing the state of mind of a person and in the interaction and communication among people. In recent times recognition and classification of human emotions from Electroencephalogram (EEG) has led to the development of brain computer interfaces which empowers computers in understanding human emotions. According to Plutchik [1], there are eight basic states of emotion as acceptance, anger, anticipation, disgust, fear, joy, sadness and surprise. Rest of the emotional states can be modeled using the basic states such as sadness and surprise make disappointment. Garrett et al [2] in their paper compared the performance of linear and non linear classifiers for emotion classification. The authors observed that the nonlinear classifiers produce better classification results. They obtained and an average classification accuracy of 66% using Linear Discriminant Analysis (LDA), 69.4% using Neural Networks (NN) and 72% using Support Vector Machine (SVM). Soleymani et al [3] in their paper used 32 channel electrodes to classify emotions based on valence and arousal values in response to video stimuli. The authors’ calculated Power spectral density (PSD) from different bands using fast Fourier transform (FFT) and Welch algorithm and an SVM classifier with RBF kernel was employed to classify the samples using features from different modalities. They obtained a best classification accuracy of 68.5 % for valence and 76.4 %for arousal labels. Murugappan [4] in his paper used 2 sets of EEG channels (64 and 32) to classify emotions. The author extracted a set of linear (power, standard deviation, and variance) and non-linear (entropy) features using multi-resolution analysis of Wavelet Transform (WT). Audio-visual stimuli (film/video clips) was used for inducing the discrete emotions and classification was done using KNN classifier. The author obtained a maximum classification accuracy of 82.87 % on 62 channels and 78.57% on 24 channels, respectively. According to Chung et al. [5] for many pattern classification problems, a higher number of features used do not necessarily translate into higher recognition rate. The authors suggested Particle Swarm Optimization (PSO) as a good feature selection algorithm and support vector machines (SVMs) with the one-versus-rest method as a fitness function of PSO for the classification problem. They obtained a higher accuracy using PSO-SVM and this means that not all features are needed to achieve total classification accuracy. M. Sreeshakthy et al. [6] have used the EEG signals from the DEAP database. DWT is applied on the preprocessed signals and statistical and energy based features are extracted from the five sub bands. These features were used to train a neural network and the alpha and gamma bands were selected based on the mean squared error. Cuckoo search and PSO algorithms are used to optimize the multilayer perceptron network. They obtained an accuracy of 96.3% using PSO optimized neural network and the highest accuracy of 97.01% was obtained on using cuckoo search with neural networks, also this classification method was found to have the least mean squared error.

III. DATASET DESCRIPTION

A multimodal dataset called the DEAP dataset [7] for analyzing the human affective states is used. It consists of EEG signals collected from 32 healthy participants, aged between 19 and 32, with an equal male to female ratio. Music videos were used to elicit emotions and the signals were recorded using a 32 channel BioSemi acquisition system at a sampling rate of 512 Hz. 32 Ag/AgCl electrodes were arranged according to the 10-20 international system. Each participant was shown 40 music videos of one minute duration each and subjectively rated their degree of valence and arousal on a scale of 1-9. The acquired signals were found to be distorted by eye blinking and muscular movements and thus were preprocessed. The signals were down sampled to 128Hz and a band pass filter of 4-45 Hz was applied. We used this segmented data free from all the artifacts.

A. Russell's Circumplex model

We adopt Russell's Circumplex model [8] to represent the emotional space. It represents the emotion on a two dimensional plane where one dimension indicates "arousing and sleepy" and the other is "pleasant and unpleasant". Discrete emotional states such as 'happy', 'sad', 'angry', 'relaxed' can be inferred from the degree of valence and arousal as shown in the Fig. 1.

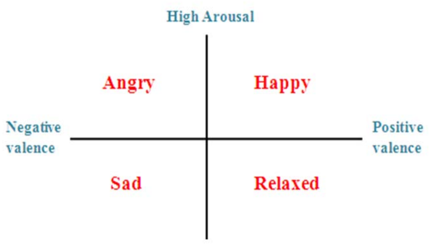

Fig. 1. Russell's Circumplex model of emotions

The subjective rating of the participants is mapped onto this model and the emotion can be inferred as:

Pleasant + Activation = Happy

Pleasant + Deactivation = Relaxed

Unpleasant + Activation = Angry

Unpleasant + Deactivation = Sad

IV. FEATURE EXTRACTION AND SELECTION TECHNIQUES

The Features extracted are Power Spectral Density, Magnitude Squared Coherence Estimate, Energy and Entropy. Particle Swarm optimization is used for feature selection.

