# Human Emotion Detection and Stress Analysis using EEG Signal

**Prashant Lahane, Mythili Thirugnanam**

***Abstract*: *Stress has become a universal emotion that people experience in day to day life. In this paper, emotion detection is carried out using benchmark DEAP dataset by implementing a new feature extraction techniques named as Teager-Kaiser Energy Operator (TKEO) with a k-nearest neighbor (KNN), neural network(NN) and Classification Tree (CT) classifiers based on Electroencephalography (EEG). The study evaluates the performance and accuracy of emotion detection which is further used for stress identification as EEG gives good correlation with stress. Also, the present work compares the implemented TKEO feature extraction technique with Relative Energy Ratio (RER), and Kernel Density Estimation (KDE) techniques regarding accuracy. This paper demonstrates how the inclusion of TKEO enhances feature extraction and proves a promising approach to emotion detection as compared to other conventional techniques. The experimental results show that TKEO when used with KNN, NN, CT classifier gives comparatively higher accuracy than KDE and RER for channel 1 alpha band and channel 17 beta band for stress detection.***

***Index Terms*: *Electroencephalography (EEG), Feature extraction, Teager-Kaiser Energy Operator (TKEO), Neural network, k-nearest neighbor (KNN), a Bandpass filter (BPF)***

## I. INTRODUCTION

Stress is one of the major problems in our day to day life, and many people suffer from it. High workload and time pressure will increase the stress level. Stress is the second work-related health problem in Europe, and 51% of European workers confess that stress is common in their workplace. Several researchers have analyzed human stress using basic emotions. To identify human emotions and stress detection Electroencephalogram (EEG) plays an important role, and it became the favorite for cognitive and neuroscience research [Shrutika, 2015]. EEG signal contains vast information about the patient's mental health and thus end up being an excellent choice for evaluating the stress level of any individual. Human emotions are related to stress as positive and negative emotions.

Positive emotions like happiness, joy, love, pride, pleasure can have a positive effect like improvement in daily work performance and negative emotions like anger, terrible, sad, disgust can have a negative impact on the health of a person. In this paper focuses on stress detection based on emotions recognition by considering two emotions happy and terrible for stress detection. Emotional signs like depression, terrible, unhappiness, anxiety, agitation, anger are responsible for stress as shown in figure 1.


**Figure 1: Positive and negative emotions.**

People undergo stress in their everyday life due to work pressure, significant life changes, relationship, financial problems, and frustration. An EEG signal embodies enormous information about a patient's mental health and thus ends up being an ideal choice for evaluating the stress level of any individual. In the present study, the Teager-Kaiser Energy Operator (TKEO) is connected to the EEG signal elements whose frequency bandwidth is identified by frequencies more impacted by harm. The TKEO is a nonlinear propeller and when applied to the signals, computes energy as the product of the square of the amplitude and the occurrence of the signal. In this energy measures thus obtained would be a good character and can be used for feature extraction along with neural network and k-nearest neighbor (KNN) classification for stress detection. It gives that how the inclusion of TKEO enhances the feature extraction and general precision outcomes as compared to other conventional techniques.

The identifying stress in human is difficult through questionnaire base method and gives less correctness. However, relying on the kind of emotion helpful to detect stress and to control the health-related issues generated from stress, stress detection technique is essential. Many researchers have used specific strategies, for instance, KDE, RER, Genetic set of rules and other. Our focus is to explore a new feature extraction technique that can be more effectively detect stress by using alpha and beta band. Feature extraction techniques play a vital role to improve the classifier accuracy. In this paper, a newly proposed feature extraction is based on the idea of Teager–Kaiser definition. In the theory of Teager, a new approach of energy measure is given by Kaiser. It includes both the amplitude and frequency of the signal. This new Teager–Kaiser meaning indicates the different energy to separate frequencies from claiming unit-amplitude signals. This Teager–Kaiser energy

**Revised Manuscript Received on March 02, 2019.**

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operator is also known as nonlinear-energy operator and because of its instantaneous measure; it may be unique concerning alternative traditional energy measures. This energy operator is a characteristic of the time and can track changes in the signal—and consequently system—energy [J. Kaiser, 1990]. For disclosure of energy, the TKE took uses a translation- invariant, sliding window filter.

