FACIAL EXPRESSIONS RECOGNITION USING EIGEN VECTOR AND EUCLIDEAN DISTANCE

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ABSTRACT : *Within the last several years, Recognition of Human's Facial Expression has been very active research area of computer vision. It has the important role in the human-computer interaction (HCI) systems. In this paper, an Eigenvector based system has been presented to recognize facial expressions from digital facial images. First of all the images were acquired and cropping of three significant portions from the image was performed to extract and store the Eigenvectors specific to the expressions. The Eigenvectors for the test images were also computed, and finally the input facial image was recognized when similarity was obtained by calculating the minimum Euclidean distance between the test image and the different expressions.*

KEY WORDS : Facial Expression Recognition, Facial Expressions, Eigenvectors, Euclidean Distance.

1. INTRODUCTION

Human beings express their emotions in everyday interactions with others. Emotions are frequently reflected on the face, in hand and body gestures, in the voice, to express our feelings or liking. Recent Psychology research has shown that the most expressive way humans display emotions is through facial expressions.

Expressions are a fundamental way to express human emotions and an effective method of non-verbal communication. Psychologist Mehrabian indicated that the verbal part (i.e. spoken words) of a message contributes only for 7 percent to the effect of the message as a whole, the vocal part (e.g. voice intonation) contributes for 38 percent, while facial expression of the speaker contributes for 55 percent to effect of the spoken message. For this aim, automatic recognition of human's facial expressions has been very active research area of machine vision within the last several years. It began from 1970s, when Ekman and Friesen introduced six universal facial expressions that are happiness, sadness, anger, fear, surprise, and disgust.

In addition, they developed Facial Action Coding System (FACS) that is a famous framework which describes human's facial expressions based on action units (AUs).FACS uses 44 AUs which are related to the movement of eyes, eyebrows and mouth show the facial actions. Each expression may be modeled by single action unit or combinations of them. The face recognition methods can be simply classified in to three categories: holistic (global) feature based matching method, local feature based matching method and hybrid matching method. For holistic (global) feature based matching method, the whole face region is used as raw input to the recognition system, like principle component analysis (PCA) projection method and an independent Gabor features (IGF) method were applied to face recognition. For local feature based matching method, local features such as eyes, nose, and mouth are first extracted and then their locations and local statistics (geometric and/or appearance) are fed in to a structural classifier. Geometrical features method and elastic bunch graph matching (EBGM) method belong to this category. For hybrid matching method both global and local features are used for the classification.

2. LITERATURE REVIEW

In 1977, Ekman and Friesen developed a famous and successful facial action coding system. The Facial Action Coding System (FACS) identifies the facial muscles that cause changes in the facial expression thus enabling facial expression analysis. This system consists of 46 Action Units describing the facial behaviors. Gao, Leung, Hui, and Tananda used the line based caricature of the facial expression for the line edge map (LEM) descriptor, measuring the line segment Hausdorff distance between the line caricature of the expression and the LEM of the test face. They achieved an optimal value of 86.6%, showing that the average recognition rate of females was 7.8% higher than that of males. In view of the color features, Lajevardi and Wu presented a tensor based representation of the static color images. They achieved 68.8% accuracy at recognizing expression with different resolutions in CIEluv color space. A neural network is proposed in that compresses the entire face region with 2-D discrete cosine transform. Ma and Khorasani extended this image compression with the constructive one hidden layer neural network with the optimal block size to be 12 and the maximum number of hidden units to be 6, thus achieving the accuracy rate of nearly 93.75%. Researchers have also used the MPEG-4 standard to provide the facial action parameters (FAPs) to represent the facial expressions. Aleksic and Katsaggelos developed a facial expression recognition system utilizing these facial action parameters basically describing the eyebrow and the outer lip features, and classifying up to 93.66% of the test expressions by calculating the maximum likelihoods generated by the multistream hidden markov model (MS-HMM). Huang and He presented a super resolution method to improve the face recognition of low resolution images. They applied canonical correlation analysis (CCA) to obtain the coherent features of the high resolution (HR) and low resolution (LR) images, and employed radial basis functions (RBFs) based non-linear mapping favoring the nearest neighbor (NN) classifier for recognition of single input low resolution image. The recognition rate of their method tested on the Facial Recognition Technology (FERET) face database was 84.4%, 93% for the University of Manchester Institute of Science and Technology (UMIST) database, and 95% for the Olivetti Research Laboratory (ORL) database. The approach of Eigenface method was given by Turk and Pentland. Murthy and Jadon enhanced this method to recognize the expression from the front view of the face, tested for the Cohn-Kanade (CK) Facial Expression database and Japanese female facial expression (JAFFE) database. Zhi, Flierl, Ruan, and Kleijn applied the projected gradient method and developed the graph-preserving sparse non-negative matrix factorization (GSNMF) for extraction of feature verified on different databases. They achieved accuracy of 93.3% recognition for eyes occlusion, 94.0% for nose occlusion, 90.1% for mouth occlusion and 96.6% for images of spontaneous facial expression.