A. Power Spectral Density(PSD)

The frequency response of a random periodic signal, called as Power Spectral Density, denotes the average distribution of power as a function of frequency. In order to characterize the variations in an EEG signal it is important to analyze the variations in the peak amplitude and frequencies. Hence EEG spectral analysis comes to the fore front. Time to compute PSD features is relatively lesser and it has also been proposed by many researchers that using PSD features enhances the performance of the classifier [9] [10].

$$S(\omega) = \sum_{n=0}^{L-1} x(n)w(n)e^{-2\pi\left(\frac{\omega}{\omega_s}\right)n} \quad (1)$$

Where $S(\omega)$ is the windowed DFT.

B. Magnitude Squared Coherence Estimate(MSCE)

Magnitude Squared Coherence, commonly known as coherence, measures the interdependence of two signals reflecting the distribution across frequency of activity common to both the signals. Coherence features are likely to be of a greater benefit when the recorded signals have a non-zero phase synchrony [11]. The functional interactions across the various regions of the brain can be well studied by using the coherence estimates.

$$C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)} \quad (2)$$

Where C_{xy} is MSCE of input signals x and y using Welch's averaged periodogram method, P_{xy} is the cross power spectral density, P_{xx} and P_{yy} are the power spectral densities of x and y respectively.

C. Wavelet Sub-Band Energy and Entropy

EEG signal contains several spectral components. The amplitude lies in the range of 10 to 100 microvolt and the important frequencies are in the range of 0.1 to 30 Hz. The standard EEG subbands are delta (0.1 to 3.5 Hz), theta (4 to 7.5 Hz), alpha (8 to 13 Hz), beta (14 to 30 Hz) and gamma (greater than 30Hz) bands. These bands contain information pertaining to brain activity which can be extracted using Discrete Wavelet Transform (DWT). DWT presents a signal as a combination of scaling functions and their wavelets at different locations (positions) and scales (duration).DWT decomposes a given signal into approximate and detailed coefficients. In order to obtain five sub bands, this method is repeated. The different mother wavelets available are: "haar", "biorthogonal", "daubechies", "symlets" and many more. The choice of wavelets must be such that they have a near optimal time-frequency localization property [12]. DWT decomposes one dimensional time signal $x(t)$ as follows:

$$DWT(x(t); a, n) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{2^a}} \Psi\left(\frac{t-2^a n}{2^a}\right) dt \tag{3}$$

where $2^a n$ and 2^a are the time localization and scale respectively, while $\Psi(t)$ denotes the mother wavelet function.

Following this the sub-band energy, relative energy and entropy features can be obtained using (4), (5) and (6):

$$E(a) = \sum_n C_a^2(n) \tag{4}$$

$$p(a) = \frac{E(a)}{\sum_{k=1}^{K} E(k)} \tag{5}$$

$$H(a) = -p(a) \log p(a) \tag{6}$$

where C_a denotes the wavelet coefficients at a^{th} decomposition level and K denotes the number of discrete wavelet decompositions.

D. Particle Swarm Optimization(PSO)

PSO is a population based self-adaptive search optimization technique introduced by Kennedy and Eberhart in 1995. It simulates the flocking of birds or schooling of fish. The algorithm begins by randomly initializing a swarm of particles in the problem domain with a certain velocity. Each particle's position is expressed a candidate of optimal solution in optimization problem. The particles search for a global optimum solution in the multidimensional problem space. The fitness value associated with every particle is optimized using the fitness function. In every iteration two positions are obtained, one being the best position of the individual particles and is called the particle best (pbest), the other is the best position of the entire swarm and is called the global best position (gbest). The velocity and the position of the particles are iteratively updated using (7) and (8):

$$v_i(t+1) = v_i(t+1)w + c_1 r_1 (x_{pbest_i}(t) - x_i(t)) + c_2 r_2 (x_{gbest}(t) - x_i(t)) \tag{7}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{8}$$

where x is the position vector, v is the velocity vector, $pbest$ is the local best position of the particle, $gbest$ is the global best position of the swarm, c_1 and c_2 are acceleration constants and r_1 and r_2 are two random values uniformly distributed between [0,1]. The stopping condition is when a maximum velocity is reached or if a maximum number of iterations are completed.

