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Correlation between Stimulated Emotion Extracted from EEG and its Manifestation on Facial Expression

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***Abstract*- Determining correlation between aroused emotion and its manifestation on facial expression, voice, gesture and posture have interesting applications in psychotherapy. A set of audio-visual stimulus, selected by a group of experts, is used to excite emotion of the subjects. EEG and facial expression of the subjects excited by the selected audio-visual stimulus are collected, and the nonlinear-correlation from EEG to facial expression, and vice-versa is obtained by employing feed-forward neural network trained with back-propagation algorithm. Experiments undertaken reveals that the trained network can reproduce the correlated EEG-facial expression trained instances with 100 % accuracy, and is also able to predict facial expression (EEG) from unknown EEG (facial expression) of the same subject with an accuracy of around 95.2%.**

***Keywords*- Facial expression, EEG, Nonlinear Correlation, Feed-forward neural learning**

I. INTRODUCTION

Psychologists are of the opinion that arousal of emotion and its manifestation in facial expressions, voice, gesture and posture may not always go together. The process of emotion arousal takes place due to substantial changes in ones personal situations [9]. Manifestation of emotion depends on both the users' feeling of the emotion and his/her intention to exhibit it in gesture and posture [6]. Consequently, in presence of emotions, sometimes its manifestation is absent. On the other hand, people may intentionally exhibit false emotion on their facial expression and voice, even when they do not experience such emotions. The paper attempts to determine correlations between the arousal of emotion and its manifestation on the facial expression. Since the electrical activity of the neurons in the human brain can be predicted from the EEG, we in this paper use the EEG measurements as the primary information for emotion classification. The process of determining correlation between emotion arousal and its manifestation is realized here in two distinct steps. In the first step, we extract features from the EEG and the facial expressions. In the latter phase, we tried to establish a non-linear relationship between the features of the EEG and the facial expressions by employing a feed-forward neural net.

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In our experiments, we aroused emotion of the subjects by audio-visual stimulus. An expert group, comprising movie -makers and -critics was appointed to classify these stimuli into different emotive classes. In other words, stimulus taken from a given class always excites emotions of the same class. Naturally, we can clearly determine the class of the EEG signals from the class of the stimulus.

As an example, a stimulus for anger is expected to yield an EEG signal indicative of anger. In case the facial expression of the subject falls in the same class of the stimulus (i.e., the subject has no pretension), we use both the EEG and the facial expression to determine their correlations. The classification of facial expression to determine its emotion class is already reported in our previous work [4], and is not discussed here for space restriction.

Our initial experiment with a large numbers (≈100) of subject reveals that a given stimulus usually arouses similar EEG pattern at a specific electrode location (F_3/F_4) [11] using the 10-20 system. The experimental findings indicate that EEG patterns provide significant information to recognize emotions of the subjects under test. Consequently, a correlation between aroused emotion and facial expression can be approximated as the correlation between EEG and facial expression. Further, if a correlation between EEG to facial expression is established, we can easily obtain the facial expression of the subject from the EEG of the same emotion class. On the other hand, if a correlation from facial expression to EEG signal can be established, we can also predict the EEG, when the facial expression of the subject is known. The paper opens up many new applications in psychotherapy, where the predicted EEG signal from facial expression might be of some use to the doctors to diagnose possible psychotherapeutic diseases.

The paper is divided into seven sections. Section II presents an experimental set-up for the overall system. In section III we present a scheme for stimulus selection by taking into consideration the opinion of different movie-experts. Feature extraction from EEG, and facial expression is covered in section IV. Elimination of Correlation from EEG data by PCA is undertaken in section V. Mapping from EEG to facial expression and vice-versa is introduced in section VI. Conclusions are listed in section VII.

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II. EXPERIMENTAL SET-UP

The experimental set-up includes a PC-based stimulator, capable of presenting audio-visual stimulus to the subjects to excite different emotions. A 10-20 EEG system [11] is used to record EEG signal at F_3 (or F_4) electrode position, and a high-resolution pan-tilt type camera is used to capture the facial expression of the subjects during the period of the audio-visual presentation. The recorded EEG signals and the facial expressions for each stimulus-input are analyzed, and a set of features is extracted from both the EEG and facial image data. A supervised neural learning algorithm is used to establish a correlation between the features of the recorded EEG and the facial expression, and vice-versa (Fig. 1).

