Efficiency Improvent of Facial Expression Recognition Using PCA

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Abstract—*Face recognition and expression analysis is one of the most challenging research areas in the field of computer vision. Though face exhibits different facial expressions, which can be instantly recognized by human eyes, it is very difficult for a computer to extract and use the information content from these expression . In this paper, you will implement a face recognition system using the Principal Component Analysis (PCA) algorithm. Automatic face recognition systems try to find the identity of a given face image according to their memory. The memory of a face recognizer is generally simulated by a training set. In this paper, our training set consists of the features extracted from known face images of different persons. Thus, the task of the face recognizer is to find the most similar feature vector among the training set to the feature vector of a given test image. Here, we want to recognize the identity of a person where an image of that person (test image) is given to the system. You will use PCA as a feature extraction algorithm in this paper.*

Keywords—eigenface, eigenvector, Principal Component Analysis, Euclidian distance

I. INTRODUCTION

Expression is the most important mode of non-verbal communication between people. . PCA is an information theory approach of coding and decoding face images may give insight into the information content of face images, emphasizing the significant local and global "features". Such features may or may not be directly related to face features such as eyes, nose, lips, and hair. We want to extract the relevant information in a face image, encode it as efficiently as possible, and compare one face encoding with a database of models encoded similarly [8]. A simple approach to extracting the information contained in an image of face is to somehow capture the variation in a collection of images, independent of any judgment of features, and use this information to encode and compare individual face images. When we are using Eigen spaces for facial expression recognition of unknown faces, one possibility is to calculate one Eigen spaces for each facial expression from a labelled database of different persons. The classification procedure corresponds to that of face recognition: Project a new image to each Eigen spaces and select the Eigen spaces, which best describes the input image. This is accomplished by calculating the residual description error [8]. However, the problem with facial expression classification is that the person, whose facial expression needs to be classified, is unrecognized. Each person uses a different smile. Nevertheless, each smile of each person should be classified as smile .In order to deal with this fact; we have modified the concept of the Eigen face method so that a separate subspace is formed for each facial expression of the human being, instead of having a single subspace for all expressions as in the original eigenface method. In other words, all six universal facial expressions will have their own expression space as a subspace of the image space. With the expression subspaces available, we could then proceed for recognition of expression in any given image .Like the images for obtaining the expression subspaces, the new image is first turned to the corresponding column vector. We then take the expression subspaces, one at a time, and measure the distances between the new image vector and the subspaces. Whichever expression space having the shortest distance to the input image, the corresponding expression will be designated as the facial expression contained in the input image.

Major difference of our approach from the original eigenface method is that, while in the original eigenface method it is the distance, in the same subspace, between the input image vector and the cluster center of each face identity is used for comparison, here it is the distance between the input image vector and the vector space of each facial expression that is used. These eigenvectors can be thought of as a set of features that together characterize the variation between face images. Each image location contributes more or less of each Eigen vector; so that we can display the eigenvector as a sort of ghostly face which we call an eigenface. Each individual face can be represented exactly in terms of a linear combination of the eigenfaces. Each face can also be approximated using only the"best" eigenfaces-those that have the largest eigenvalues and which therefore account for the most variance within the set of face images. The best M eigenfaces span an M-Dimensional subspace- "face space" – of all possible images. .

II. Mathematical Formula's of PCA

Let the training set of face images be X1, X2, X3…Xn, then the average set or mean of faces be defined as:

Notice that the symbol m to indicate the mean of set X. The average distance of each face from the mean of the data set is given by

Q1=X1-m,Q2=X2-m,…..Qn=Xn-m

Which is the standard deviation?

The covariance matrix is given by

C = A*A'

where A= [Q1 Q2 Q3…………..Qn].

In order to reduce the dimensionality, co-variance can be calculated as

C = A'*A.

Now Eigen values and Eigen vectors are calculated for the covariance matrix. All the face images in the database are projected in to Eigen space and weight for each image is calculated. Then image vectors for each face image is obtained as

$$\text{Image vector} = \sum_{i=1}^{10} \text{Weight}(i) * \text{Eigenvector}(i)$$

Expression Recognition Algorithm
In this algorithm basically there are three steps which we are discussed here:

II. Pre Processing

The image is first processed in order to extract the features, which describe its contents. The processing involves filtering, normalization, segmentation, and object identification. The output of this stage is a set of significant regions and objects. Image pre-processing often takes the form of signal conditioning (such as noise removal, and normalization against the variation of pixel position or brightness), together with segmentation, location, or tracking of the face or its parts. Expression representation can be sensitive to translation, scaling, and rotation of the head in an image. To combat the effect of these unwanted transformations, the facial image may be geometrically standardized prior to classification.
We performed pre-processing on the images used to train and test our algorithms as follows:
1. The location of the eyes is first selected manually
2. Images are scaled and cropped to a fixed size keeping the eyes in all images aligned
3. The image is histogram equalized using the mean histogram of all the training images to make it invariant to lighting, skin color etc.
4. A fixed oval mask is applied to the image to extract face region. This serves to eliminate the background, hair, ears and other extraneous features in the image which provide no information about facial expression.

