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An Efficient Mixture Model Approach in Brain-Machine Interface Systems for Extracting the Psychological Status of Mentally Impaired Persons Using EEG Signals

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ABSTRACT We propose an efficient mixture classification technique, which uses electroencephalography (EEG) signals for establishing a communication channel for the physically challenged or immobilized people, by the usage of the brain signals. In order to identify the emotion expressions by an immobilized person, we introduce a novel approach for emotion recognition based on the generalized mixture distribution model. The main benefit of utilizing this model is that it is an asymmetric distribution, which helps to extract the EEG signals, which are either in symmetric or asymmetric form. The skew Gaussian distribution helps to identify the small duration EEG signal sample and helps toward better recognition of emotions in both clean and noisy EEG signals. The proposed method is particularly well suited for the high variability of the EEG signal allowing the emotions to be identified appropriately. The features of the brain signals are extracted by using cepstral coefficients. The extracted features are classified into different emotions using mixture classification techniques. In order to validate the model, six mentally impaired subjects are considered in the age group of 60–68, and an 8-channel EEG signal is utilized to collect the EEG signals under audio-visual stimuli. The basic emotions considered in this study include happy, sad, neutral, and boredom and an average emotion recognition accuracy of 89% is achieved.

INDEX TERMS Brain–computer interaction (BCI), emotion recognition, affective computing, electroencephalography (EEG), Gaussian mixture, cepstral analysis.

I. INTRODUCTION

Emotion recognition plays a significant role in understanding the psychological behavior of the humans. A lot of research was done in this area to extract the emotions using the audio signals [1], [2] and categorize these signals into different emotions, thereby paving the way to identify the individual's feelings and behaviour.

Emotions arise as a response to specific conditions or problems, and reflect the current stage of progress toward a target [3]. For example, happiness indicates satisfaction of reaching a goal, anger represents reaction to a failed goal, sadness reflects lost hope of reaching a goal, while boredom indicates the lack of a goal [4]. Although, emotions cannot be quantitatively measured, they still can be evaluated by identifying the facial expressions, and some psychophysiological values like skin conductance and heart beat rate changes abruptly while a person enters into a particular emotional state. The emotions induce physiological changes in the brain that can be measured and assessed from the central nervous system via acquisition and analysis of electroencephalography (EEG) signals. Affect is a strong and sufficiently short emotional reaction. This concept describes emotion, mood and attitude. Emotion or emotional response

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is a direct reaction of a subject to an event (stimulus) important to the subject [5]. Mood is formed by several emotional states created by different events. The attitude is shaped by the change of emotional state and mood associated with a particular object. Human emotional state is defined as the limited number of individual states associated to one of the main emotions, such as anger, disgust, fear, happiness, surprise, and sadness, or a combination thereof [6]. Emotional states can be caused by visual and acoustic stimuli, thoughts, life events or biological rhythms of nature.

Imaging an emotional state on a certain scale is based on two well-established patterns:

1. Displaying the main emotional states on the nominal scale of measurements. This method is based on the principle that there are a certain number of emotional states (e.g., angry, happy, sad, frightened, disgusted, surprised) in which a person may be present.
2. A two- or three-dimensional model that allows any emotional state to be represented by a three-dimensional interval scale [7]. Relevant dimensions express levels of attractiveness, excitement and dominance. For example, anger and frustration have a negative appeal and a high level of excitement, but the dominance of anger is strong and frightening is weak.

The Emotional State Imaging Model [7] is based on the approach to emotion as a degree of excitement and attractiveness. In this way, any emotional state can be represented in two-dimensional space in terms of excitement and attractiveness, where excitement is treated as the amount of energy mobilized by the subject in response to the stimulus, and attractiveness means the excitement of the subject to the subject. We can treat the impact recognition as the transformation of physiological parameters into classes that describe the human emotional state or the size of emotional dimensions defined in the interval scale.

Various methods are used to identify and evaluate the impact, using sensory systems, data discovery, knowledge imaging methods, and other principles of artificial intelligence that allow to read, analyse and interpret human physiological parameters. Most of methods used to transform physiological parameters into impact-related emotional states are attributed to the field of machine training and pattern recognition. Effect recognition is usually based on human biological feedback, which allows the system to assess the human physiological state and to recognize human response to environmental effects. Feedback can optionally capture one or more indicators that reflect the processes in the body. According to the available human condition monitoring methods, human physiological signals (skin galvanic reaction (GSR), electrocardiogram (ECG), EEG, electromyogram (EMG), temperature, heart rate, pulse rate, etc.) can be used to identify the emotional states. For example, the GSR sensitively reacts to emotional excitement and thus conveys a human reaction to environmental change in a sufficiently informative way. Cardiac activity reflects many essential

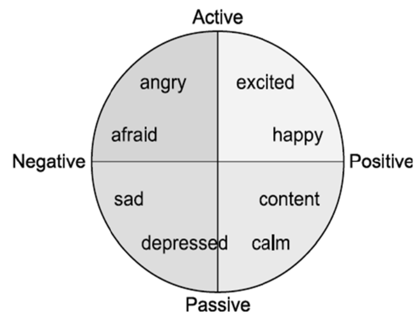


FIGURE 1. Different emotional states of mind.

psychological and physiological states, as it is strongly linked to the sympathetic and parasympathetic nervous system.

Emotion recognition has been applied in Brain Computer Interfaces (BCI), where individual emotion features are extracted using either the temporal or spectral features of EEG signal [8], which refers to the measures of brain electric activity. Activation refers to the intensity of the emotion and evaluation is a measure of emotion [9]. The measurement of the brain electrical activity can be obtained by the placing the EEG electrode on the brain scalp. Most of the techniques used for emotion recognition are based on the extraction of brainwave signals, where the signals are generated by subject reacting to artificial or generated stimuli. Every extracted emotion can be broadly classified using two groups, categorical (discrete) descriptor and dimensional (continuous) descriptor. Emotions that are identified using the categorical descriptors include, the basic emotions such as happy, sad, neutral, boredom and angry (Figure 1).

