

## Research Article

### Effectiveness of Statistical Features for Human Emotions Classification using EEG Biosensors

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**Abstract:** This study proposes a statistical features-based classification system for human emotions by using Electroencephalogram (EEG) bio-sensors. A total of six statistical features are computed from the EEG data and Artificial Neural Network is applied for the classification of emotions. The system is trained and tested with the statistical features extracted from the psychological signals acquired under emotions stimulation experiments. The effectiveness of each statistical feature and combinations of statistical features in classifying different types of emotions has been studied and evaluated. In the experiment of classifying four main types of emotions: Anger, Sad, Happy and Neutral, the overall classification rate as high as 90% is achieved.

**Keywords:** EEG, human emotions, neural network, statistical features

## INTRODUCTION

In recent years, a considerable amount of research and efforts have been directed towards the identification and utilization of the information of human emotions. Various ways of human-computer interactions have been explored to enable the computer to be more alert to the emotional and affective needs of humans. Studies have been carried out on distinguishing human emotions using various techniques, one of which is the Electroencephalogram (EEG). Other techniques previously employed in emotions recognitions include: face emotion recognition using vision system, tone of voice and respiration rate (Picard *et al.*, 2001). EEG records the information of the human brain activities as the neurophysiologic measurement of the electrical activity of the brain may indicate the emotional state of the subject by recording from electrodes placed on the scalp (Teplan, 2002). The EEG is chosen as it can record the changes in brain waves in response to the alteration of feelings (Ishino and Hagiwara, 2003). The advantages of EEG that have encouraged growing efforts in this area are: EEG has high performance speed and EEG is non-invasive and painless which is important in acquiring natural and real emotions.

There are difficulties in seeing beyond the EEG data to underlying organizations, structures and processes as the number of associations between EEG and various aspects of emotions is large (Teplan, 2002). In the past decade, emotion recognition systems are continuously developed to facilitate the interaction between humans and computers by utilizing signal processing and artificial intelligence techniques in the analysis of brain waves. There are growing interests in development of EEG-based emotion classification schemes. The emotion recognition process generally involves feature extraction from EEG signals and matching of features through classification algorithm.

Current published techniques on EEG feature extraction include statistical features (Picard *et al.*, 2001; Takahashi and Tsukaguchi, 2005), wavelet transform (Murugappan *et al.*, 2009; Hazarika *et al.*, 1997; Ubeyli, 2009), higher order crossings (Kedem, 1994; Petrantonakis and Hadjileontiadis, 2010) and fractal dimension analysis (Accardo *et al.*, 1997; Liu *et al.*, 2010). These techniques are combined with various classification methods such as Support Vector Machine (SVM) (Cristianini and Shawe-Taylor, 2000), Quadratic Discriminate Analysis (QDA) (Krzanowski, 1988), K-Nearest Neighbour (*k*NN) (Cover and Hart, 1967), Mahalanobis distance (Mahalanobis, 1936), Neural Network (NN) models (Chaudhuri and

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Bhattacharya, 2000; Subasi and Ercelebi, 2005; Orhan *et al.*, 2011; Kiymik *et al.*, 2008) and bipolar model (Russell, 1979).

Ishino and Hagiwara (2003) applied Fast Fourier Transform (FFT), Wavelet Transform, Principal Component Analysis, mean and variance to extract features from the EEG data and NN as classifier. The highest classification rate for four types of emotions (joy, sorrow, relax and anger) is 67.7%. Ryu *et al.* (1997) proposed an EEG-based discrimination between "Yes" and "No" using SVM to classify features extracted using FFT in which the recognition rate is up to 80%. Takahashi and Tsukaguchi (2005) compared the performance of NN and SVM in recognizing two emotions: pleasure and displeasure. Using statistical features, the recognition rates of 62.3% with NN as the classifier and 59.7% with the SVM are achieved. Takahashi (2004) proposed an emotion recognition system using SVM as classifier and statistical features are computed from the EEG raw signal. In experiments of recognizing five emotions: joy, anger, sadness, happiness and relax, the recognition rate is 41.7%. Khalili and Moradi (2009) proposed a fusion scheme between EEG and peripheral signals (galvanic skin resistance, respiration, blood pressure and temperature) for emotion detection. Statistical features were extracted from EEG signals and QDA classification technique was applied in emotion recognition. The classification rate was further improved through the inclusion of nonlinear (correlation dimension) features in the EEG signals. In recent researches, Wang *et al.* (2011) used movie elicitation to classify four types of emotion (joy, relax, sad and fear) based on time domain (statistical) and frequency domain features and achieved average accuracy of 66.51% through *k*NN, multilayer perceptron and SVM classification schemes. Murugappan *et al.* (2010) combined surface Laplacian filtering, wavelet transform and statistical features to classify 5 discrete emotions (happy, surprise, fear, disgust and neutral) and achieved maximum average classification rate of 83.04% (on 62 channels) and 79.17% (on 24 channels) by using *k*NN classification scheme. The results were compared to other published works (Teixeira *et al.*, 2009; Khalili and Moradi, 2009; Charles and Zlatko, 1996; Wanpracha *et al.*, 2007; Kristina and Tanja, 2009; Panagiotis and Leontios, 2009) where the maximum classification rate ranges from 47.11% to 82.27% with 2 to 4 types of emotion and the subject size ranges from 2 to 17.