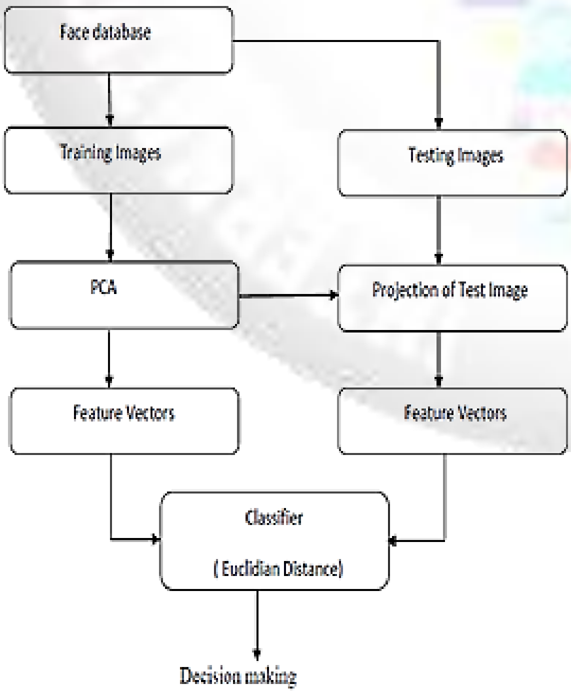

Fig. 2: PCA Flowchart

III. Feature Extraction

Features such as shape, texture, colour, etc. are used to describe the content of the image. Image features can be classified into primitives.

A. Normalized pixel intensities

Every image in our training set is normalized by subtracting the mean of all training set images. The masked region is then converted to a column vector which forms the feature vector. This is a common (albeit naïve) approach and produces a feature vector of length 15,111 elements [9].

B. Constructing Eigenfaces

The feature vectors discussed above suffer from high dimensionality, which can cause over-fitting during classification. One approach to reducing the dimension of the feature vectors is to apply principal component analysis. In [14], eigenfaces are used to generate a mask that eliminates pixels that very little across training samples in different labels. In our system, we modify the approach to generate a separate mask for each expression class. These eigenvectors can be thought of as a set of features that together characterize the variation between face images. Each image location contributes more or less of each Eigen vector; so that we can display the eigenvector as a sort of ghostly face which we call an eigenface. Each individual face can be represented exactly in terms of a linear combination of the eigenfaces. Each face can also be approximated using only the "best" eigenfaces-those that have the largest eigenvalues and which therefore account for the most variance within the set of face images. The best M eigenfaces span an M-Dimension subspace-"face space" – of all possible images. The procedure [13] is as follows:
1. PCA is applied separately to images in each class and the first 10 principal components are stored to represent the class subspace
2. Images of a given class are projected onto all other subspaces and then reconstructed
3. The average reconstruction error is determined for all training samples within a class.
4. Pixels above the 90th percentile rank (i.e. high reconstruction error) are used in the mask for the corresponding class.

This approach stresses those facial regions (and pixels) that are most significant in defining a particular expression.

C. Classifier

EigenFaces are used to classify facial expression. It has been assumed that, facial expression can be classified into some discreet classes (like anger, happiness, disgust or sadness) whereas:
1. Absence of any expression is the "Neutral" expression.
2. Intensity of a particular expression can be identified by the level of its "dissimilarity" from the Neutral expression.

Representing the facial expressions in this way has several advantages. Firstly several kinds of expressions can be represented using only two types of information (1. class that an expression belongs to and 2. intensity of the expression). Secondly, it is possible to identify an expression as a mixture of two or more expressions (such as 60% anger, 20% disgust and 20% sad etc.).

SIMULATION RESULT

In this paper, you will use the JAFFE face database which contains . 145 images of 9 people having 7 different facial expressions are taken for Train images , 66 images for test images. The images for expressions Anger, Disgust , Fear, Happy, Neutral, Sad, Surprise. Training and test set images will be under \train_ images and \test_ images For each subject images (instances) will be put into training set, and the rest of the images will be put into the test set. Directories , respectively reads automatically the images under these directories.

IV. IMPLEMENTATION OF FACIAL EXPRESSION RECOGNISION USING PCA

For the training of the JAFFE database the pictures are classified in thefollowing expression classes. Here JAFFE database has Grey scale images.