The main disadvantages of the signal acquired from categorical descriptor include: the need of large training data for analysis, it is limited to the identification of a single emotion from the signal, and the emotion extracted from the signal usually comprises a mixture of the several emotions.

Related works on this topic used physiological signals such as ECG, skin conductivity, EMG and heart rate variability (HRV) for emotion recognition [10], [11]. EEG is a practical modality with which the affective states can be evaluated, especially the emotional primitives of valence and arousal [12]. The main advantage of EEG signals is that the electrical activity of the human brain can be captured very quickly. However, the EEG method can only measure the total activity expressions of many neurons rather than the activity of individual neurons. Therefore, the analysis of EEG signals due to their complexity is a very relevant issue.

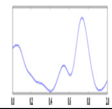
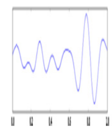
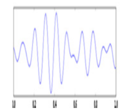
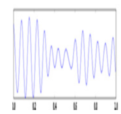
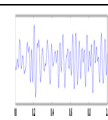
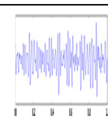
Various features of EEG such as the alpha and beta bands are useful for identifying positive self-evaluation emotions (awe, gratitude, hope, inspiration, and pride), the theta and gamma bands – for enjoyment emotions (amusement, interest, and joy) [13], while steady state visually evoked potential (SSVEP) is used to register positive motivation [14]. In order to effectively apply machine learning techniques, it is necessary to distinguish the characteristic features of human physiological signals (bio-markers) that reflect the main physiological processes. For example, elevated body temperature is a biological sign of infection. In spite of huge progress recently made in the identification of biomarkers, there are still no reliable features that could be used to recognize emotions and their disorders.

Typically, with EEG-based systems, time-frequency domain features (e.g., [15]) and Wavelet Transform [16] have been widely used, while more rarely used are motif series and graph-based features [12]. EEG signals are very sensitive to noise and external irritants such as eye blinking and muscular activity. To overcome such issues, artefact removal algorithms can be used [17]. Since EEG measurements may have a very large number of features that causes the curse of dimensionality problem, the dimensionality reduction approaches such as Principal Components Analysis (PCA), and optimization methods such as those based on genetic algorithms have been proposed [18]. Among methods used for emotion recognition of EEG signals are common spatial pattern (CSP), linear discriminant analysis (LDA) [19], artificial neural networks (ANNs) [20], convolutional neural networks (CNN) [21]. A more complex approach includes Empirical Mode Decomposition (EMD), whence EEG channels are decomposed into intrinsic mode functions (IMFs) and features extracted from the IMFs are forwarded for classification [22], [23].

Little work has been done on using EEG data to study the emotional state of immobilized, mentally impaired, incapacitated or locked-in persons [24]–[26]. Emotion recognition using EEG for people with severe disabilities such as the ones with an advanced stage of Parkinson's or Huntington's disease, patients with severe brain injury, patients in coma, or in persistent vegetative state, or locked-in subjects presents an considerable challenge. Evaluating emotion recognition can allow to better evaluate other cognitive functions (e.g., such as working memory) in patients, which may be essential in establishing a correct medical diagnosis. For example, Pan *et al.* [8] used P300 and emotion recognition to improve the ability to capture signs of consciousness in eight severely brain-damaged patients. For an in-depth review on the topic, the readers can consult a survey presented in [27].

Many models have been proposed in the literature for computational modelling and analysis of EEG signals such as based on Hidden Markov Models (HMM) [28], Bayesian Network (BN) [29], Gaussian Mixture Models (GMM) [30], PCA and Vector Quantization (VQ) [31]. However these methodologies have their own disadvantages. VQ and PCA are dimensionality reduction techniques, which are aimed towards the reduction of feature vectors, however, the emotions play a vital role and compression of these emotional signals may result into falsifying the emotions. Therefore to model the emotions more accurately, the generative models are mostly preferred, among these model based on GMM is mostly utilized for emotion EEG signal recognition. The GMM has its own disadvantage of considering infinite range and symmetric nature. However in the reality the range of EEG signal signals extracted from the EEG signal samples will be finite in range and, therefore, it is required to truncate the EEG signal samples so as to convert the data into finite size.

TABLE 1. Units for EEG Properties- different rhythms of brain.

Rhythm	Frequency	Range Location	Reason	Frequency bands
Delta (δ)	(0-4) Hz	Frontal lobe	Deep sleep	
Theta (θ)	(4-7) Hz	Midline, temporal	Drowsiness and meditation	
Alpha (∞)	(8-13) Hz	Frontal, Occipital	Relaxing, closed eyes,	
Mu (μ)	(8-12) Hz	Central	Contra lateral Motor acts	
Beta (β)	(13-30) Hz	Frontal, central	Concentration and thinking	
Gamma (γ)	(30-100+) Hz		Cognitive functions	

In this article, we focus on emotion recognition in brain diseased persons. Our novelty is the use of the estimates of the model parameters of the Generalized Mixture Distribution Model are updated using the Expectation Maximization (EM) algorithm, proposed by McLachlan and Krishnan [32].

The research article is organized as follows. Section II presents an outline of the methodology. In Section III, the Generalized Mixture Distribution Model is presented. Section IV presents the experimental results, and Section V concludes the paper.

II. OUTLINE OF METHODOLOGY

The brain signals from the subjects are extracted using EEG acquisition device, and the signals are preprocessed to minimize noise, and the amplitude signals are extracted which are normalized into different ranges basing on the rhythm, for the dimensionality reduction, data feature extraction and classification for emotion recognition. The brain signals in the EEG data can be analyzed in terms of 5 different rhythms: delta (δ), theta (θ), alpha (α), mu (μ), beta (β), and gamma (γ). Each rhythm has different frequency ranges and each reflects a specific element of brain activity. The range and effect of each rhythm is shown in Table 1.