This study focuses on the study of effectiveness of statistical features on emotion classification using EEG signals. Similar research from Takahashi (2004) used 6 statistical features from 3 bio-potential signals (EEG, pulse and skin conductance) respectively to classify human emotions. Results showed that not all emotions had achieved improvement in classification rate compared to using single bio-potential signal. Besides that, using all statistical features in classification might lead to longer processing time. Thus, the efficiency of

all the 6 basic statistical features on EEG emotion classification will be studied and evaluated in this study. In the past decades, the outcomes of the researches revealed that the classification rates range from 41.7% to 83.04% for 7 major emotions are still far from satisfactory and practicality. In this study, we aim to reduce the complexity and focus on only 4 main human emotional states in nature (Nawrot, 2003): Anger, Happy, Sadness and Neutral for classification. Six types of statistical feature vectors are first extracted from the EEG signals. Various combinations among the features are formed to classify the four main emotional states. The efficiency of each of the statistical features as well as combinations will be studied based on the classification rate generated by artificial neural networks without prior processing. An overall improvement of 5% on the classification rate has been achieved by combining the two most significant features with the highest success rates from the individual efficiency studies.

## EEG DATA ACQUISITION

This section describes the development of a database of physiological feature patterns acquired using the EEG under emotions stimulation experiments.

**Emotion elicitation:** The prevalent strategy of requiring an actor to feel or express a particular mood has been widely used for emotion assessment from face expressions as well as physiological signals (Min *et al.*, 2005). However, it is difficult to ensure the physiological responses are consistent or reproducible by non-actors, thus, actor-play database are often far from real emotions found in our daily lives (Chanel *et al.*, 2005).

Alternately, the approach of inducing emotions by presenting stimuli either by visual, audio or combination of both stimuli has the advantage of producing responses that are closer to real life. In this study, visual stimuli are employed where a set of emotion database is acquired using adult facial stimuli (Minear and Park, 2004). Each of the images is evaluated by the subjects as the emotions induced during the experiments may differ from the ones expected. This may be likely due to individual differences in past experience and personal understanding (Chanel *et al.*, 2005).

**Protocol of experiment:** The data is acquired from 6 subjects (3 males and 3 females, aged from 23 to 26 years old) and tested for four main emotion states. This is comparable to the subject size (5 to 20) and types of emotion (3 to 5) in the published works (Murugappan *et al.*, 2010; Teixeira *et al.*, 2009; Khalili and Moradi, 2009; Charles and Zlatko, 1996; Wanpracha *et al.*, 2007; Kristina and Tanja, 2009; Panagiotis and Leontios, 2009). The recording is done through Nervus