Since the time of invention, researchers have demonstrated the handiness and applicability of TKEO in many fields eg.-for energy estimation, [Atit 1999, Choi 2002], for time-frequency estimation [Hamila,1999], in contrast, enhancement [Mitra, 1991] and image processing [Thurnhofer 2001]. This operator is extensively used because of its easy implementation. In this paper, the TKE operator is used for energy measures and considered as a new feature. The extracted features are then categorized by using distinctive classifier i.e KNN, NN, CT. Classified outcomes are utilized for emotion acknowledgment and as per that stress is identified. Thus, the purpose of this paper is to search for the feature extraction techniques and classifier which are able to recognize human stress with reasonable accuracy.

## II. RELATED WORK

Numerous feature extraction techniques have been recommended by some researcher for evaluation of EEG signals including the most common, Fast Fourier Transformations (FFT) [Xiyuan, 2015], Genetic Algorithms (GA) [Swati, 2015], Wavelet Transformations (WT) [Murugappan, 2010], KDE [Nawasalkar, 2015], RER [Norizam, 2011], Wavelet Packet Decomposition (WPD) [Wu Ting, 2007] and FCC [Prashant, 2017]. Most commonly used Genetic Algorithm is not suitable for dynamic dataset whereas the performance of KDE degrades for larger dimension [Prashant, 2016]. The two feature extraction algorithms FFT and Wavelet Transformation provide less accurate results and RER, and TKEO is relatively worthy to perform[Prashant, 2018].

A Teager-Kaiser energy operator may be a new idea and additionally employed by exceptional authors for distinct applications. Litvina et al. used the Teager energy operator (TEO) separation algorithm for separation of speech from music. Navid Shokouhi introduces a new approach to detect the overlap of speech of two speakers using TKEOShokouhi. The author Solnik in 2010 first suggested the use of TKE operator for EMG onset detection methods. Utilizing the usage of this operator, the false onset detection is reduced and it also makes data analysis less tedious. Guojun Zhou likewise utilized TKEO to detect the presence of stress in speech and to increase the robustness of speech recognition systems. The Teager- Kaiser Energy operator can also be used for multi-frequency tone detectors. This operator offers comparatively high accuracy results and can be implemented at low cost. This form of tone detectors is quick over response, exceptionally efficient and enhanced the time resolution. In this only a couple of parameters are used that can be effectively adjustable [Valentin Emiya,2004].

A new experiment was conducted to achieve the high accuracy results of feature extraction and for this, a combined approach of three different types of filter-bank cepstra (TE-FB-CEPs) based on Teager energy is introduced by Chandrakar Kamath in 2013. An altered model of Teager- Kaiser Energy operator is also used in the field of image processing for image analysis [Cexus, 2010] and howling detection[Khoubrouy, 2014]. Jitendra et al. also proposed a fault detection method during power swing by calculating negative sequence current using TKEO. This proposed technique works fine for a vast range of excessive resistance fault and loads angle. TKEO is extremely easy to implement and extensively used in many more fields. As choosing an appropriate approach for feature extraction determines the classification of results. Therefore in stress detection requires a new method of feature extraction and it is elaborated in the following section.

## III. METHODOLOGY

TKE operator is presented in this paper. The outcomes are obtained for channel 1 and channel 17 in light of the fact that these two channels are adequate and offer maximum accuracy results. The proposed architecture is presented in Fig.2 and portrayal of every module is clarified in the following sections.

*3.1Data Gathering:*

Pre-processed EEG signals are used as input of this experiment. For pre-processing DEAP dataset is used to acquire the frequencies of range 4.0-45.0 Hz and downsampling is performed to 128Hz.

