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Biometric Emotion Recognition Using Adaptive Neuro Fuzzy Inference System

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Abstract: Automated recognition of facial expression is an important area in computer vision research because of its relevance in the study and development of human-computer interaction (HCI). Extracting and validating emotional cues by facial expression analysis is of high importance for improving the level of interaction in man machine communication systems. Our approach to facial expression recognition is based on a Neuro Fuzzy Inference System. The features of the images are being extracted using PCA technique which calculates the principal components and the neuro fuzzy based system ANFIS is used for classification. The performance of the proposed approach is validated and the result shows the effectiveness of the recognition system.

Key words: Emotion Recognition · Feature Extraction · Classification · ANFIS

INTRODUCTION

Human face plays an essential role in interpersonal communication. The face is the way to understand someone's emotional state on the basis of facial expression. Facial expressions help to coordinate conversation and form the major modality in human communication. Facial expression provides sensitive indication about emotion and plays a major role in human interaction and non-verbal communication. Automating facial expression analysis makes man-machine interaction more efficient. Emotions are a natural and powerful way of communication among the living beings. Interpretation of emotions through facial expression analysis will highly improve the level of interaction in man-machine communication systems. Automatic human emotion recognition is a multidisciplinary area including psychology, speech analysis, computer vision and machine learning. The term affective computing [1] is gaining popularity in the research field of Human Computer Interfaces (HCI) which enables computers to observe, understand and synthesize emotions and to behave vividly. Apart from HCI, emotion recognition by machine vision has many real-time applications like virtual reality, video-conferencing and anti-social intentions and so on. Regarding to these applications arena, emotion recognition through machine vision has attracted much attention.

Automatic facial expression recognition involves two vital aspects: facial feature representation and classification. Facial feature representation is to derive a set of features from original face images. Obtaining an effective facial representation from original face images is the fundamental step for successful facial expression recognition. Two common approaches to extract facial features are geometric feature-based methods and appearance-based methods [2]. In Geometric feature-based methods, the shape and locations of facial components are extracted to form a feature vector that represents the face geometry. Geometric feature-based methods require accurate and reliable facial feature detection and tracking [3]. The Appearance features present the appearance or skin texture changes of the face, such as wrinkles and furrows. The appearance features from either the whole-face or specific regions of a face image [4]. While regarding the classification, many classifiers have been applied to expression recognition such as neural network [5, 6], Support Vector Machine [7, 8], Linear Discriminant Analysis (LDA) [9] and Bayes Classifier [10, 11]. One of the hybrid approaches in classification is Neuro Fuzzy Systems (NFS) which refer to combinations of artificial neural network and fuzzy logic. NFS combines human-like reasoning style of fuzzy systems with the learning and connectionist style of neural network [12]. Adaptive Neuro Fuzzy Inference System (ANFIS) has established itself as one of the

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popular techniques in the field of control systems, expert systems and classification. This hybrid combination enables to utilize both the verbal and the numeric power of intelligent systems [13]. ANFIS is adopted here for accomplishing the training process.

Related Work: The origins of facial expression analysis go back into 19th century, when Darwin proposed the concept of facial expressions in man and animals. Ekman and Friesen [14] provided evidences to support human facial expressions.

The Facial Action Coding System (FACS) was designed to measure all visible facial behavior [15]. FACS distinguishes 44 action units which are minimal units that are fundamental actions of individual muscles or groups of muscles. Any facial movement can be described by a particular action unit or in combination with other units produced it. Ekman and Friesen defined 46 Action Units, or AUs which correspond to each independent motion of the face. FACS separates expressions into upper and lower face action and will describe any visually distinguishable facial action. Black and Yacoob [16] proposed that parametric flow models are related to the motion of facial features during facial expressions and showed how expressions such as anger, happiness, surprise, fear, disgust and sadness can be recognized from the local parametric motions in the presence of significant head motion. Yacoob and Davis [17] utilized optical flow computation to identify the directions of rigid and non-rigid motions that are caused by human facial expressions. Ching-Chih Tsai *et al*. [18] proposed an emotion recognition system which is composed of Harr Wavelet Transform to decrease the image dimension, Principal Component Analysis (PCA) method for finding face candidates and Support Vector Machine (SVM) for face identification and expression recognition. Evaluation of facial representation based on statistical local features, Local Binary Patterns, for person-independent facial expression recognition have been done by Caifeng Shan *et al*. [19]. LBP features were evaluated to describe appearance changes of expression images. Ligang Zhang and Dian Tjondronegoro in 2011 [20] utilized the features of facial element and muscle movements. In this work, facial movement features have been captured in static images based on distance features. The distances are obtained by salient patch-based Gabor features and then performing patch matching operations. Valstar and Pantic in 2012 [21] proposed the recognition of 22 AUs and modeled their temporal characteristics. This method used a facial point detector to automatically localize 20 facial fiducial points. A method called packet filtering with factorized likelihoods is being used to track the points through a sequence of images. In [22], the method proposed is to extract discrete wavelet transform features which are provided to a bank of seven parallel Support Vector Machines (SVMs) each trained for a particular expression class.

