# Classification of Human Emotions from EEG Signals using Statistical Features and Neural Network

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Abstract

A statistical based system for human emotions classification by using electroencephalogram (EEG) is proposed in this paper. The data used in this study is acquired using EEG and the emotions are elicited from six human subjects under the effect of emotion stimuli. This paper also proposed an emotion stimulation experiment using visual stimuli. From the EEG data, a total of six statistical features are computed and back-propagation neural network is applied for the classification of human emotions. In the experiment of classifying five types of emotions: Anger, Sad, Surprise, Happy, and Neutral. As result the overall classification rate as high as 95% is achieved.

Keywords: EEG, Human emotions, Neural network, Statistical features.

## 1. INTRODUCTION

A considerable amount of research effort has been channeled towards the identification and utilization of information of human emotions. Various ways of human-computer and human-machine interaction have been studied in the effort of enabling computers and machines to be more alert to the emotions and affective needs of human beings. Information of human emotions are gathered from a living body using various channels including the use of electroencephalogram, in which the brainwaves are directly extracted from a human and the patterns of the waves are studied to classify emotions. Other techniques explored in the classification of emotions including face emotion recognition using vision system, respiration rate and tone recognition from human voice [1].

EEG is used to record information of the human brain activities in the form of measurement of electrical activity of the brain. The electrical activities of the brain are recorded from electrodes placed on the scalp and this measurement may indicate the emotion state of human subject while the information is recorded [2], [11], [15]. Researches believe that the states of the brain changes as feelings change, therefore, EEG is suitable for the task of recording the changes in brain waves which vary in accordance to feelings or emotions [3]. The EEG has a few advantages that enable it to be chosen in the study of human emotions, that is, EEG has high speed, non-invasive and causes no pain to the human subjects. These are important aspects so as to acquire natural and real emotions from human subjects. However, there are difficulties in understanding the EEG data. There are a large number of organizations, structures, processes involved in the underlying EEG data. The number of associations and aspects of emotions is also large [2].

The analysis of brain waves [16] has utilized various signal processing and artificial intelligence skills in the effort to develop emotions classification. These systems are mainly developed to facilitate the interaction between human and computer and further to be incorporated in various machines such as robots to develop various intelligent systems and machines such as patients monitoring systems in hospitals and medical robots.

The expressions 'Yes' and 'No' are the most essential expressions in the interactions among humans. Chang Su Ryu [4] developed a system to discriminate 'Yes' and 'No' using Support Vector Machine (SVM) to classify features extracted by Fourier Fast Transform (FFT). The recognition rate of 80% is achieved. Ishino and Hagiwara [3] applied FFT, Wavelet Transform, Principal Component Analysis, mean and variance to extract features from the EEG data. Neural network is used for classification of four types of emotions (joy, sorrow, relax and anger) and the highest success rate is 67.7%. Takahashi [5] developed an emotion recognition system using SVM for to classify five emotions (joy, anger, sadness, happiness and relax) based on statistical features computed from the raw signal. The recognition rate is 41.7%. Takahashi and Tsuguchi [6] compared the effectiveness of neural network and SVM in classifying two emotions: pleasure and displeasure. In this study, statistical features are used and the recognition rates achieved are 62.3%

and 59.7% for neural network and SVM respectively.

Fuzzy logic provided new possibilities into control, data analysis and data modeling. One of the issues in using fuzzy clustering based classification is setting the number of clusters in each class. The generalization is acceptable when large sets of samples are available for classification [12]. Fuzzy C-Means [13], [14] has been one of popular researches in recent researches.

## 2. DATA ACQUISITION

This section describes the acquisition of physiological signals from EEG under emotion stimulation experiments. Various ways of elicitation emotions in human subjects have been employed in the aim to develop databases of brain waves data for different states of emotions. Some of the methods studied include: acquisition of EEG data from subjects who act out the emotions based on imagination and by employing stimuli such as audio and visual stimuli.