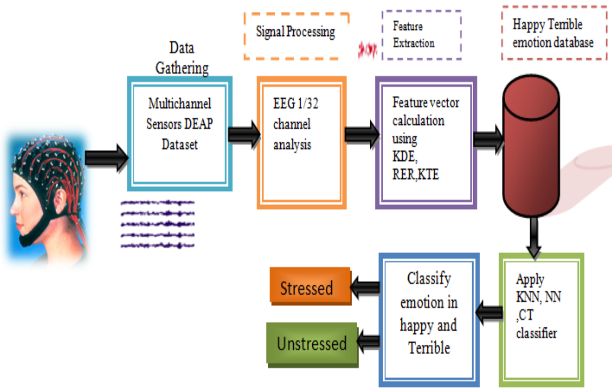


Figure 2: Developed System Framework

*3.2 Feature Extraction using Energy Logistic Coefficients (ELC) of TKEO*

A DEAP dataset comprises a frequency range of 4 to 45 Hz. In this paper, a bandpass filter is employed and considered only alpha and beta band frequencies. For feature extraction, TKE operator is used to estimating the energy that relies upon two parameters amplitude and frequency. The procedure can be understood with the aid of following fig 3.Teager Kaiser Energy Operator(TKEO) is used to calculate the energy of the signal in the time domain using the following steps.


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*1. EEG Signal*

The EEG Bands are separated by using bandpass filter. The bandpass filter is an electronic device or circuit that allow the signals between two specific frequencies to pass, but they discriminate against the signals at the other frequencies. The cutoff frequencies f1 and f2 are the frequencies at which the specific EEG band starts and ends respectively. The value f2-f1 expressed in the hertz is called filter bandwidth. The of frequencies between f1 and f2 is called a filter passband.

$$x(t) = \{x(t_1), x(t_2), x(t_{3)}, \ldots x(t_n) \mid 0 < t < n\}$$

Band Separations={Delta, Theta, Alpha, Beta, Gamma}

$$x=\{x^{\delta}, x^{\theta}, x^{\alpha}, x^{\beta}, x^{\gamma}\}$$

**Table 1: EEG band with a frequency range**

| EEG Band | Frequency Range |
|---|---|
| ($x^{\delta}$)Delta | $0.5 < f < 4$ |
| ($x^{\theta}$) Theta | $4 < f \leq 8$ |
| ($x^{\alpha}$) Alpha | $8 < f \leq 13$ |
| ($x^{\beta}$) Beta | $13 < f \leq 30$ |
| ($x^{\gamma}$) Gamma | $30 < f \leq 56+$ |

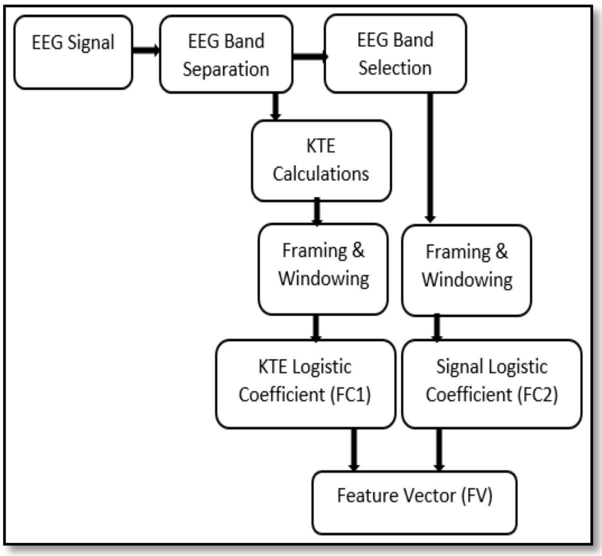


**Figure 3: Proposed Energy Logistic Coefficient (ELC) Algorithm for Feature extraction**

The energy estimation using KTE logistic coefficients (FC1) and signal logistic coefficients (FC2) and appropriate feature vector were generated as shown in the above figure.

*2. Band Selection:-* Band selection consists of selecting any one of the EEG rhythms that is $x^{\delta}, or\ x^{\theta}, or\ x^{\alpha},\ or\ x^{\beta},\ or\ x^{\gamma}$ for further detailed analysis.