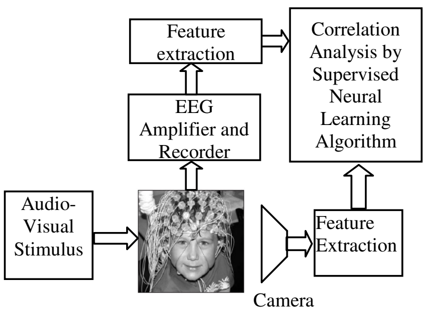


Fig. 1 Experimental set-up for correlation estimation.

III. STIMULUS SELECTION

Prior experiments were undertaken over the last two years to identify the appropriate audio-visual movie clips that cause arousal of five different emotions: anxiety, disgusting, fear, happiness, and sadness.. A questionnaire was prepared to determine the consensus of the observers about the arousal of the above five emotions using a given set of audio-visual clips. It includes questions to a given observer on the percentage level of excitation of different emotions by a set of sixty audio-visual movie clips. The independent response of 50 observers from different students, faculties, non-teaching staff and family members of the staff of Jadavpur University were taken, and the results obtained from the questionnaire is summarized in the format of Table I. It is apparent from Table I that row- sum assigned to the emotions by a subject should be hundred.

To identify the right movie clip capable of exciting specific emotion, we now need to define a few parameters with respect to Table I, which would clearly indicate a consensus of the observers about an arousal of the emotion.

Let

$O_{ji,\ k}$= percentage level of excitation of emotion j by an observer k using audio-visual clip i,

E_{ji} = Average percentage score of excitation assigned to emotion j by n-no. of observers using clip i,

σ_{ji}=standard deviation of the percentage score assigned to emotion j by all the subjects using clip i,

n= total no. of subjects, assessing emotion arousal.

TABLE I: ASSESSMENT OF THE AROUSAL POTENTIAL OF SELECTED AUDIO-VISUAL MOVIE CLIPS IN EXCITING DIFFERENT EMOTIONS

Subjects used to assess the emotion aroused by the audio-visual clips	Title of audio-visual clip	**Percentage of arousal of different emotions by a clip**					
		Anger	Anxiety	Happiness	Sadness	Fear	Relax ation
Subject 1	Clip 1	0	0	80	0	0	20
Subject 2	Clip1	0	0	75	0	0	25
………	……….						
Subject 50	Clip1	0	0	78	0	0	22
………..							
Subject 1	Clip 2	0	82	0	9	9	0
Subject 2	Clip 2	0	80	0	12	8	0
………..	……….						
Subject 50	Clip 2	0	84	0	10	6	0
Subject 1	Clip 60	78	10	0	0	12	0
Subject 2	Clip 60	80	16	0	0	4	0
………	……….						
Subject 50	Clip 60	84	8	0	0	8	0

Then E_{ji} and σ_{ji} are evaluated using the following expressions.

$$E_{ji}= \sum_{k=1}^{n} O_{ji,\ k} / n \qquad (1)$$

$$\sigma_{ji} = \sqrt{[\sum_{k=1}^{n} (O_{ji,\ k} - E_{ji})^2/n]} \qquad (2)$$

Now, to determine E_{wi}, i.e. the largest percentage average assigned to an emotion using audio-visual clip i, we compare E_{ji}s, and identify E_{wi}, such that $E_{wi} >= E_{ji}$ for all j. Consequently, the emotion w, for which $E_{wi} >= E_{ji}$ for all j, is the most likely aroused emotion due to excitation by audio-visual clip i. The above process is then repeated for 60 audio-visual clips, used as stimulators for the proposed experiments.

We next select only six audio-visual movies from the pool of 60 movie samples, such that the selected movies best excite six specific emotions. The selection was performed from the measure of average to standard deviation ratio for competitive audio-visual clips used for exciting the same emotion. The audio-visual clip for which the average to standard deviation ratio is the largest is considered to be the most significant sample to excite a desired emotion. We formalize this as follows.

For a specific emotion m, we determine E_{mi}/σ_{mi} where the audio-visual clip i best excites emotion m, i.e., $E_{mi} >= E_{ji}$, for any emotion j. Now, to identify the clip k that receives the best consensus from all the subjects, we evaluate E_{mi}/σ_{mi} for all possible clips i that best excites emotion m. Let S be the set of possible samples, all of which best excite emotion m. Let k be a sample in S, such that $E_{ki}/\sigma_{ki} >= E_{mi}/\sigma_{mi}$ for $i \in S$. Then we consider the k-th audio-visual movie sample to be the right choice to excite emotion m. This process is repeated to identify the most significant audio-visual movie sample for the stimulation of individual emotions.