1. Image001 to Image020 = Anger
2. Image021 to Image040 = Disgust
3. Image041 to Image062 = Fear
4. Image063 to Image084 = Happy
5. Image085 to Image104 = Neutral
6. Image105 to Image125 = Sad
7. Image126 to Image145 = Surprise

Another image set is used for testing purpose. These images are taken in quite an arbitrary fashion. It also includes some expressions that are not contained in the training set. And then we do the same procedure as above. In this we just use a one feature extraction method which is PCA. Based on this method we got results and those results are we presented here in a tabular form.

V. RESULTS USING JAFFE DATABASE

Test images	distance	Best match
Image01.jpg	8649	Disgust
Image02.jpg	7676	Fear
Image03.jpg	12589	Anger
Image04.jpg	11495	Anger
Image05.jpg	10419	Anger
Image06.jpg	12530	Anger
Image07.jpg	9996	Anger
Image08.jpg	11042	Anger
Image09.jpg	7616	Anger
Image10.jpg	15005	Anger
Image11.jpg	9652	Disgust
Image12.jpg	7552	Disgust
Image13.jpg	8582	Anger
Image14.jpg	7457	Disgust
Image15.jpg	11455	Fear
Image16.jpg	9786	Disgust
Image17.jpg	7738	Disgust
Image18.jpg	11558	Sad
Image19.jpg	9215	Fear
Image20.jpg	7871	Neutral
Image21.jpg	15472	Fear
Image22.jpg	8490	Surprise
Image23.jpg	9847	Sad
Image24.jpg	10769	Surprise
Image25.jpg	7286	Fear
Image26.jpg	9544	Fear
Image27.jpg	7855	Fear
Image28.jpg	8464	Fear
Image29.jpg	9039	Happy
Image30.jpg	8155	Happy
Image31.jpg	13752	Happy
Image32..jpg	10500	Sad
Image33.jpg	11496	Happy
Image34.jpg	8656	Sad
Image35.jpg	8508	Happy
Image36.jpg	8382	Happy
Image37.jpg	12254	Happy
Image38.jpg	10499	Neutral
Image39.jpg	9048	Neutral
Image40.jpg	17434	Sad
Image41.jpg	11392	Neutral
Image42.jpg	11938	Neutral
Image43.jpg	10314	Sad
Image44.jpg	9554	Neutral
Image45.jpg	7974	Neutral
Image46.jpg	8826	Neutral
Image47.jpg	8035	Sad
Image48.jpg	9991	Sad
Image49.jpg	7552	Disgust
Image50.jpg	15519	Sad
Image51.jpg	11347	Sad
Image52.jpg	8274	Disgust
Image53.jpg	9676	Neutral
Image54.jpg	9551	Happy
Image55.jpg	7273	Sad
Image56.jpg	13866	Sad
Image57.jpg	9966	Fear
Image58.jpg	8756	Surprise
Image59.jpg	20496	Surprise
Image60.jpg	11292	Surprise
Image61.jpg	8309	Surprise
Image62.jpg	6490	Surprise
Image63.jpg	7693	Surprise
Image64.jpg	9144	Surprise
Image65.jpg	8164	Neutral
Image66.jpg	12053	Surprise

VI. RESULTS ANALYSIS

For input we have taken total 66 pictures. There are 9 anger faces, 9 disgust, faces, 10 fear faces, 9 happy faces, 11 Neutral face, and 10 Sad faces and 10 surprise faces in the testing set.

EIGENVALUES 1 TO 28								
EXPRESSION	ANGER	DISGUST	FEAR	HAPPY	NEUTRAL	SAD	SURPRISE	ACCURACY
ANGER	7	1	1					78.00%
DISGUST	3	5	1					56.00%
FEAR			6		1	1	2	60.00%
HAPPY				7		2	2	78.00%
NEUTRAL					7	2		78.00%
SAD		2		1	1	6		60.00%
SURPRISE			1		1		8	80.00%

(Confusion Matrix of Algorithm with PCA using JAFFE

Database.) Here higestefficency of surprise images is 80%,anger images is 78%, happy images is 78%,neutral images is 78%.)

VII. CONCLUSION

In this paper we discussed how PCA actually works and how it is use for facial expression recognition which is a novel and effective subtle facial expression analysis approach. We have used the different database and get results.This method gives significant results. But in case of luminance variations in image it will not give satisfactory results. So for best results we have to enhance this PCA method and also we have to combine different methods to get good results. As facial expressions plays important role in human-to-human communication, our future work is to develop a facial expression recognition system, which combines body gestures of the user with user facial expressions.

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