For effective recognition of the emotions, feature vectors based on Mel-frequency Cepstrum Coefficients (MFCC), MFCC-LPC (Linear Prediction Coefficients) and

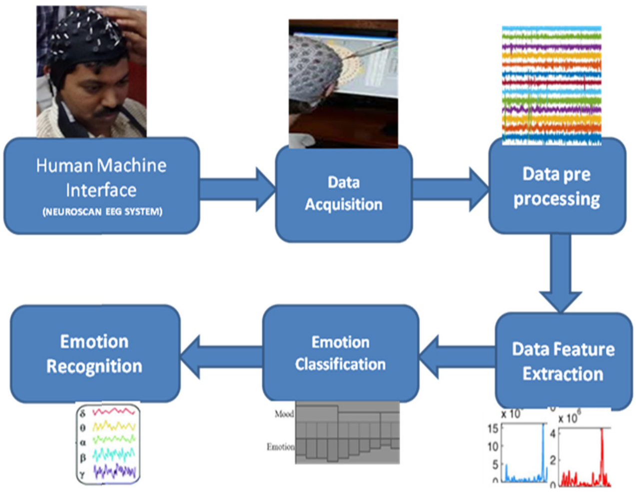


FIGURE 2. Block diagram for emotion recognition using EEG signals.

MFCC-LPC-SDC (Shifted Delta Coefficients) are utilized.

The developed model is evaluated using the classification performance measures of Precision and Recall. The methodology is summarized in Figure 2.

III. GENERALIZED MIXTURE MODEL DISTRIBUTION

To have accurate feature extraction from the EEG signals extracted from the brain, maximum posterior estimation models are to be considered [30]. Hence in this paper, a Generalized Mixture Distribution Model (GMDM) is utilized with the combination of truncation and Skew GMM for classifying the brain signals into different emotions. GMDM represents the truncation can be applied towards the right side, or left side, or to both ends of a distribution, and for asymmetric distributions.

A. PROBABILITY DENSITY FUNCTION OF GMM

The probability density function (PDF) of GMM is given by:

$$f(z) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-1}{2}\left(\frac{z-\mu}{\sigma}\right)^2}; \quad -\infty < z < \infty \tag{1}$$

here, $-\infty < z < \infty, 0 < \sigma$

In Eq. (1), the Z value ranges are above some upper truncation points Z_M as well as below some lower truncation points Z_L. With that reason the distribution is truncated either left of right or both sides, and the PDF is defined as:

$$g(z) = \frac{z(z)}{\int_{Z_M}^{Z_L} f(z)dz}, \quad -\infty \le z < \infty \tag{2}$$

$$A = \int_{-\infty}^{Z_L} \frac{e^{\frac{-1}{2}\left(\frac{z-\mu}{\sigma}\right)^2}}{\sqrt{2\pi}\sigma} dz \tag{3}$$

$$B = \int_{-\infty}^{Z_M} \frac{e^{\frac{-1}{2}\left(\frac{z-\mu}{\sigma}\right)^2}}{\sqrt{2\pi}\sigma} dz \tag{4}$$

$$g(z) = \frac{\frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}\left(\frac{Z-\mu}{\sigma}\right)^2}}{\int_{-\infty}^{Z_M} \frac{e^{\frac{-1}{2}\left(\frac{z-\mu}{\sigma}\right)^2}}{\sqrt{2\pi}\sigma} dz - \int_{-\infty}^{Z_L} \frac{e^{\frac{-1}{2}\left(\frac{z-\mu}{\sigma}\right)^2}}{\sqrt{2\pi}\sigma} dz} \tag{5}$$

here Z_L is lower truncation points, Z_M is upper truncation points.

B. EXPECTATION-MAXIMIZATION ALGORITHM FOR ESTIMATION OF MODEL PARAMETERS

Z1, Z2,..., Zn are sample likelihood function observations

$$L(\theta) = \pi_{s=1}^{N} \left[\sum_{i=1}^{k} \alpha_i \frac{1}{\sqrt{2\pi}\sigma(B-A)} e^{\frac{-1}{2}\left(\frac{z-\mu}{\sigma}\right)^2} \right] \tag{6}$$

$$= \sum_{s=1}^{N} \log \left(\sum_{i=1}^{k} \alpha_i g_i(z_s, \theta) \right) \tag{7}$$

$$\theta^l = \sum_{s=1}^{N} \log h(Z_S; \theta) = \log L(\theta)$$

$$= \sum_{s=1}^{N} \log\left(\sum_{i=1}^{k} \alpha_i g_i(Z_s; \theta)\right) \tag{8}$$

$$Z_s = = \pi_{s-1}^{N} \left[\sum_{i=1}^{k} \alpha_i \frac{\frac{-1}{2}\left(\frac{Z-M_i}{\sigma_i}\right)^2}{\sqrt{2\pi}\sigma\,(B-A)} \right] \tag{9}$$

For segment K:

$$t_k\left(Z_s; \theta^l\right) = \frac{\alpha_k^l g_i\left(Z_s, \theta^l\right)}{h\left(Z_s; \theta^l\right)} = \frac{\alpha_k^l g_k\left(Z_s, \theta^l\right)}{\sum_{i=1}^{k} \alpha_k^l g_i\left(Z_s, \theta^l\right)} \tag{10}$$

Since here the distribution is truncated.
where

$$f_i(z, \theta) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-1}{2}\left(\frac{z-\mu}{\sigma}\right)^2} \tag{11}$$

Therefore,

$$Q\left(\theta, \theta^{(l)}\right) = \sum_{i=1}^{k} \sum_{s=1}^{N} E^{(l)} \times \left\{ t_i\left(z, \theta^l\right) (\log g_i(z; \theta) + log\alpha_i) \right\} \tag{12}$$

Substitute the value of $\log g_i(z; \theta)$ in equation 12, we have

$$\sum_{t=1}^{s} \sum_{s=1}^{N} E^{(l)} \times \left\{ t_i\left(z, \theta^l\right) (\log f(z; \theta) - \log(B-A)) + \log\alpha_i \right\} \tag{13}$$