Features: Features are categorized into two: facial features and face model features. The facial features are the prominent features of the face – eyes, eyebrows, chin, mouth and nose. The face model features are the features used to model the face. Feature extraction is having key importance to the whole classification process. The two most common approaches to the facial feature extraction are the geometric feature-based methods and the appearance-based methods. Geometric features present the shape and locations of facial components (including mouth, eyes, eyebrows and nose). The facial components or facial feature points are extracted to form a feature vector that represents the face geometry. The appearance features present the appearance (skin texture) changes of the face, such as wrinkles and furrows.

The appearance features can be extracted on either the whole face or specific regions in a face image. The Appearance based representations describe the visual texture of the face regions.

The most well known appearance-based pattern recognition approach is probably the so-called Eigenface method [23]. Face images are considered as vectors that span a low dimensional sub-space of the high-dimensional space of general images. Face images are decomposed into a small set of characteristic feature images called eigen faces. Besides PCA, many other methods which comes under appearance- based methods are LCA, ICA or Wavelet representations.

Proposed Work: The proposed methodology for emotion recognition consists of three stages, namely, preprocessing, feature extraction and classification.

Preprocessing: In the Preprocessing stage, histogram equalization is being done, which is a very popular technique for contrast enhancement. This method is commonly used due to its simplicity and better performance on all types of images. In histogram equalization, remapping the gray levels of the image based on the probability distribution of input gray levels is being performed.

Score Value Calculation Using Principal Component Analysis (PCA): Principal component analysis is a standard technique used in the statistical pattern recognition for data reduction. The pattern may often contain redundant information. Mapping this pattern to a feature vector can get rid of redundant information and also it will preserve most of the intrinsic information of the pattern. The images are given to the next process in order to calculate the score values using Principle Component Analysis (PCA) technique. Principal component analysis transforms a set of data obtained from possibly correlated variables into a set of values of uncorrelated variables called principal components. The number of components can be less than or equal to the number of original variables. PCA can be used to find out the most important abstract features of faces collected in the database. The score values so obtained from the PCA techniques are then used by ANFIS classier.

Principal Component Analysis (PCA): The average (mean) face vector is computed from the set of images. Subtracting the images from the average vector gives the variance which are the distinctive features that separate one image from the rest of images. By this process, the common features will be removed. From this, covariance matrix will be computed, with large dimension.

The algorithm of PCA method is as follows. Consider the training set of M face images f={x_1, x_2,……x_m}of N-dimensional vectors. The average face of the training set is defined by

$$\psi = \frac{1}{m}\sum_{i=1}^{m} x_i$$

The error vector $\Phi_i = x_i - \Psi$, I = 1 to m.

From this matrix say A, the covariance matrix, C, of the training data is given by

$$C = \sum_{i=1}^{m} \Phi_i \Phi_i^T = A\ A^T$$

where A = [$\Phi_1 \Phi_2 \ldots\ldots \Phi_m$]

The eigenvector of the covariance matrix C is computed by

$Cu_k = \lambda_k u_k$,

where u_k is the eigenvector.

The face image vector w_k, called eigenface can be formed using,

$w_i = u_k (x_i - \Psi,)$ i = 1 to m

The Eigen vectors are sorted by decreasing the eigen values. The Eigen vectors with highest eigen values are the principal components of an image. pca(x_1), pca(x_2), pca(x_3), …, pca(x_m) are principal components obtained from the PCA process. These components are then given to ANFIS classifier for classification.