In recent years, automated recognition of facial expression has also gained popularity. Mase and Pentland estimated the activity of the facial muscles using dense optical flow. In this approach was extended combined with the face model, using recursive estimation and achieved an accuracy of 98%. Keith Anderson and Peter W. McOwan used an enhanced ratio template algorithm to detect the frontal view of the face, and chose the multichannel gradient model (MCGM) for the motion of the face. They analyzed their recognition system using support vector machine classifier (SVM) and noted a recognition rate of 81.82%.In, the elastic graph matching (EGM) algorithm has been proposed and the analysis conducted for the feature extraction was a novel 2-class kernel discriminant analysis to improve the performance for the facial expression recognition. The recognition accuracy achieved for the Gabor-based elastic graph matching method was 90.5% whereas for the normalized morphological based elastic graph matching method was 91.8%. Facial expression recognition has been analyzed on visible light images, but constructed a database for recognition of expression from both visible and infrared images. Gabor wavelets were also useful for recognition as it shows the enticing properties of specific spatial location and sparse object representation. Liu and Wechsler presented a Gabor-Fisher based classification for face recognition using the Enhanced Fisher linear discriminant Model (EFM) along with the augmented Gabor feature, tested on 200 subjects. Zhang and Tjondronegoro presented patch-based Gabor feature extraction from the automatically cropped images, in the form of patches. They matched the patches of the input image with the trained images by comparing the distance metrics and classification carried out by four different kernels SVM. The results were seen for two databases, obtaining correct recognition rate of 92.93% for JAFFE database and 94.8% for CK database. Two novel methods were proposed in, first detecting the dynamic facial expressions directly and second, the facial action units based detection. The classification was performed using SVMs. The recognition rate of 99.7% and 95.1% were achieved for both the methods respectively.

3. THEORETICAL BACKGROUND

Eigenvectors and Eigenvalues are dependent on the concept of orthogonal linear transformation. An Eigenvector is basically a non-zero vector. The dominant Eigenvector of a matrix is the one corresponding to the largest Eigenvalue of that matrix. This dominant Eigenvector is important for many real world applications.

Steps used to find the features for expressions:-

Organizing the data set- Consider the data having a set of M variables that are arranged as a set of N data vectors. Thus the whole data is put into a single matrix *X* of dimensions M x N.

Calculating the mean-

$$\mu_x - \frac{1}{N}\sum_{n=1}^{N} X[m,n]$$

Where, μ_x is the mean of the matrix *X*; m and n are indices and m=1, 2… M and n=1, 2… N

Subtracting off the mean for each dimension-

$$X = X - \mu_x$$

The new matrix *X* comprises of the mean-subtracted data. The subtraction of mean is important, since it ensures that the first principal component indicates the direction of maximum variance.

Calculating the covariance matrix-

Covariance has the same formula as that of the variance. Assume we have a 3-dimensional data set (*p, q, r*), then we can measure the covariance either between *p* and *q*, *q* and *r* or *r* and *p* dimensions. But measuring the covariance between *p* and *p*, *q* and *q, r* and *r* dimensions gives the value of variance of the respective *p, q, r* dimension. Variance is measured on a single dimension whereas covariance on multi-dimensions.