Maximum likelihood estimation for segment weight α_k

$$L = E^{(l)} \left[\log L(\theta^l) + \lambda(1 - \sum_{i=1}^{k} \alpha_i^l \right] \tag{14}$$

$$\sum_{s=1}^{N} E^l(t_k\left(z_s, \theta^l\right)) = \lambda\alpha_k \tag{15}$$

$$E^l\left\{ t_k\left(Z_s, \theta^l\right) \right\} = \frac{\alpha_k^l \int_{Z_L}^{Z_M} g_k\left(Z_s, \theta^l\right) dz}{\int_{Z_L}^{Z_M} h\left(Z_S, \theta^l\right) dz} \tag{16}$$

$$\alpha_k^{l+1} = \frac{1}{N} \sum_{s=1}^{N} E^l\left\{ t_k\left(Z_s, \theta^l\right) \right\} \tag{17}$$

$$\alpha_k^{l+1} = \frac{1}{N} \sum_{s=1}^{N} \frac{\alpha_k^l}{H\left(Z_M, \theta^l\right) - H\left(Z_L, \theta^l\right)} \tag{18}$$

$$\frac{\partial}{\partial \mu_k}\left(\log g_k(z;\theta)\right) = \frac{\partial}{\partial \mu_k}\left(-\log\sqrt{2\pi} - \log\sigma_k - \frac{1}{2}\left(\frac{z-\mu_k}{\sigma_k}\right)^2 - \log\int_{z_l}^{z_m}\frac{1}{\sqrt{2\pi}\sigma}e^{\frac{-1}{2}\left(\frac{z-\mu_k}{\sigma_k}\right)^2}dz\right) \tag{19}$$

This implies that $\frac{\partial}{\partial \mu_k}(\log g_k(z;\theta)) = \frac{1}{\sigma_k^2}(z-\mu_k) - \frac{\int_{Z_l}^{Zm}\frac{\partial}{\partial \mu_k}f_k(z,\theta)dz}{\int_{z_l}^{Zm}f_k(z,\theta)dz}$

$$zf_k\left(z,\theta^l\right) = \mu_k f_k\left(z,\theta^l\right) + \sigma^2\frac{\partial}{\partial\mu_k}f_k\left(z,\theta^l\right) \tag{20}$$

Therefore:

$$-\left[\frac{\int_{z_l}^{z_m}\frac{z-\mu_k}{\sigma_k^2}f_k(z,\theta)dz}{\int_{z_l}^{z_m}f_k(z,\theta)dz}\right] = -\left[\frac{\mu_k^l}{\sigma_k^2} - \frac{\sigma_k^2}{\sigma_k^2}\left(\frac{f(z_m)-f(z_l)}{B-A}\right) - \frac{\mu_k^l}{\sigma_k^2}\right] = \left(\frac{f(z_m)-f(z_l)}{B-A}\right) \tag{21}$$

From eq.(20) we get,

$$\sum_{s=1}^{N} E^{(l)}\left\{t_i\left(z_s,\theta^l\right)\frac{\partial}{\partial\sigma_k^2}(\log f_k(z;\theta))\right\}$$
$$\sum_{s=1}^{N} E^{(l)}\left\{t_k\left(z_s,\theta^l\right)\left(\frac{1}{2\sigma_k^2}\left(\frac{z-\mu}{\sigma_k^2}\right)-1\right) - \frac{\int_{z_l}^{z_m}\frac{\partial}{\partial\sigma_k^2}f_k(z;\theta_k)dz}{\int_{z_l}^{z_m}f_k(z;\theta_k)dz}\right\} \tag{22}$$

$$\frac{\int_{Z_L}^{Z_M}\frac{\partial}{\partial\sigma_k^2}f_k(z,\theta_k)dz}{\int_{Z_L}^{Z_M}f_k(z,\theta_k)dz} = \frac{-1}{2\sigma_k^2}\left(\frac{1}{B-A} - 1 - (1+\mu_k)\left(\frac{f_k\left(Z_L,\theta^l\right)-f_k(Z_M,\theta^l)}{B-A}\right) + \frac{Z_M f_k\left(Z_M,\theta^l\right) - Z_L f_k\left(Z_L,\theta^l\right)}{B-A}\right) \tag{23}$$

We substitute equation

$$\frac{\partial Q(\theta,\theta^l)}{\partial\sigma_k^2} = \sum_{s=1}^{N} E^l\left(t_x\left(z,\theta^l\right)\right)\left[\frac{1}{2\sigma_k^2}\left(\frac{Z-\mu}{\sigma_k^2}\right)^2 - \frac{1}{2\sigma_k^2} + \frac{1}{2\sigma_k^2} - \frac{1}{2\sigma_k^2(B-A)} + \frac{1+\mu_k}{2\sigma_k^2}\left(\frac{f_k\left(Z_L,\theta^l\right)-f_k\left(Z_M,\theta^l\right)}{B-A}\right) - \frac{1}{2\sigma_k^2}\frac{f_k\left(Z_L,\theta^l\right)-f_k\left(Z_M,\theta^l\right)}{B-A}\right] \tag{24}$$

$$\sigma_k^{2(l+1)} = \frac{\sum_{s-1}^{N}E^l\left(t_k\left(Z,\theta^l\right)\right)\left(Z_s-\mu_k^{l+1}\right)^2}{D\sum_{s-1}^{N}E^l\left(t_x\left(Z,\theta^l\right)\right)} \tag{25}$$