The strategy of requiring an actor to feel or express a particular mood has been widely used for emotions assessment from facial expressions and physiological signals [7]. This strategy has a major weakness as it is highly difficult to ensure that the physiological signals obtained can consistently reproducible by non-actors. Therefore, actor-play database is often far from real emotions found in the real scenario [8]. Alternatively, visual, audio or combination of both stimuli can be used as an approach of inducing emotions. This method is capable of producing responses that are closer to real life. In this study, visual stimuli are used in the emotion stimulation experiment where adult facial stimuli [9] were used. Evaluation is carried out after the stimulation experiment as the emotions induced during the experiments may vary from the expected emotions. This can be explained by individual differences in past experience and personal understanding when viewing the stimuli [8].

The database developed in this study consists of the EEG data acquired from 6 human subjects (3 males and 3 females, aged from 23 to 26 years old). A 64-channel biosensor is used, in which 62 channels are occupied for the EEG electrodes and the remaining 2 channels for the

Table 1: Emotions assessment results by human subjects [%]

| | Very weak | Weak | Moderate | Strong | Very strong |
|---|---|---|---|---|---|
| Anger | 33.33 | 0.00 | 16.67 | 16.67 | 33.33 |
| Happy | 0.00 | 16.67 | 33.33 | 16.67 | 33.33 |
| Sadness | 0.00 | 16.67 | 0.00 | 50.00 | 33.33 |
| Neutral | 0.00 | 0.00 | 0.00 | 83.33 | 16.67 |
| Surprise | 16.67 | 16.67 | 33.33 | 33.33 | 0.00 |

Table 2: Ratings of emotions elicited by human subjects [%]

| In/Out | Anger | Happy | Sadness | Neutral | Surprise | No Emotion |
|---|---|---|---|---|---|---|
| Anger | **66.67** | 0.00 | 16.67 | 16.67 | 0.00 | 0.00 |
| Happy | 0.00 | **83.33** | 0.00 | 16.67 | 0.00 | 0.00 |
| Sadness | 0.00 | 0.00 | **83.33** | 0.00 | 0.00 | 16.67 |
| Neutral | 0.00 | 0.00 | 0.00 | **100.00** | 0.00 | 0.00 |
| Surprise | 0.00 | 0.00 | 0.00 | 0.00 | **100.00** | 0.00 |

electrodes of electrooculogram (EOG) for the detection of eye blinks and eye movements. The signals were sampled at the rate of 256 Hz. For the recording of EEG data during the experiment, the subject wearing the EEG and EOG sensors sits comfortably in front of a computer screen presenting the stimuli in the format of Windows Microsoft Office PowerPoint with the transition of slides made automated.

First, before the experiment is started, a slide containing the instructions is displayed for 10 seconds to prepare the subject for the experiment which includes: reminder for subjects to minimize physical movements and eye blinks. A set of 4 images consisting relaxing sceneries is presented for a period of 20 seconds to record the 'neutral' emotion from the subject. Then, an introductory slide is displayed to prepare the subject to react to the visual stimuli about to be shown. Next, two sets of visual stimuli consisting 6 images of facial stimuli [9] are displayed for 3 seconds for each images to stimulate one emotion. In between each set, a dark screen is displayed for 5 seconds to facilitate a short 'rest' period for the subject.

After running the two sets of visual stimuli, a dark screen is shown for 45 seconds and soothing music is played for the subject to relax and prepare for the next emotion stimuli. This completes a cycle of stimulation for one emotion. The total time consumed for the stimulation of one emotion is approximately two minutes. The flow of stimuli as described above is repeated for the stimuli of 5 types of emotions: 'happy', 'anger', 'surprise' and 'sadness'. An assessment is carried out after the whole experiment for the subjects to describe the particular emotions elicited when the stimuli shown during the experiment and rate the strength of the emotions felt. The subjects are also required to specify if multiple emotions were aroused during the display of a particular emotion stimulus.

The results of assessment for the emotion elicitation experiment are as shown in Table 1 and Table 2. Table 1 shows the results of the emotions categorized by the subjects based on the visual stimuli. For example, the ratings for emotion 'anger': 33.33% of the subjects rated the emotion 'anger' that they felt was 'very weak', 16.67% rated 'moderate', 16.67% rated 'strong' and 33.33% rated 'very strong'. Table 2 shows the ratings of strength of the emotions felt when viewing the stimuli. For example, when stimulus for the emotion 'anger' is viewed, 66.67% of the subjects correctly classified the stimulus as 'anger'.