Fig. 2 presents the five most significant audio-visual movie clips selected from the pool of 60 movies, where each clip obtained the highest consensus to excite one of five different emotions. The selected clips are presented before eight hundred people, and their facial expressions are recorded for the entire movie. The facial expressions of the subjects recorded for the respective stimulus of Fig. 2 are given in Fig. 3 for one lady in the age group 22-25 years.

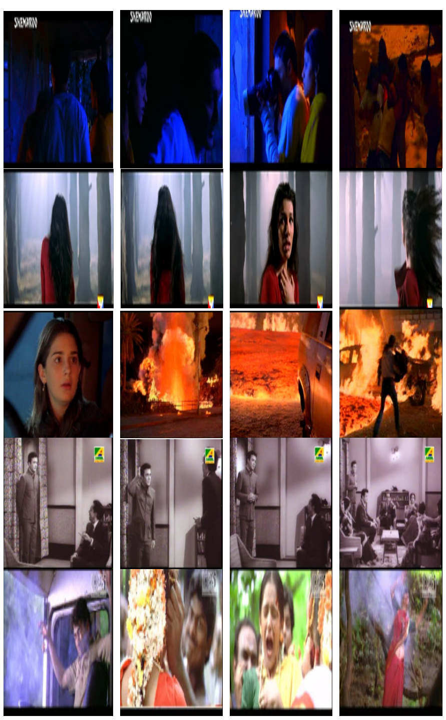


Fig. 2: Movie clips containing four frames (row-wise) used to excite anxiety, disgust, fear, happiness and sadness.

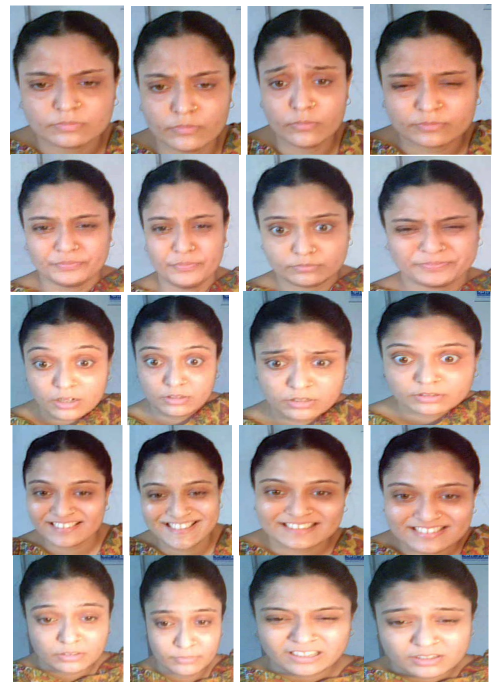


Fig.3 Arousal of anxiety, disgust, fear, happiness, and sadness (row-wise) using the stimulations given in Fig. 2 in order.

IV. FEATURE EXTRACTION

Extraction of features from EEG, voice and facial expression is indeed very important to recognize emotions. In this section, we present a list of features for different bio-potential signals, and employ principal component analysis to reduce the dimensionality of the extracted feature vector.

A. Feature Extraction from EEG Data

Both time- and frequency- domain features are extracted from the EEG signal. The frequency-domain features include peak power and average powers of δ (0-4 Hz), θ (4-8Hz), lower α (8-10Hz), upper α (10-12Hz), β_1 (12-16Hz), β_2 (16-24Hz), γ (24-32 Hz) bands [2], [9], while the time-domain features include 16 Kalman filters coefficients, and spatio-temporal features include 132 wavelet coefficients.

B. Feature Extraction from Facial Expression

Before extracting facial features, we need to segment and localize mouth region, eye region and eyebrow region, and then determine eye opening, mouth opening, and eyebrow constriction, details of which are given in [8]. Next, we fuzzify mouth opening, eye opening, and eyebrow constriction in three fuzzy sets: HIGH, LOW, and MODERATE as indicated below.

$$\mu_{HIGH}(x) = 1 - \exp(-a\,x),\ a>0,$$
$$\mu_{LOW}(x) = \exp(-b\,x),\ b>0,$$
$$\mu_{MODERATE}(x) = \exp[-(x - x_{mean})^2 / 2\sigma^2]$$

where $x \in \{mo, eo, ebc\}$ and a, b, c, x_{mean} and σ are fixed experimentally. These fuzzified features are used to represent facial expressions in the subsequent part of this work.