Finally, we have

$$\sigma_k^{2(l+1)} = \frac{1}{D}\left\{\alpha_k^l\mu_k^{2l} + \left[\frac{f_k\left(Z_M,\theta^l\right)-f_k\left(Z_L,\theta^l\right)}{f\left(Z_M,\theta^l\right)-f\left(Z_L,\theta^l\right)}\right] - \left(\alpha_k^l\sigma_k^{2l} - \alpha_k^l\mu_k^l\sigma_k^{2l}\right) - \alpha_k^l\sigma_k^{2l}\left(\frac{Z_M f_k\left(Z_M,\theta^l\right)-Z_L f_k\left(Z_L,\theta^l\right)}{f_k\left(Z_M,\theta^l\right)-f_k\left(Z_L,\theta^l\right)}\right) - 2\mu_k\left[\frac{\alpha_k^l\mu_k^{(l+1)}}{f\left(Z_M,\theta^l\right)-f\left(Z_L,\theta^l\right)} - \frac{\alpha_k^l\sigma_k^{2l}}{f\left(Z_M,\theta^l\right)-f\left(Z_L,\theta^l\right)}\right] - \mu_k^{2(l+1)}\right\} \tag{26}$$

For asymmetric distribution, which helps to extract the EEG signals, which are either in symmetric or asymmetric form, and to identify the small duration of EEG sample region follow a skew normal distribution. The PDF of EEG signal is defined as follows, here λ is the skewness parameter and k is the number of regions, $\alpha_i > 0$ are weights such that $\sum_{i=1}^{k}\alpha_i = 1$ and

$$g\left(y_i|\mu_i,\sigma^2,\lambda\right) = \frac{2}{\pi}.\frac{1}{\sqrt{2\pi}}.e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2}.\Phi\left(\lambda\left(\frac{y-\mu}{\sigma}\right)\right) \tag{27}$$

here,

$$\Phi\left(\lambda\left(\frac{y-\mu}{\sigma}\right)\right) = \int_{-\infty}^{\lambda\left(\frac{y-\mu}{\sigma}\right)}\frac{1}{\sqrt{2\pi}}.e^{-\frac{t^2}{2}}dt \tag{28}$$

C. ESTIMATION OF MODEL PARAMETERS

Let us have

$$L(\theta) = \sum_{s=1}^{N}\left[\sum_{i=1}^{k}\left[\prod_{i=1}^{N}\left(\sum_{i=1}^{k}\alpha_i \times\left[\frac{2}{\sigma}.\frac{1}{\sqrt{2\pi}}.e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2}\Phi\left(\lambda\left(\frac{y-\mu}{\sigma}\right)\right)\right]\right)\right]\right] \tag{29}$$

here $\Phi\left(\lambda\left(\frac{y-\mu}{\sigma}\right)\right) = \int_{-\infty}^{\lambda\left(\frac{y-\mu}{\sigma}\right)}\frac{1}{\sqrt{2\pi}}.e^{-\frac{t^2}{2}}dt$ and based on $L(\theta) = \prod_{s=1}^{N}\left(\sum_{i=1}^{k}\alpha_i g_i(Z_s,\theta)\right)$

From the E-Step

$$Q\left(\theta;\theta^{(0)}\right) = \sum_{s=1}^{N}\log h(y_s,\theta) = \log L(\theta) = \sum_{s=1}^{N}\log\left(\sum_{i=1}^{k}\alpha_i g_i(y_s;\theta)\right) \tag{30}$$

here log L(θ) with respect to the initial parameter vector $\theta^{(0)}$ is calculated, initial parameters $\theta^{(l)}$, one can compute the density of any observation y_s, as

$$h(y_s,\theta) = \prod_{i=1}^{N}\left(\sum_{i=1}^{k}\alpha_i\left[\frac{2}{\sigma}.\frac{1}{\sqrt{2\pi}}.e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2}\times\Phi\left(\lambda\left(\frac{y-\mu}{\sigma}\right)\right)\right]\right) \tag{31}$$

here

$$\Phi\left(\lambda\left(\frac{y-\mu}{\sigma}\right)\right)=\int_{-\infty}^{\lambda\left(\frac{y-\mu}{\sigma}\right)}\frac{1}{\sqrt{2\pi}}.e^{-\frac{t^2}{2}}dt \tag{32}$$

then segment 'k' is:

$$t_k\left(y_s,\theta^{(l)}\right)=\frac{\alpha_k^{(l)}g_i\left(y_s,\theta^{(l)}\right)}{h\left(y_s,\theta^{(l)}\right)}=\frac{\alpha_k^{(l)}g_k\left(y_s,\theta^{(l)}\right)}{\sum_{i=1}^{k}\alpha_k^{(l)}g_i\left(y_s,\theta^{(l)}\right)} \tag{33}$$

here $h\left(y,\theta^{(l)}\right)=\sum_{i=1}^{k}\alpha_i^{(l)}g\left(y_s,\theta^{(l)}\right)$ and we get

$$Q\left(\theta;\theta^{(l)}\right)=\sum_{i=1}^{k}\sum_{s=1}^{N}\left\{t_i\left(y_i;\theta^{(l)}\right)(\log g_i(y;\theta)+\log\alpha_i)\right\} \tag{34}$$

But

$$g_i(y,\theta)=\frac{2}{\sigma}.\frac{1}{\sqrt{2\pi}}.e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2}\Phi\left(\lambda\left(\frac{y-\mu}{\sigma}\right)\right) \tag{35}$$

Finally

$$Q\left(\theta;\theta^{(l)}\right)=\sum_{i=1}^{k}\sum_{s=1}^{N}\left\{t_i\left(y_i;\theta^{(l)}\right)\times\left(\log\left(\frac{2}{\sigma}.\frac{1}{\sqrt{2\pi}}.e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2}\Phi\left(\lambda\left(\frac{y-\mu}{\sigma}\right)\right)\right)+\log\alpha_i\right)\right\}\text{(the expectation value)} \tag{36}$$

D. CALCULATE MAXIMUM LIKELIHOOD VALUE

Basic condition $\sum_{i=1}^{k}\alpha_i=1$, Lagrange type function L and weights α_k derivative of L with respect to a particular α_k as follows

$$L=\left[\log L\left(\theta^{(l)}\right)+\beta\left(1-\sum_{i=1}^{k}\alpha_i^{(l)}\right)\right] \tag{37}$$

$$\frac{\partial L}{\partial\alpha_k}=0=\frac{\partial}{\partial\alpha_k}\left[\log L\left(\theta^{(l)}\right)+\beta\left(1-\sum_{i=1}^{k}\alpha_i^{(l)}\right)\right]=0 \tag{38}$$

$$\sum_{i=1}^{N}\left[\frac{g_k\left(y_s,\theta^{(l)}\right)}{h\left(y_s;\theta^{(l)}\right)}\right]-\beta=0 \tag{39}$$