*3. Windowing and Framing:-* Windowing consists of diving entire EEG signals into a number of windows of specific time intervals which is 1 min selected. Framing consists of the diving selected window into a number of frames of the specified time interval. Frames can be overlapping and non-overlapping. Typically it is selected as 1sec.

Windowing of beta band is considered as follows.

$$x_{window} = \{x^{\beta}, \mid 0 < t < min\}$$

Over the one frame, the signal is assumed to have minimum variation having the same properties.

*4.KTE calculation***:** Kaiser-Teager Energy is calculated for selected EEG rhythms over entire window of the beta band.

$$\mathrm{kte}(n) = x^{\beta}(n) - x^{\beta}(n-1).x^{\beta}(n+1)..$$

Where n represents the nth sample of the window.

KTE Logistic Coefficients($C_{kte}$): KTE Logistic Coefficients is calculated over every frame.

$$C_{kte} = \frac{\mathrm{kte\_mu}}{1 + e^{-\mathrm{kte\_std}}}$$

where $\mathrm{kte\_mu} = \frac{\sum_{i=1}^{N_{frame}} (\mathrm{kte}^{\beta}(i)}{\mathrm{N\_frame}}$ and $\mathrm{kte}_{std} =$ i=1N_frame(kteβi− kte_mu)2N_frame.

N_frame= Number of samples in one frame. So for a selected band window got a set of the logistic coefficients.

$\boldsymbol{C_{kte}} = \{\, c_{kte,}^{1} c_{kte,}^{2} \ldots c_{kte,}^{Nf} \mid Nf = No. of\ frames\}$

Similarly, the **logistic coefficients for signal energy($c_s$)** for selected band beta band are calculated using the following equations. $x_e^{\beta}$

$$c_s = \frac{x\_mu^{\beta}}{1 + e^{-x_{e\_std}^{\beta}}}$$

Where $x_{\_mu}^{\beta} = \frac{\sum_{i=1}^{N\_frame} x^{\beta}(i)}{N\_frame}$ and $x_{std}^{\beta} = \sqrt{\frac{\sum_{i=1}^{Nframe} (x^{\beta}(i) - x_{mu}^{\beta})^2}{Nframe}}$

So, for selected beta band window, get set of signal logistic coefficient as follows.

$$\mathbf{C_x} = \{\, c_{x,}^{1} c_{x,}^{2} \ldots c_{x,}^{Nf} \mid \mathrm{Nf} = \mathrm{No. of\ frames}\}$$

*5. Feature Vector (FV):-* Feature vector consists of a set of KTE logistic coefficients and a set of signal logistic coefficients.

FV={ $\{c_{kte}\}$,$\{c_x\}$ } This feature vector is considered for emotion classification.

Moreover, the calculated feature vector are precise and predict actual emotion through alpha and beta frequency bands.

*3.3 Classification*

Many classification algorithms are introduced by different authors e.g. SVM, ANN, KNN, classification tree etc. Among those algorithms, the neural network is a promising one that is a powerful tool of pattern recognition. The main benefit of neural networks is that it does not require any explicit specification and uses the self-adaptive techniques to adjust to the data. KNN and NN are first trained by using training dataset and then used for classification of emotions. Variable K is defined as 2 for this experiment to achieve good classification results. In this paper, features like amplitude and frequency are extracted from the input signal. Then, these extracted features are given to NN which is designed and trained by training data to classify the emotions as happy and terrible with good accuracy results. The neurons are organized in layers, and signals are sending to the forward direction, and errors are propagated towards the backward direction. The algorithm uses the concept of


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backpropagation to minimize the error and it performs repetitively until the NN learns the training data. The same training data is given to the other technique KNN to produce the classifier outputs. This algorithm is simplest amongst all machine learning algorithms.

*3.4 Stress detection*

The essential features are extracted and alpha and beta band energy is calculated as a feature vector. The extracted feature are fed to different classifiers like KNN, classification tree and neural network for emotion detection in happy and terrible. These emotions are responsible for the stressed and unstressed state of the individual. As happy emotion is considered as unstressed state and terrible emotion is considered as a stressed state of the human.