V. SVM Classifier

SVM is a discriminative classifier formally defined by a separating hyperplane which can be effectively used to classify a high dimensional feature set. The hyper plane should be such that it maximizes the interclass separation. It is a supervised learning model where predefined class values are used for training. The EEG data can also be converted to a higher dimensional mapping. The mapping function can be found using Kernel functions. The most popular kernel function is RBF kernel. Solving the constrained optimization problem as in (9) produces an optimal hyperplane.

$$\min_{w \in \mathbb{R}^d, \xi_i \in \mathbb{R}^+} ||w||^2 + C \sum_i^N \xi_i \tag{9}$$

subject to $y_i(w^T x_i + b) \geq 1 - \xi_i$ for $i = 1 \ldots N$

where C is the regularization constant ξ_i is the slack variable. This results in the dual problems

$$\max_{\alpha} \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \tag{10}$$

subject to $0 \leq \alpha_i \leq C, i = 1, \ldots, n,$

$$\sum_{i=1}^{n} \alpha_i y_i = 0$$

where α_i is the Lagrange multiplier. The training samples for which Lagrangian multiplier is not zero are called support vectors.

VI. Methodology

The preprocessed signals from the DEAP dataset are used for classifying human emotions in this paper. MATLAB (Matrix Laboratory) is the software that we have used to perform feature extraction and classification methods. MATLAB is a proprietary programming language developed by MathWorks. As the signals are already down sampled and filtered we perform feature extraction. The one sided power spectral density is computed for all the 32 channels using N point FFT with a sampling frequency of 128 Hz. MSCE is extracted using the Welch's averaged periodogram method with a hamming window using 128 Hz sampling frequency. A five level DWT is performed to obtain the wavelet coefficients using "db8" as the mother wavelet. Wavelet energy and entropy are extracted from these five subbands. Thus our features consist of PSD, MSCE, Energy and Entropy. Owing to high dimensionality of this feature it is important to find the features which are of relevance to the classifier. Thus we perform feature selection. PSO algorithm is chosen for optimization [13]. The classifier is trained based on these crucial features. SVM classifier is used for classification. RBF kernel is selected because of its high learning capacity. The feature extraction, selection and classification procedure was further repeated for different channel combinations. The results of the classifier with and without optimization are compared.

VII. Results and Discussion

Table I summarizes the classification accuracy using an SVM classifier with RBF kernel and a 10 fold cross validation for different electrode combinations. It is found that the classification accuracies vary upon choosing different combinations of electrodes. A maximum classification accuracy of 74.062 % was obtained using the 16 electrode combination. It is also observed that the highest valence and arousal accuracies of 80% and 85% respectively are obtained using the five electrode combination (P7, P3, PZ, T7, T8).

Table II summarizes the classification accuracies for the four discrete classes namely happy, angry, sad and relaxed.

The highest accuracy is obtained using the sixteen electrode combination but sufficiently high classification accuracy is obtained using the five electrode combination (P7, P3, PZ, T7, T8) thereby reducing the number of electrodes required.

TABLE I. ACCURACY USING DIFFERENT ELECTRODE COMBINATIONS

Electrode Combination	**Accuracy %**		
	Valence	***Arousal***	***Overall***
FP1, FP2	46.153	65.625	46.875
F3, F4, FP1, FP2, FPZ	75.937	72.187	57.812
P7, P3, PZ	71.25	75.937	55.312
P7, P3, PZ, T7, T8	80	85	70.625
P7, P3, PZ, PO3,O1,CP2, C4	76.875	70.312	57.187
F3, F4, FP1, FP2, F7, F8, FTC1, FTC2, C3, C4, O1, O2, T7, T8, P3, P4	84.375	83.437	74.062

TABLE II. CLASSIFICATION ACCURACY

Electrode Combination	**Accuracy %**			
	Class 1 Happy	***Class 2 Sad***	***Class 3 Angry***	***Class 4 Relaxed***
FP1, FP2	46.153	37.878	45.833	58.730
F3, F4, FP1, FP2, FPZ	57.812	56.944	54.717	61.971
P7, P3, PZ	60.483	50	47.169	57.746
P7, P3, PZ, T7, T8	73.387	66.67	64.15	74.647
P7, P3, PZ, PO3,O1,CP2, C4	60.483	59.722	49.056	54.929
F3, F4, FP1, FP2, F7, F8, FTC1, FTC2, C3, C4, O1, O2, T7, T8, P3, P4	74.193	69.444	77.358	76.056

VIII. CONCLUSION

The preprocessed EEG signals from the DEAP dataset are successfully classifies into four discrete emotional states based on the Russell's circumplex model. The core element of this paper is PSO which optimizes the classifier thus providing sufficiently higher classification accuracy. Also adding MSCE led to a better feature set as it estimates the coherence between various frequency domain signals. Moreover after experimenting with different electrode combinations we observed that a good classification accuracy of 70.625% was obtained using a reduced set of 5 electrodes P7, P3, PZ, T7 and T8.

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