By multiplying and dividing the above equation is with α_k, we get

$$\frac{1}{\alpha_k}\sum_{s=1}^{N}\left[t_k\left(y_s,\theta^{(l)}\right)\right]-\beta=0 \tag{40}$$

Here

$$t_k\left(y_s,\theta^{(l)}\right)=\frac{\alpha_k g_k\left(y_s,\theta^{(l)}\right)}{h\left(y_s,\theta^{(l)}\right)} \tag{41}$$

Then, α_k^{l+1}, is the next level after α_k^{l}, this implies $\sum_{s=1}^{N}\left[t_k\left(y_s,\theta^{(l)}\right)\right]=\beta.\alpha_k$

Finally

$$\alpha_k^{(l+1)}=\frac{1}{N}\sum_{s=1}^{N}\frac{\alpha_k^{(l)}g_i\left(y_s,\theta^{(l)}\right)}{h\left(y_s,\theta^{(l)}\right)} \tag{42}$$

E. UPDATING THE μ VALUE

For updating the parameter μ_k, k= $1,2\ldots$, K, we consider the derivative of $Q\left(\theta;\theta^{(l)}\right)$ with respect to μ_k equated to ZERO, we have $Q\left(\theta;\theta^{(l)}\right)=E\left[\frac{\partial\log L(\theta;\theta^{(l)})}{\partial\mu}\right]$ therefore $\frac{\partial Q(\theta;\theta^{(l)})}{\partial\mu_k}=0$, finally, (43), as shown at the top of the next page.

Since μ_i appears only in one region i= $1,2,3,\ldots$, k (regions) we have (44), as shown at the top of the next page.

Hence, the updated equation for μ is

$$\mu^{(l+1)}=y+\sigma^{2(l)}+\frac{1}{\int_{-\infty}^{\alpha^{(l)}\left(\frac{y-\mu^{(l)}}{\sigma^{(l)}}\right)}e^{-\frac{1}{2}\left(\frac{t-\mu^{(l)}}{\sigma^{(l)}}\right)^2}dt}+\int_{-\infty}^{\alpha^{(l)}\left(\frac{y-\mu^{(l)}}{\sigma^{(l)}}\right)}\left(t-\mu^{(l)}\right)e^{-\frac{1}{2}\left(\frac{t-\mu^{(l)}}{\sigma^{(l)}}\right)^2}dt-\sigma^{(l)}\alpha^{(l)}e^{\frac{\left[\left(\alpha^{(l)}+\sigma^{(l)}\right)\mu^{(l)}-\alpha^{(l)}y\right]^2}{2\sigma^{4(l)}}} \tag{45}$$

F. UPDATING $\sigma 2$

For updating σ^2, we consider the derivative of $Q\left(\theta;\theta^{(l)}\right)$ with respect to σ^2 and equate it to zero. i.e., (46), as shown at the top of the next page, the updated equation for σ is

$$\sigma^{(l+1)}=1\Big/\frac{\left(y-\mu^{(1)}\right)^2}{\sigma^3(1)}+\frac{1}{\int_{-\infty}^{\alpha(1)}\left(\frac{y-\mu^{(1)}}{\sigma^{(1)}}\right)_e-\frac{1}{2}\left(\frac{t-\mu^{(1)}}{\sigma^{(1)}}\right)^2}+\int_{-\infty}^{\alpha}\left(\frac{y-\mu^{(1)}}{\sigma^{(1)}}\right)\frac{\left(t-\mu^{(1)}\right)^2}{\sigma^3(I)}e^{-\frac{1}{2}\left(\frac{t-\mu^1}{\sigma^{(1)}}\right)^2}dt+\alpha^{(1)}\left(\frac{\mu^{(1)}-y}{\sigma^2(1)}\right)e^{\frac{\left[\left(\alpha^{(1)}+\sigma^{(1)}\right)\mu^{(1)}-\alpha^{(1)}y\right]^2}{2\sigma^4}} \tag{47}$$

G. UPDATING α

To update α, we equate $Q\left(\theta;\theta^{(l)}\right)$ with respect to α to zero. i.e.:

$$\int_{-\infty}^{\alpha\left(\frac{y-\mu}{\sigma}\right)}\frac{e^{-\frac{1}{2}\left[\frac{t-\mu}{\sigma}\right]^2}}{\sqrt{2\pi}}dt\cdot\left[\frac{e^{-\frac{1}{2}\left[\frac{\alpha\left(\left(\frac{y-\mu}{\sigma}\right)-\mu\right)}{\sigma}\right]^2}}{\sqrt{2\pi}}\left(\frac{y-\mu}{\sigma}\right)\right].t_i\left(y_s,\theta^{(l)}\right)=0 \tag{48}$$