Classification: Fuzzy inference systems (FIS) is a computing frameworks based on the concepts of fuzzy set theory. ANFIS is used for classification phase. ANFIS is a fuzzy inference system (FIS) implemented in the framework of an adaptive fuzzy neural network. It combines the explicit knowledge representation of an FIS with the learning power of artificial neural networks. ANFIS is to integrate the best features of fuzzy systems and neural networks. Using a given input and output data set, ANFIS constructs a FIS whose membership function parameters are adjusted using either a back propagation algorithm alone or in combination with a least squares type of method. Essential parts of a fuzzy inference system consists of five layers which are input layer, fuzzification layer, fuzzy rule layer, normalization layer and defuzzification layer as in Fig.2. The fuzzification unit includes the antecedent fuzzy set of fuzzy rules. The fuzzy rule layer consists of a set of fuzzy rules which receives input from the input layer. The normalization layer calculates the value of the mass firing of all rules based on the current values of all fuzzy variables. Defuzzification layer calculates the value defuzzified of value of the overall fuzzy output of the normalization layer.

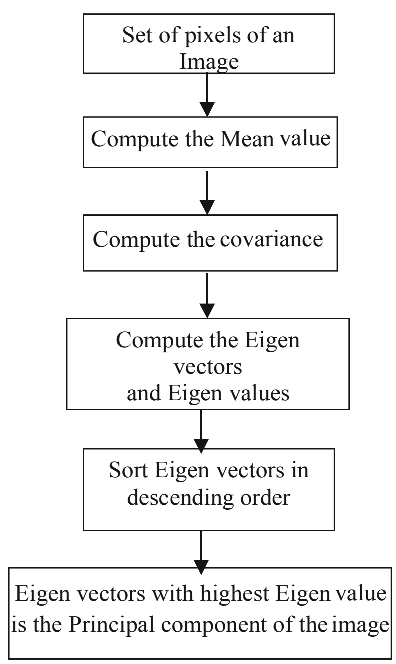

Fig. 1: Methodology of Principal Component Analysis

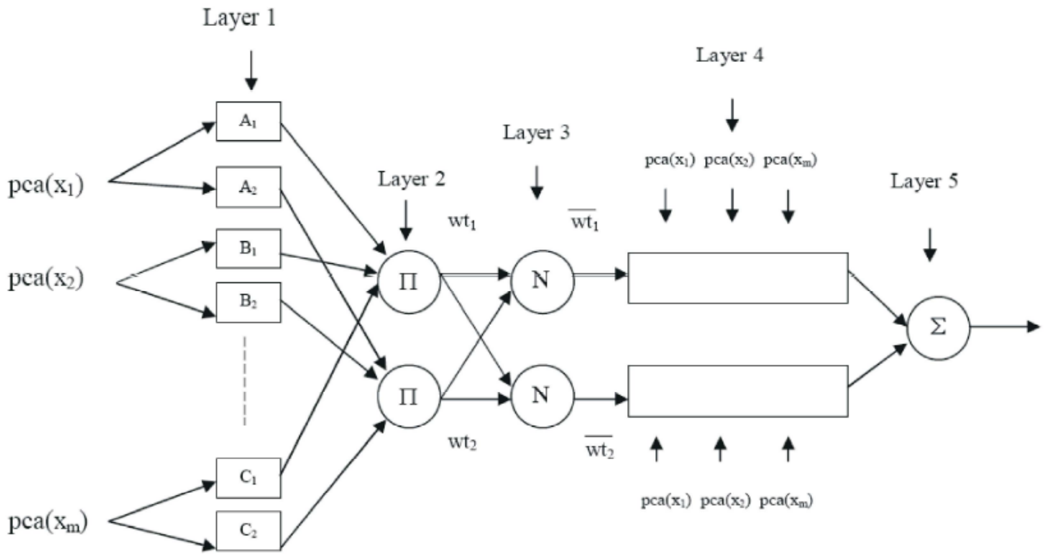

Fig. 2: Architecture of ANFIS Classifier

The learning process of ANFIS is carried out on Eigen vectors.

If pca(x_1) is A_i, pca(x_2) is B_i and pca(x_m) is C_i then
Rules $_i$ = a_i pca(x_1) + b_i pca(x_2) + c_i pca(x_m) + f_i

where pca(f_1), pca(f_2), pca(f_3), ……. pca(f_m) are the inputs. A_i, B_i & C_i are the fuzzy sets, Rules $_i$ is the output within the fuzzy region specified by the fuzzy rule, a_i, b_i c_i and f_i are the design parameters that are determined by the training process.