For 1-dimension,

$$Cov(x) = Var(x) = \frac{\sum_{i=1}^{N}(X-\mu_x)(X-\mu_x)}{N-1}$$

Where *Var* is the variance matrix;
For 2-dimension say (x, y),

$$Cov(x, y) = \frac{\sum_{i=1}^{N}(X-\mu_x)(Y-\mu_y)}{N-1}$$

Where *Cov(x, y)* is the covariance matrix and μ_y is the mean of another matrix Y.
Calculating the Eigenvectors and Eigenvalues of the covariance matrix- For computing the matrix of Eigenvectors that diagonalizes the covariance matrix *C*

$$E \cdot Cov \cdot E^{-1} = D$$

Where *Cov* is the covariance matrix; *E* is the matrix of all the Eigenvectors of *Cov*, one Eigenvector per column; *D* is the diagonal matrix of all the Eigenvalues of *Cov* along its main diagonal, and which is zero for the rest of the elements.
The Eigenvector associated with the largest Eigenvalue displays the greatest variance in the image while the Eigenvector associated with the smallest Eigenvalue displays the least variance.

4. PROPOSED SYSTEM

The Facial expression recognition system consists of a Camera, Image Pre-processing, Feature Extraction and Classification. Figure shows a block diagram of the Facial expression recognition system.
The block diagram for the proposed system is represented in Figure 1.

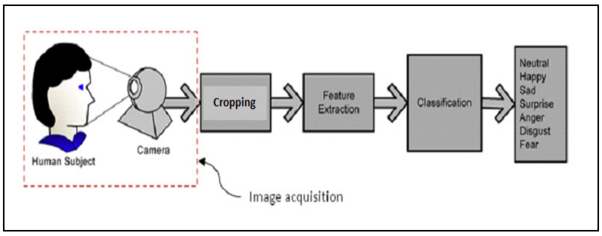


Figure 1 Block Diagram for the Expression Recognition System

A. Image acquisition-
Image acquisition is the first stage of facial expression recognition (FER).In this section image is acquired by digital camera, printer or scanner.

Figure 2 Happy, Surprise, Angry, Disgust

B. Cropping-
Eyes, nose and lips take different shapes for different expressions and significant information is carried by them. So instead of processing the entire face, eyes, nose and lip are processed. Before going for further processing, three significant portions are cropped from the image as shown in Fig. 3 and it shall be called as feature image.

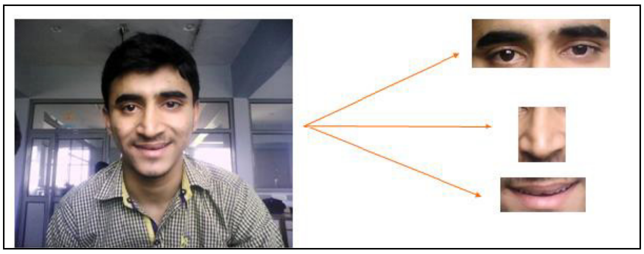


Figure 3 Cropping of eyes, nose and lips

C. Feature extraction-
In this work, the expressions are set into four classes as the training images. Eigenvectors and Eigenvalues of five different individual segments of the image is computed and stored. For a single class, after the selection of a particular feature, a matrix is obtained which is stored as, say L of dimension P x Q. Similarly for the rest of the features also, Eigenvectors and Eigenvalues are computed and stored as a matrix.
First the mean centered feature image vectors is obtained by subtracting the mean from the feature image. This image vectors are depicted as matrix only. Then the covariance matrix of each individual feature image is obtained by calculating the covariance of the matrix of each mean centered image vectors, and from each covariance matrix, the associated eigenvectors and Eigenvalues for the individually extracted features are computed.
Three significant Eigenvectors are considered for further processing which are sorted in the decreasing order of the associated Eigenvalues of the covariance matrix. With the available eigenvectors of expressions, separate subspaces for all the four expressions are created. With the available expression subspaces, the input image could be identified by incorporating a decision making system.
D. Classifier-
The classifier based on the Euclidean distance has been used which is obtained by calculating the distance between the image which are to be tested and the already available images used as the training images. Then the minimum distance is observed from the set of values.
In testing, the Euclidean distance (ED) has been computed between the new (testing) image Eigenvector and the Eigen subspaces for each expression, and minimum Euclidean distance based classification is done to recognize the expression of the input image. The formula for the Euclidean distance is given by,

$$ED = \sqrt{\sum(x_2 - x_1)^2}$$

5. RESULTS AND DISCUSSIONS

The testing process for the expression ‘Happy’ with the eyes being considered is summarized in Table 1. The Eigenvectors are obtained from the input image, then EDs between each Eigenvectors and the reference Eigenvectors of each trained expressions are obtained. If two expressions are same, then ED will be minimum. From minimum ED, a decision can be made of certain expression (in this case it is happy). Since three principal vectors are being considered, there will be three selections. In this case, out of the three vectors, the expression happy has been shown by two Eigenvectors and the expression disgust has been shown by another one Eigenvector.