Now, for finding the updated equation for α

$$\frac{\partial}{\partial\alpha}[\log f(y)]=\left[0-0+0+\frac{1}{\int_{-\infty}^{\alpha\left(\frac{y-\mu}{\sigma}\right)}e^{-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2}dt}+\int_{-\infty}^{\alpha\left(\frac{y-\mu}{\sigma}\right)}0+e^{\frac{-\frac{1}{2}\left[\alpha\left(\frac{y-\mu}{\sigma}\right)-\mu\right]^2}{\sigma^2}}\cdot\frac{d}{d\alpha}\left[\alpha\left(\frac{y-\mu}{\sigma}\right)\right]-0\right].t_i\left(y_s,\theta^{(l)}\right) \tag{49}$$

$$\sum_{s=1}^{N}\left[\sum_{i=1}^{k}\sum_{s=1}^{N} t_i\left(y_s,\theta^{(l)}\right)\left\{\begin{array}{l}\left[\left(\frac{y-\mu_k}{\sigma^2}\right)+\frac{1}{\int_{-\infty}^{\alpha\left(\frac{y-\mu}{\sigma}\right)}\frac{e^{-\frac{1}{2}\left[\frac{t-\mu}{\sigma}\right]^2}}{\sqrt{2\pi}}dt}\right].\\ \left[\begin{array}{l}\int_{-\infty}^{\alpha\left(\frac{y-\mu}{\sigma}\right)}\frac{e^{-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2}}{\sqrt{2\pi}}.2\left(\frac{t-\mu}{\sigma^2}\right)(-1)dt+\\ \frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}\left[\frac{\alpha\left(\left(\frac{y-\mu}{\sigma}\right)-\mu\right)}{\sigma}\right]^2}\end{array}\right]\end{array}\right\}\right]=0 \tag{43}$$

$$\frac{\partial}{\partial\mu i}\left[\sum\sum t_i\left(y_s,\theta^{(l)}\right)\right]=\frac{\partial}{\partial\mu i}\left[\sum_{i=1}^{k}\sum_{s=1}^{N} t_i\left(y_s,\theta^{(l)}\right)\left\{\begin{array}{l}\left[\left(\frac{y-\mu_k}{\sigma^2}\right)+\frac{1}{\int_{-\infty}^{\alpha\left(\frac{y-\mu}{\sigma}\right)}\frac{e^{-\frac{1}{2}\left[\frac{t-\mu}{\sigma}\right]^2}}{\sqrt{2\pi}}dt}\right].\\ \left[\begin{array}{l}\int_{-\infty}^{\alpha\left(\frac{y-\mu}{\sigma}\right)}\frac{e^{-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2}}{\sqrt{2\pi}}.2\left(\frac{t-\mu}{\sigma^2}\right)(-1)dt\\ +\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}\left[\frac{\alpha\left(\left(\frac{y-\mu}{\sigma}\right)-\mu\right)}{\sigma}\right]^2}\end{array}\right]\end{array}\right\}\right] \tag{44}$$

$$\sum_{s=1}^{N} t_i\left(y_s,\theta^{(l)}\right)\times\left[\left[-\frac{1}{2\sigma^4}(y-\mu)^2\right]+\left\{\begin{array}{l}\frac{1}{\int_{-\infty}^{\alpha\left(\frac{y-\mu}{\sigma}\right)}\frac{e^{-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2}}{\sqrt{2\pi}}dt}.\\ \left[\begin{array}{l}\int_{-\infty}^{\alpha\left(\frac{y-\mu}{\sigma}\right)}\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2(t-\mu)^2.\frac{1}{\sigma^4}}dt+e^{-\frac{1}{2}\left[\frac{\alpha\left(\left(\frac{y-\mu}{\sigma}\right)-\mu\right)}{\sigma}\right]^2}.\alpha\,(y-\mu).\left(-\frac{1}{2\sigma^3}\right)\\ -\frac{1}{2\sigma^2}\end{array}\right]\end{array}\right\}\right]=0 \tag{46}$$

This implies

$$\sum_{s=1}^{N} t_i\left(y_s,\theta^{(l)}\right)\left[\log\left(\frac{y-\mu}{\sigma}\right)+\frac{\left[(\alpha+\sigma)\,\mu-\alpha y\right]^2}{2\sigma^4}\right]=\sum_{s=1}^{N} t_i\left(y_s,\theta^{(l)}\right)\left[-\log\left(\frac{1}{\int_{-\infty}^{\alpha\left(\frac{y-\mu}{\sigma}\right)}e^{-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2}dt}\right)\right] \tag{50}$$

the updated equation for α

$$\alpha^{(l+1)}=\frac{\sqrt{2}\sigma^{2^{(l)}}}{\mu^{(l)}-y}\left[\log\left(\int_{-\infty}^{\alpha^{(l)}\left(\frac{y-\mu^{(l)}}{\sigma^{(l)}}\right)}e^{-\frac{1}{2}\left(\frac{t-\mu^{(l)}}{\sigma^{(l)}}\right)^2}dt\right)-\log\left(\frac{y-\mu^{(l)}}{\sigma^{(l)}}\right)\right]^{\frac{1}{2}}-\frac{\sigma^{(l)}\mu^{(l)}}{\mu^{(l)}-y} \tag{51}$$

IV. EXPERIMENTAL RESULTS

In this paper, we have considered 4 different emotions from 16 subjects with an advanced stage of Parkinson's. Ethical procedures were adhered to following the Helsinki declaration and an informed consent was obtained. The EEG electrodes were placed using 64-channel international 10–20 system. However, we used only 8 electrodes configuration as shown in Figure 3.

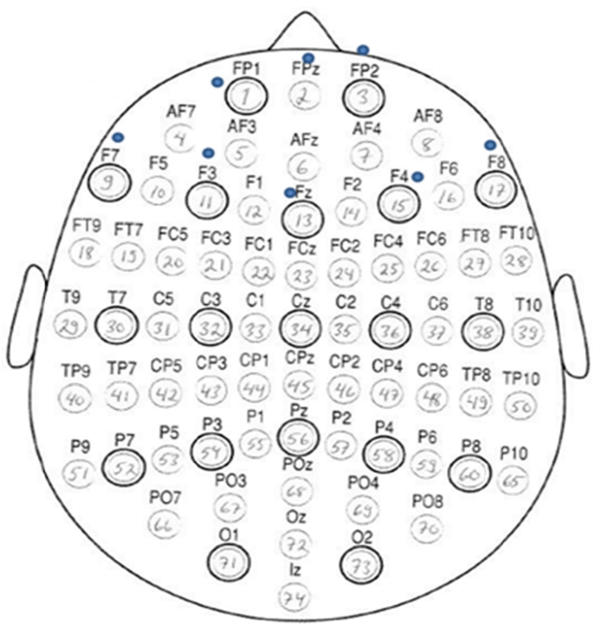


FIGURE 3. Top head view with the electrode positions.