## IV. RESULT ANALYSIS

Experiments are conducted to test the efficiency of feature extraction using TKE operator on DEAP dataset. The accuracy results are obtained for KDE, RER, and KTE algorithms using different classifiers KNN, NN, classification tree are demonstrated in below tables. Here, the outcomes are acquired only for channel 1 and channel 17 as these two channels gives comparatively more stress-related information. Accuracy results of different algorithms using different classifier for Happy and Terrible emotions are demonstrated in figure 4,5 and 6.

**Table 1: Accuracy level of two different emotions Happy and Terrible using KNN classifier**

| KNN Classifier | | | | |
|---|---|---|---|---|
| Channel | Band | KDE % Accuracy Happy n Terrible | RER % Accuracy Happy n Terrible | KTE % Accuracy Happy n Terrible |
| 1 | Alpha | 83.33 | 85 | 88.33 |
| 17 | Alpha | 85.33 | 81.66 | 86.66 |
| 1 | Beta | 85.33 | 85 | 86.66 |
| 17 | Beta | 86.66 | 81.66 | 87 |


**Figure 4: Accuracy Results using KNN Classifier**

**Table 2: Accuracy level of two different emotions Happy and Terrible using NN classifier.**

| Neural Network | | | | |
|---|---|---|---|---|
| n Channel | Band | KDE % Accuracy Happy n Terrible | RER % Accuracy Happy n Terrible | KTE% Accuracy Happy n Terrible |
| 1 | Alpha | 50 | 90 | 93 |
| 17 | Alpha | 76.66 | 88.33 | 90 |
| 1 | Beta | 85 | 89 | 90 |
| 17 | Beta | 85 | 88.3333 | 90 |

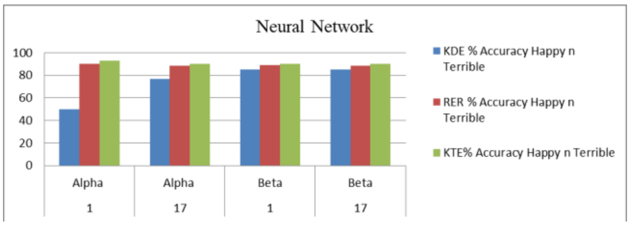


**Figure 5: Accuracy Results using NN Classifier**

**Table 3: Accuracy level of two different emotions Happy and Terrible using Classification tree classifier.**

| Classification Tree | | | | |
|---|---|---|---|---|
| Channel | Band | KDE % Accuracy Happy n Terrible | RER % Accuracy Happy n Terrible | KTE % Accuracy Happy n Terrible |
| 1 | Alpha | 76.66 | 80 | 88.33 |
| 17 | Alpha | 76.66 | 85 | 86 |
| 1 | Beta | 80 | 80 | 83.33 |
| 17 | Beta | 71.66 | 80 | 83 |

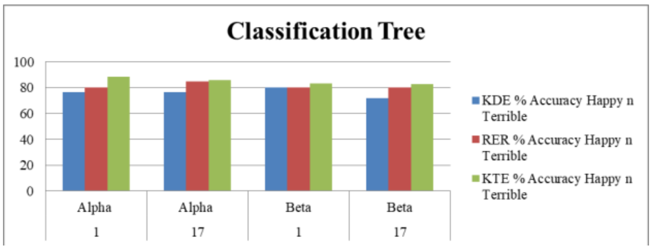


**Figure 6: Accuracy Results using Classification Tree**

## V. CONCLUSION

In this paper, a nonlinear, reliable and feasible feature extraction technique is proposed with the ultimate objective of human stress detection. This study presents the comparative results of existing techniques with a new proposed approach that uses TKE operator for feature extraction. A band-pass filter was introduced to extract alpha and beta band from the input EEG signal. The accuracy of various algorithms is classified by a neural network, classification tree, and KNN classification algorithm. Objective assessments indicated that this novel scheme prompts a considerable improvement in stress evaluation. The results of the study demonstrated that feature extraction using Teaser–Kaiser energy operator performs well in all cases for all the classifier. However, the beauty of TKE is its simplicity and less complexity with fast execution.

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