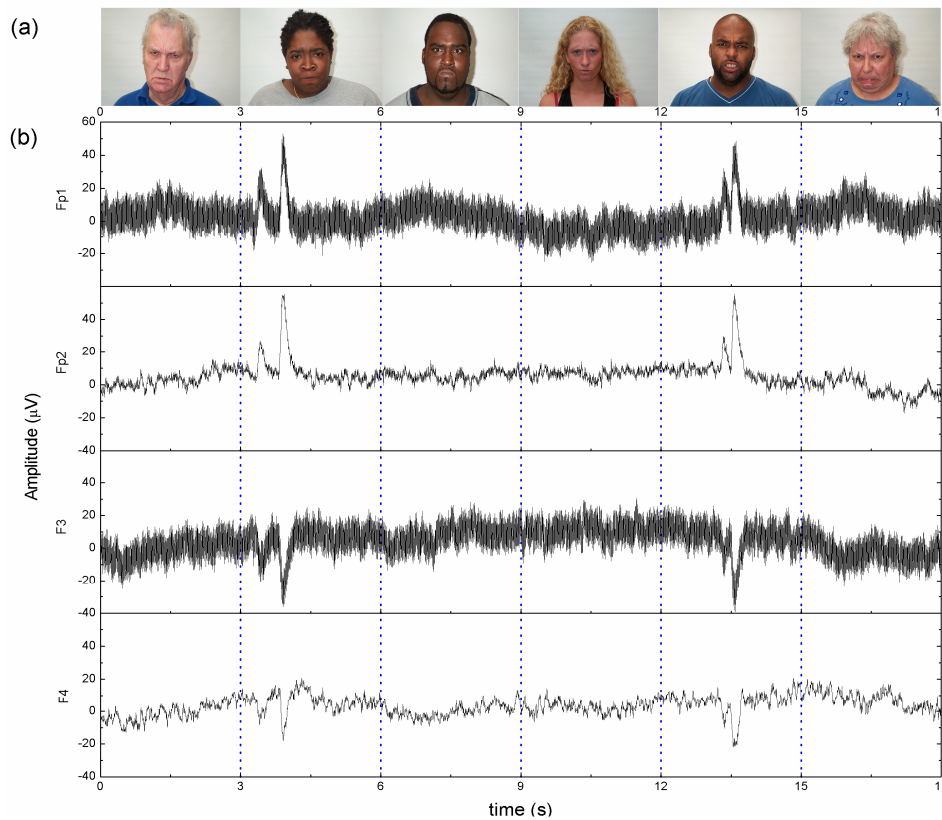


Fig. 1: (a) 6 images of facial stimuli representing anger (Minear and Park, 2004) and (b) the raw EEG data (only signals from 4 electrodes Fp1, Fp2, F3 and F4 are shown) of subject 1

EEG, USA with 64 channel electrodes which includes 2 Electrooculogram (EOG) electrodes for eye blinks and movements detection. The raw signals were sampled at 256 Hz rate. All the electrodes are placed over the entire scalp using International standard 10-20 system. The impedance of the electrodes is kept below 5 k $\Omega$ .

In each experimental recording, 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. A slide of instructions is first displayed for 10 sec to prepare the subject for the experiment which includes: reminder for subjects to minimize movements and eye blinks. A set of 4 images consisting relaxing sceneries is presented for a period of 20 sec 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 (Minear and Park, 2004) are displayed for 18 sec each to stimulate one emotion. In between each set, a dark screen is displayed for 5 sec to facilitate a short 'rest' period for the subject. After running the two sets of visual stimuli, a dark screen is shown for 45 sec and soothing music is played for the subject to relax and prepare for the next emotion stimuli. The experiment is

continued with the 'neutral' stimuli and the flow of stimuli as described above is repeated for the stimuli of 3 types of emotions: 'happy', 'anger' and 'sadness'. Figure 1 shows the raw EEG signals of Subject 1 for a duration of 18 sec when 6 angry images of facial stimuli were presented to the subject. The spiky responses observed at around 4 s and 14.5 s were probably due to the subject being overreacted to the change in facial stimuli. An emotion assessment is carried out after the whole flow for the subjects to describe the particular emotions aroused when the stimuli are shown and rate the strength of the emotions felt as well as noting down if multiple emotions were aroused during the display of a particular emotion stimuli'

**Assessment results:** The results of assessment for the emotion elicitation experiment are as shown in Table 1 and 2.

Table 1 shows the results of the emotions recognized and categorized by the subjects based on the visual stimuli. For example, when stimulus for the emotion 'anger' is viewed, 66.67% of the subjects correctly classified the stimulus as 'anger'. Table 2 shows the ratings of strength of the emotions felt when viewing the stimuli. For example, the ratings for emotion 'anger': 33.33% of the subjects rated the

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

In/out	Anger	Happy	Sadness	Neutral	No emotion
Anger	66.67	0.00	16.67	16.67	0.00
Happy	0.00	83.33	0.00	16.67	0.00
Sadness	0.00	0.00	83.33	0.00	16.67
Neutral	0.00	0.00	0.00	100.00	0.00

Table 2: Ratings of emotions elicited 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

emotion ‘anger’ that they felt was ‘very weak’, 16.67% rated ‘moderate’, 16.67% rated ‘strong’ and 33.33% rated ‘very strong’.

### 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 Xn represents the value of the nth sample of the raw signal, where , with N = 1024 (1024 samples corresponds to 4 sec of the EEG recording). In this study, six statistical features are computed from the EEG data (Picard *et al.*, 2001; Takahashi and Tsukaguchi, 2005) and investigated:

The means of the raw signals:

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

- The standard deviation of the raw signals:

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

- The means of the absolute values of the first differences of the raw signals:

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

- The means of the absolute values of the first differences of the normalized signals:

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

- The means of the absolute values of the second differences of the raw signals:

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

- The means of the absolute values of the second differences of the normalized signals:

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

The features chosen can cover and extend a range of typically measured statistics in the emotion physiology literature (Vyzas and Picard, 1998). Means and variance are commonly computed features while the first difference of the signals approximates a gradient. Not all the chosen features here are independent; in particular,  $\tilde{\delta}_x$  and  $\tilde{\gamma}_x$  are derived by normalizing  $\delta_x$  and  $\gamma_x$  through a factor  $\sigma_x$ . To investigate the relationship between common, independent and derived statistical features, a few combinations of statistical feature vectors are shown as below:

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

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

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

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

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

### EEG CLASSIFICATION

Artificial neural network is an information processing paradigm that is inspired by the way biological nervous system (human brain) works (Ishino and Hagiwara, 2003). Neural network comprises of processing elements which are in the form of 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 (Ishino and Hagiwara, 2003).