For data acquisition, we have used Emotiv EPOC, 14-channel wireless device for EEG signal scanning. Data processing and visualization was performed using MATLAB (Mathworks Inc.).

Happiness

FIGURE 4. Example of emotion-inducing visual stimuli: Sadness and happiness.

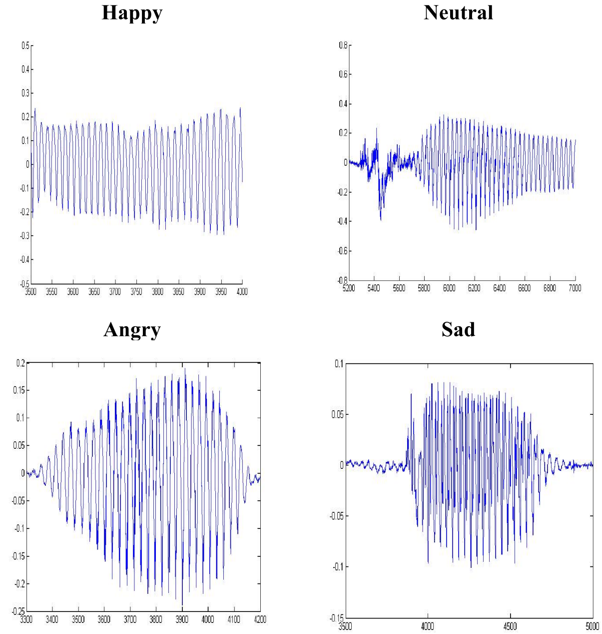


FIGURE 5. Examples of emotions (happy, angry, calm, sad) wave forms as per the standard range of frequency.

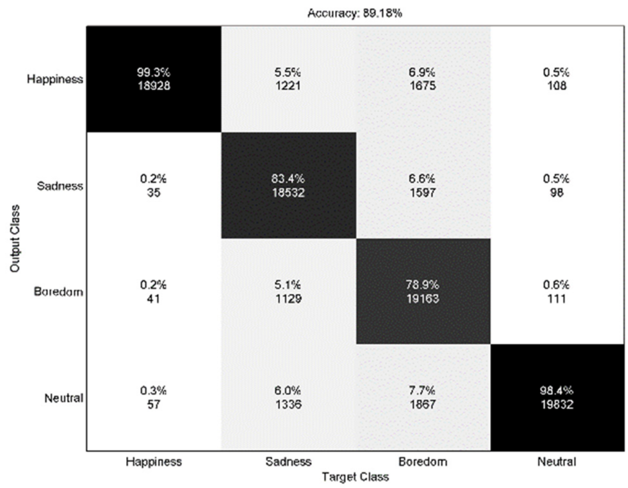


FIGURE 6. Confusion matrix of emotion classification results.

The obtained EEG signals are processed using Generalized Mixture Distribution Model. The mean and variance of the signals is found and the probability density function of distribution is found for each input signal. This process facilitates in removal of noise and identifying to which emotion the input signals exactly belongs to.

The experiment was carried to recognize four emotions (happy, calm, angry, sad) of 16 subjects with Parkinson's disease of advanced stages (4-5 stage according to Hoehn-Yahr scale). During the experiment, the subject were comfortably lying in a noise-insulated room. Audio-visual stimuli were presented to the subjects using an overhead-mounted tablet in the form of 30 sec long movie clips with an accompanying music. An example of screenshots from presented movie clips are shown in Figure 4.

As there is an inevitable noise present in the obtained brain signal due to various reasons like movement of eyes, and muscular tremor of the subjects, the signals get distorted. To remove any movement-induced noise during recording of EEG signals we have applied the modified BEADS filter described in [17].

Pre-processed signal data is further applied to generalized distribution method as described in Section III. The example of the signals extracted can be seen in Figure 5, showing the recorded EEG signals and corresponding emotion.

In order to classify the emotions, we have considered the alpha band features of EEG signal and used the results of the self-assessment as labels for classification of emotions (happy, sad, angry and calm). We have achieved the emotion classification accuracy of 89.1% as demonstrated by the confusion matrix in Figure 6. The best accuracy of recognition was achieved for the happiness emotion (99.3%), while boredom was recognized with an accuracy of only 78.9%. Happiness was most often confused with neutral emotion, sadness – with neutral, boredom – with neutral and neutral – with boredom. Summarizing, recognizing the neutral emotion was most difficult, since its emotional arousal was low.

V. CONCLUSION

Emotion recognition is crucial when aiming to advance human-computer interaction. Emotion recognition has vital role in supporting physically challenged people, timely disease diagnosis of neurodegenerative diseases such as Parkinson's, and feedback of the usage of drug administered.

In this paper, we have introduced a novel approach for emotion recognition based on Generalized Mixture

Model (GMM) using the electroencephalogram (EEG) signal dataset. The main benefit of utilizing this model is that, it is an asymmetric distribution which helps to extract the EEG signal, which are either in symmetric or asymmetric form, another advantage of skew Gaussian distribution is that GMM is its particular case. The Skew Gaussian Distribution helps to identify the small duration EEG signal sample and help towards better recognition of the emotional recognition in both clean and noisy EEG signals. The proposed method is particularly well suited for high variability of the EEG signal allowing to record the emotions exactly the feature vectors are to be identified appropriately. The main benefit of using Doubly Truncated Gaussian Distribution Model is that the infinite range of the EEG signal samples can be truncated between a certain limits and the recognition of the emotions can be carried out using the finite range. Another advantage of this proposed distribution is, it will be very useful to recognize the small duration EEG sample signals and useful towards best identification of human emotions.

The results reported in this article demonstrate the applicability of our approach to enable accurate emotion recognition based on the EEG signal analysis for immobilized persons. The limitations of the current study include a small number of subjects. The selection of audio-visual stimuli dataset also may have influenced the results.

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