## 3. METHODOLOGY: STATISTICAL FEATURES

For the emotion classification stage, significant and important features need to be extracted from the EEG raw data for training and testing. Let the signals recorded from the EEG be designated by $X$ and $X_n$ represents the value of the $n^{th}$ sample of the raw signal, where $n = 1,\dots,N$ , with $N$ = 1024 (1024 samples corresponds to 4 seconds of the EEG recording). In this study, six statistical features are computed from the EEG data [1], [6]:

$$\mu_x = \frac{1}{N}\sum_{n=1}^{N} X_n \qquad (1)$$

1. The means of the raw signals

$$\sigma_x = \left(\frac{1}{N-1}\sum_{n=1}^{N}(X_n - \mu_x)^2\right)^{1/2} \qquad (2)$$

2.The standard deviation of the raw signals

$$\delta_x = \frac{1}{N-1}\sum_{n=1}^{N-1}\left|X_{n+1} - X_n\right| \qquad (3)$$

3.The means of the absolute values of the first differences of the raw signals

$$\tilde{\delta}_x = \frac{1}{N-1}\sum_{n=1}^{N-1}\left|\tilde{X}_{n+1} - \tilde{X}_n\right| = \frac{\delta_x}{\sigma_x} \qquad (4)$$

4. The means of the absolute values of the first differences of the normalized signals

$$\gamma_x = \frac{1}{N-2}\sum_{n=1}^{N-2}\left|X_{n+2} - X_n\right| \qquad (5)$$

5. The means of the absolute values of the second differences of the raw signals

$$\tilde{\gamma}_x = \frac{1}{N-2}\sum_{n=1}^{N-2}\left|\tilde{X}_{n+2} - \tilde{X}_n\right| = \frac{\gamma_x}{\sigma_x} \qquad (6)$$

6.The means of the absolute values of the second differences of the normalized signals

The features chosen can cover and extend a range of typically measured statistics in the emotion physiology literature [10]. The combinations of statistical features computed from equation (1) – (6) are defined as feature vectors, $c_n$ below:

$$\chi_1 = [\,\mu_x \quad \sigma_x\,] \qquad (7)$$

$$\chi_2 = [\,\delta_x \quad \gamma_x\,] \qquad (8)$$

$$\chi_3 = [\,\tilde{\delta}_x \quad \tilde{\gamma}_x\,] \qquad (9)$$

$$\chi_4 = [\,\delta_x \quad \tilde{\delta}_x\,] \qquad (10)$$

$$\chi_5 = [\,\gamma_x \quad \tilde{\gamma}_x\,] \qquad (11)$$

## 4. METHODOLOGY: CLASSIFICATION USING BACK–PROPAGATION NEURAL NETWORK

Neural network is inspired by the way human brain works [3]. It is an information processing paradigm that is closely related to biological nervous system of a human. Neural network comprises of processing elements which are highly interconnected neurons that work in unison in solving specific problems. Neural network possesses a few advantages over other classification techniques because it has the ability to derive meaning from complex and imprecise data which means it can be used to extract and detect trends and patterns that are too complex [3].

In this study, the combinations of statistical features are first used for classification of 5 types of emotions using neural network. The features are computed using equations (1) – (11). The number of input learning data is 30 for each emotion, amount to 150 and the neural network is tested with 60 data from each emotion, amount to 300. The target output for each emotion is set as '000' for 'anger', '001' for 'happy', '010' for 'sadness', '011' for 'neutral' and '100' for 'surprise'. The assumptions applied to the output of the neural network to obtain final result: result = 0 if output is less than 0.5, result = 1 if output is more than or equal to 0.5 and rejecting output more than 1.0.

For the combination that produced the highest success rate in classifying the emotions, a second study is carried out using the combination. In the second study, the neural network is trained and tested with input extracted from 4 emotions, then 3 emotions and lastly 2 emotions. This is to justify if the number of categories to be classified by the neural network affects the performance. Table 3 shows the parameters used for the back-propagation neural network.