In this study, two separate cases are studied using neural network. In the first case, each of the computed statistical features is individually fed into neural network with parameters as shown in Table 3. In the second case, combinations of statistical features are developed and fed into neural network with parameters as shown in Table 4.

Table 3: Parameters of neural network for individual statistical features

Number of input layer units	1
Number of hidden layer units	20
Number of output layer units	2
Learning rate	0.01
Maximum epoch	10000
Learning goal	0.01

Table 4: 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	2
Learning rate	0.01
Maximum epoch	10000
Learning goal	0.01

The number of input learning data is 30 for each emotion, amount to 120 and the neural network is tested with 60 data from each emotion, amount to 240. The target output for each emotion is set as ‘00’ for ‘anger’, ‘01’ for ‘happy’, ‘10’ for ‘sadness’ and ‘11’ for ‘neutral’. 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.

## RESULTS AND DISCUSSION

Table 5 shows the results of classification rate and time consumption of six statistical features individually. The effectiveness of each type of statistical feature is tested in terms of classification rate and time needed by neural network in the learning process. In this case, the highest classification rate of 85.00% can be achieved using  $\gamma_x$  in Eq. (5) and the time consumed by the neural network for learning process is comparatively high: 9.15 sec. In terms of fastest learning process,  $\mu_x$  achieved the lowest processing time but the overall classification rate is only 49.17%, the second lowest performance among all individual statistical features.

This study also investigated combinations of statistical features in the attempt to increase the classification rate as well as investigate the penalty in time needed for the learning of neural network. Table 6 shows the results obtained for the combinations of statistical features. From the results, it is shown that the classification rate can be improved by using combinations of features instead of individual features, achieving correct classification from 50.83% to 90.00% but relatively more time is consumed in the learning process for combination of features (6.34 sec to 20.14 sec) compared to individual features (3.23 sec to 18.74 sec).

The highest classification rate is achieved by combining the two highest individual statistical feature classification rate ( $\delta_x$  of 80% and  $\gamma_x$  of 85%), achieving 90.00% in overall correct classification with neural network time consumption of 9.02 sec. Table 7 shows

Table 5: Overall classification rate and time consumption for individual statistical features

Statistical features	Time consumption (s)	Classification rate (%)
$\mu_x$	30.23	49.17
$\sigma_x$	18.74	55.00
$\delta_x$	60.80	80.00
$\tilde{\delta}_x$	50.22	47.50
$\gamma_x$	90.15	85.00
$\tilde{\gamma}_x$	40.00	52.20

Table 6: Overall classification rate and time consumption for combinations of statistical features

Combinations	Time consumption	
	(s)	Classification rate (%)
$X_1 = [\mu_x \sigma_x]$	9.14	50.83
$X_2 = [\delta_x \gamma_x]$	9.02	90.00
$X_3 = [\tilde{\delta}_x \tilde{\gamma}_x]$	6.34	64.17
$X_4 = [\delta_x \tilde{\gamma}_x]$	20.14	68.33
$X_5 = [\gamma_x \tilde{\gamma}_x]$	16.05	68.33

Table 7: Classification result for the combination of  $[\delta_x \gamma_x]$  [%] (Highest overall classification rate among combinations)

In/out	Anger	Happy	Sadness	Neutral
Anger	93.33	3.33	1.67	1.67
Happy	1.67	95.00	0.00	3.33
Sadness	0.00	0.00	100.00	0.00
Neutral	5.00	0.00	3.33	91.67

the classification result based on emotions for this combination. 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 91.67% to 95.00%, which means some of the inputs were mistaken for the wrong emotion, producing incorrect outputs. Combinations of two features are suggested over all six features to be used jointly to reduce the complexity due to high dimensionality for the learning process by neural network. The result shows that combinations of two features are effective in the task of classifying emotions in achieving high classification rate using neural network.

## CONCLUSION

The preliminary results presented in this study paper have suggested that statistical features can be used effectively in the attempt of classifying basic emotions using the EEG. With the right combination of features, classification rate as high as 90% is achievable by using neural networks. The results have also proven that it is possible to differentiate and classify basic human emotions better by using the combination of first and second difference of the raw signals without prior processing. The linear and derived statistical features in this study can be easily computed and advantageous for online applications. Future work should emphasize in the development of an algorithm for the classification of more emotional states, achieving high accuracy with less time consumption and complexity.

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