If two inputs are considered to be x and y, z being the output,

Layer 1: Every node *i* in this layer is a square node with a node function

$$O_i^1 = \mu_{Ai}(x)$$

0_i^1 is the membership function of A_i and it specifies the degree to which the given x satisfies the quantifier A_i

$\mu_{Ai}(x)$ is chosen to be bell-shaped with maximum equal to 1 and minimum equal to 0.

$$\mu A_i(x) = \frac{1}{1 + [\left(\frac{x - c_i}{a_i}\right)^2]^{b_i}}$$

where a_i, b_i c_i are the parameter set. The parameters in this layer are referred to as premise parameters.

Layer 2: Every node in this layer is circle node labeled Π which multiplies the incoming signals and sends the product out.

$$w_i = \mu A_i(x) \times \mu B_i(y),\ i = 1, 2.$$

Each node output represents the firing strength of a rule.

Layer 3: Every node in this layer is a circle node labeled N. The *i*th node calculates the ratio of the *i*th rule's firing strength to the sum of all rules' firing strengths.

$$\bar{w}_i = \frac{w_i}{w1 + w2},\ i = 1, 2.$$

The outputs of this layer will be called *normalized firing strengths.*

Layer 4: Every node *i* in this layer is a square node with a node function

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i)$$

where $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to as *consequent parameters.*

Layer 5: The single node in this layer is a circle node labeled ¢² that computes the overall output as the summation of all incoming signals:

$$O_1^5 = overall\ output = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i},$$

Fig. 3: Sample images from JAFFE database

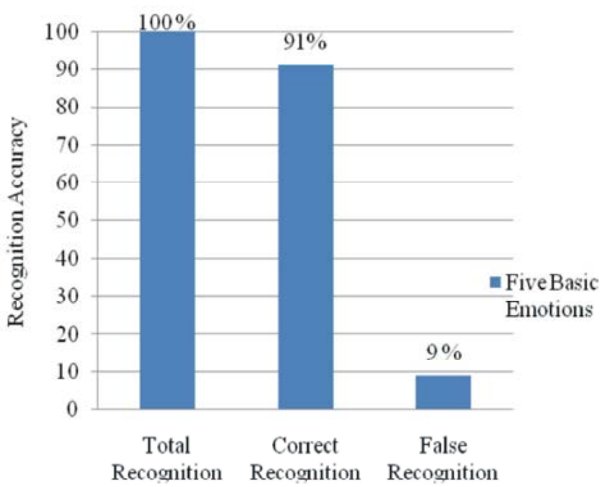

Fig. 4: Overall emotion recognition accuracy for basic emotion categories

The result of the neural network Z is compared with the predefined threshold value. If the neural network output Z is greater than the threshold value, then the given input image is recognized and if Z is less than the threshold value, the image is not recognized. The ANFIS is trained using the score values obtained from PCA. The ANFIS is tested with the images in the database.

Experimental Results and Discussion: The proposed method using the neuro-fuzzy is implemented in MATLAB. A single image is preprocessed using histogram equalization. Then this image is used to calculate the principal components which are given as input to the ANFIS classifier. The data analyzed is based on JAFFE database which is publicly available. All the images in the database are expressing one of the seven basic emotions like Anger, Disgust, Fear, Happy, Neutral, Sad and Surprise.

JAFFE Database: The Japanese female facial expression (JAFFE) database [24] contains 213 gray images of seven facial expressions (six basic and neutral) posed by 10 Japanese females. Each image has a resolution of 256*256 pixels. Each object has three or four frontal face images for each expression and their faces are approximately located in the middle of the images. All images have been rated on six emotion adjectives by 60 subjects.

In conducting the experiment, 213 images in JAFFE database has been used. Figure 3 shows an overall of 91% correctly classified (Fig.4).

CONCLUSION

In this paper, an emotion recognition system using Adaptive Neuro Fuzzy Inference system has been proposed. The feature extraction is being done using the PCA method. The proposed system supports the recognition of seven emotions Anger, Disgust, Fear, Happy, Neutral, Sad and Surprise. Future work will exploit the investigations of these emotions with different databases and the use of more classification techniques.

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