Table 3: Parameters of neural network for combinations of statistical features

| | |
|---|---|
| Number of input layer units | 2 |
| Number of hidden layer units | 30 |
| Number of output layer units | 3 |
| Learning rate | 0.01 |
| Maximum epoch | 10000 |
| Learning goal | 0.01 |

## 5. DISCUSSIONS

The results for the classification of 5 types of emotions are as shown in Table 4. The effectiveness of the combinations of statistical features is compared based on rate of correct classification as well as time consumed for the training of the neural network. The results show that the combination computed using equation (8) produced the highest rate of correct classification. Using the features computed by this combination, 95% of correct classification rate is achieved for the classification of 5 types of emotions with 12.68 seconds consumed for training. In terms of time consumption, the combination of equation (9) is the lowest at 7.50 seconds but only achieved 78.33% in terms of performance.

Table 5 shows the classification result for combination $\left[d_x \quad g_x\right]$ based on emotions. From the table, 100% correct classification is achieved for emotion 'sadness', which means all the testing inputs for 'sadness' were correctly identified as 'sadness', while other emotions achieved correct classification rate of between 90.00% to

Table 4: Overall classification rate and time consumption for combinations of statistical features

| Combinations | Time Consumption (s) | Classification Rate (%) |
|---|---|---|
| $\chi_1 = \left[\mu_x \quad \sigma_x\right]$ | 36.69 | 69.00 |
| $\chi_2 = \left[\delta_x \quad \gamma_x\right]$ | **12.68** | **95.00** |
| $\chi_3 = \left[\tilde{\delta}_x \quad \tilde{\gamma}_x\right]$ | 7.50 | 78.33 |
| $\chi_4 = \left[\delta_x \quad \tilde{\delta}_x\right]$ | 36.56 | 78.00 |
| $\chi_5 = \left[\gamma_x \quad \tilde{\gamma}_x\right]$ | 23.26 | 81.00 |

Table 5: Classification result for the combination of $[d_x \quad g_x]$ [%]
(Highest overall classification rate among combinations)

| In/Out | Anger | Happy | Sadness | Neutral | Surprise |
|---|---|---|---|---|---|
| Anger | **95.00** | 1.67 | 0.00 | 3.33 | 0.00 |
| Happy | 1.67 | **91.67** | 0.00 | 6.67 | 0.00 |
| Sadness | 0.00 | 0.00 | **100.00** | 0.00 | 0.00 |
| Neutral | 1.67 | 1.67 | 0.00 | **96.67** | 0.00 |
| Surprise | 8.33 | 0.00 | 1.67 | 0.00 | **90.00** |

Table 6: Classification results for 5 emotions, 4 emotions, 3 emotions and 2 emotions

| Emotions | Time Consumption (s) | Classification Rate (%) |
|---|---|---|
| Sad, Neutral, Happy, Anger, Surprise | 12.68 | 95.00 |
| Sad, Neutral, Happy, Anger | 8.91 | 95.42 |
| Sad, Neutral, Happy | 5.36 | 97.20 |
| **Sad, Neutral** | **2.87** | **97.50** |

96.66%. The results shows that there are some of the inputs which were mistaken for the wrong emotion, therefore, such cases produced wrong outputs.

This study also investigates the effect of number of categories to be classified to the performance of the neural network. The combination of $[d_x \quad g_x]$ produced the highest correct classification, therefore, this combination is used in comparing the number of emotions and their rates of successful classification. Table 6 shows the results of the classification using neural network, where the emotions are broken down into smaller number of states. From the table, it can be observed that as the number of stated to classified is reduced, the performance improved. The classification of only 2 types of emotions (neutral and sadness) produced the highest percentage of correct classification at 97.50%. The percentage is then followed by the classification of 3 emotions, 97.20%, 4 emotions, 95.42% and 5 emotions, the lowest performance at 95.00%. Combinations of two features are used instead of all six features to be used jointly to processing time needed by the algorithm in producing positive results.

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