V. ELIMINATION OF CORRELATION FROM EEG FEATURES BY PRINCIPAL COMPONENT ANALYSIS

Let X be a vector of $(n \times 1)$ dimension, containing n number of features of an EEG signal. Then for five emotions we have a vector Y of $(n \times 5)$ dimension. We now evaluate a matrix $\varphi = Y\,Y^T$, of $(n \times n)$ dimension. Next we evaluate eigen values: $\lambda_1, \lambda_2, \lambda_3, \ldots\ldots, \lambda_n$. Let $\lambda_1 > \lambda_2 > \lambda_3 > \ldots\ldots > \lambda_n$. We now determine the eigen vectors corresponding to the first k eigen values: λ_1 through λ_k where $k << n$, and group these eigen vectors to construct a matrix M, whose i^{th} column denotes the eigen vector corresponding to λ_i. The eigen vector matrix M is given by

$$M = [\,EV_1\ \ EV_2\ \ \ldots\ \ EV_k]_{(n \times k)}. \quad (3)$$

Given an unknown EEG vector of $(n \times 1)$, we can project the EEG vector in k-dimensional space by multiplying EEG vector by M [1]. Let the result be F. So,

$$F_{(k \times 1)} = M^T_{(n \times k)} \times EEG_{(n \times 1)} \quad (4)$$

VI. MAPPING FROM EEG TO FACIAL EXPRESSION AND VICE-VERSA

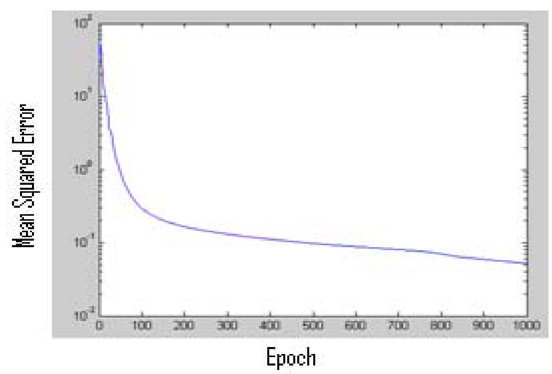
In this section, we present a scheme for mapping features from EEG data to facial expression and vice-versa. Any supervised learning algorithm can realize this. In this paper, we employed back-propagation neural learning algorithm with momentum for training the EEG-facial/voice features to the network. After the training is complete, we can use this network for mapping EEG space to facial expression space. In other words, given an unknown EEG vector, we can determine the features of facial expression by using the trained neural networks. This helps reconstruction of facial expression from EEG data.

In our experiments, we took three hidden layers and an output layer. Transfer functions for the hidden layer were tansigmoid while that in case of the output layer was linear. There were 50 neurons in each of the hidden layers, while the number in case of output layer was equal to the dimension of the target (output) vectors, 18 in case of facial expression data and 40 in case of EEG data. If input has n dimension, the input matrix was multiplied with an $n \times 50$ weight matrix and this was fed to the first layer of neurons.

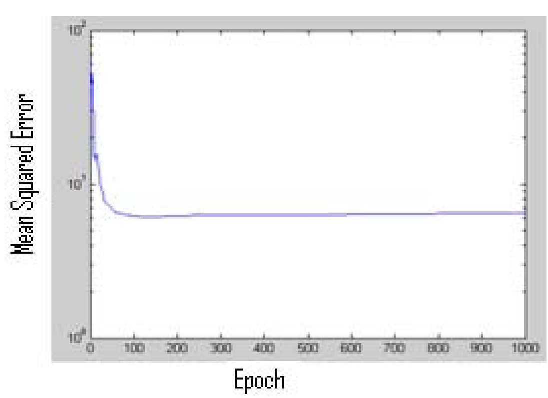
The weight matrices were of dimension $n \times 50$, 50×50, 50×50, $50 \times m$ where n=dimension of input data and m=dimension of target (output) data. Bias matrices were of the dimension 1×50, 1×50, 1×50, $1 \times m$, where m=dimension of target (output) data. All the elements of the weight matrices and the bias matrices were chosen as random numbers.

The learning rate and the momentum co-efficient were taken to be 0.05 and 0.9 respectively. Data taken was in the form such that each vector was present in each column. So the input matrix was of dimension $m \times n$, where n=dimension of input data and m=number of input vectors. Same was done in case of target data (matrix).