Table 1. Euclidean Distance (Ed) For the Eyes

TESTING IMAGE	TRAINING IMAGE	ED1	ED2	ED3
 EYES 	 SURPRISE	1.1019	1.5947	0.4928
	 HAPPY	0.1808	1.3151	1.4959
	 ANGRY	1.1128	1.5914	0.4786
	 DISGUST	1.1626	1.5744	0.4118
	RESULT	HAPPY	HAPPY	DISGUST

In Table 2, the testing process for the expression 'Happy', with the nose being considered is summarized. The Eigenvectors are computed from the input image and the EDs are calculated for the Eigenvectors of the input image and the Eigenvectors of the trained images. For the similar two expressions, their Euclidean distance will be minimum. Considering that, the particular expression can be decided. Since three significant vectors are taken into account, three selections are made and from Table 2, it is seen that the expression happy has been shown by two Eigenvectors and the expression surprise has been shown by one Eigenvector.

In Table 3, the testing process for the expression 'Happy', in view of the lips is summarized. The Eigenvectors of the input image are attained. The EDs of each Eigenvectors in reference to the trained expression's Eigenvectors are obtained. The ED of the same two expressions will be minimum of all the EDs. The particular expression can be determined from the minimum ED. In this case, since three principal vectors have been considered, there will be three alternatives. From Table 3, it has been observed that expression disgust, surprise and happy has been selected one time.

Table 2. Euclidean Distance (ED) For the Nose

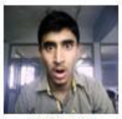
TESTING IMAGE	TRAINING IMAGE	ED1	ED2	ED3
 NOSE 	 SURPRISE	1.5947	0.4928	1.1019
	 HAPPY	1.4959	0.1808	1.3151
	 ANGRY	1.5914	0.4786	1.1128
	 DISGUST	1.5744	0.4118	1.1626
	RESULT	HAPPY	HAPPY	SURPRISE

Table 3. Euclidean Distance (ED) for the lips

TESTING IMAGE	TRAINING IMAGE	ED1	ED2	ED3
 LIPS 	 SURPRISE	0.4928	1.1019	1.5947
	 HAPPY	1.3151	1.4959	0.1808
	 ANGRY	0.4786	1.1128	1.5914
	 DISGUST	0.4118	1.1626	1.5744
	RESULT	DISGUST	SURPRISE	HAPPY

The testing for the four expressions has been performed. Finally, the summarization of the values of the lowest Euclidean distance measured for the different features for the particular expression is given in Table 4. The expression that gets selected more number of times is considered as the decided expression. From this table, it has been observed that the expression 'Happy' has been selected the maximum number of times. Thus, a decision can be taken that the expression in the testing image is 'Happy'.

Table 4. Testing Results

TEST IMAGE	FEATURES	NO. OF VOTES FOR THE SELECTED FEATURES				RECOGNIZED EXPRESSION
		SURPRISE	HAPPY	ANGER	DISGUST	
	EYES	0	2	0	1	
	NOSE	1	2	0	0	
	LIPS	1	1	0	1	
	TOTAL VOTES	2	5	0	2	

6. CONCLUSION AND FUTURE WORK

Euclidean distance based facial expression recognition system is very efficient method for recognition human expression and it will playing essential role in advanced robotics. The system has been proposed using MATLAB version 8.1.0.604 (R2013a) and Intel(R) Core(TM) i3-2330M CPU @ 2.40 GHz processor machine, Windows 7 HP (64 bit), 4 GB RAM and a 1.3 MP camera

It is very challenging part when you discuss about facial expression recognition using machine and our future work is to develop software which will most efficient with real time human interaction.

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