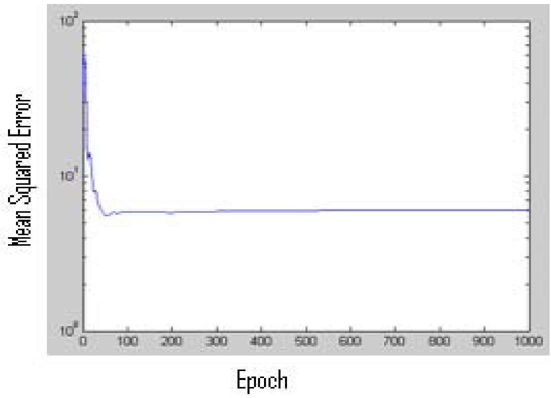
The inputs were divided randomly into three groups, containing 60%, 20% and 20% of the data. The first group containing 60% of the data was used for training the network. The 2nd group, containing 20% of the data was used for validation while the last group containing the rest 20% of the data was used for testing. Training error, validation error and test error were checked separately after each epoch. The error was calculated in the form of Mean Squared Difference between the desired output (target) and the output of the neural network. The best network was taken for which the validation error was minimum. The mean square error plots for training, validation and testing simulated in MATLAB 7.7 are presented in Fig. 4 and 5 respectively for EEG-facial Expression, and facial expression-EEG neural correlation networks.



(a) Plot for training

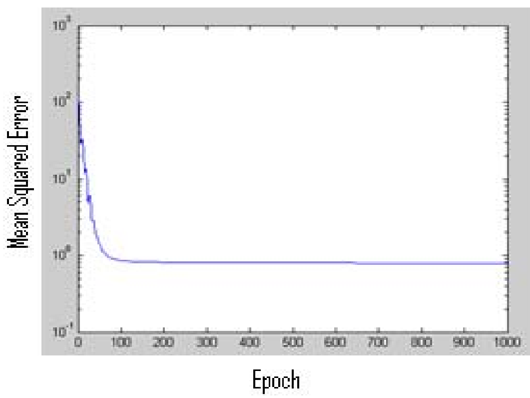


(b) Plot for validation

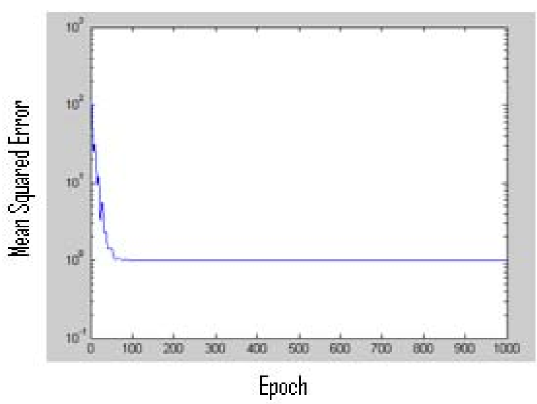


(c) Plot for testing

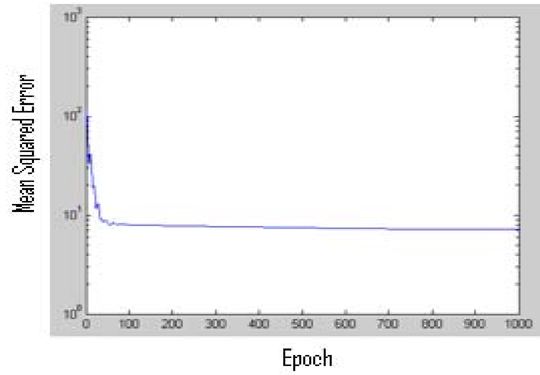
Fig. 4.The mean-square error plots versus learning epoch for the back-propagation neural net with EEG features as input and facial expression features as output.



(a) Plot for training



(b) Plot for validation



(c) Plot for testing

Fig. 5. The mean-square error plots versus learning epoch for the back-propagation neural net with Facial expression features as input and EEG features as output.

A Gaussian type noise with mean zero and standard deviation up to 50% of standard deviation of each feature is added to training EEG instances (facial expression instances), and the correlated facial expressions (EEG) obtained are classified using linear Support Vector Machine classifier. The % mis-classification is found to be 4.8% on a large number of datasets for 100 subjects.

VII. CONCLUSIONS

The paper proposed a novel approach to mapping of evoked related potentials, reliably measured by electroencephalography, to facial expressions, and vice-versa by a neural correlation realized with feed-forward neural networks. The experimental results reveal that training instances could accurately produce all the correlated EEG/facial expression vectors. Further, the robustness of the method is also studied by adding Gaussian noise with zero mean and small variance up to 0.5 units. The experimental results envisage that the noisy correlated EEG-facial expression data could also be correctly recovered to as high in 95.2% cases. The proposed scheme has interesting applications in EEG detection from facial expression for close monitoring of Psychological patients. It is equally useful to fraud detection, as attempting to modify facial expression can be correctly identified, if the training dataset for the individuals is complete [8] [5] [10].

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