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# Canonical Correlated PCA method For Face Recognition

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***ABSTRACT:*** *Low-resolution (LR) of face images significantly decreases the performance of face recognition. To address this problem, we present a super-resolution method that uses nonlinear mappings to infer coherent features that favor higher recognition of the nearest neighbor (NN) classifiers for recognition of single LR face image. Canonical correlation analysis is applied to establish the coherent subspaces between the principal component analysis (PCA) based features of high-resolution (HR) and LR face images. Then, a nonlinear mapping between HR/LR features can be built by radial basis functions (RBFs) with lower regression errors in the coherent feature space than in the PCA feature space. Thus, we can compute super-resolved coherent features corresponding to an input LR image according to the trained RBF model efficiently and accurately. And, face identity can be obtained by feeding these super-resolved features to a simple NN classifier. The proposed method outperforms the state-of-the-art face recognition algorithms for single LR image in terms of both recognition rate and robustness to facial variations of pose and expression.*

***Keywords***:- *Canonical correlation analysis, face recognition, radial basis function, super resolution.*

## I. INTRODUCTION

A facial recognition system is a computer application for automatically identifying or verifying a person from a digital image or a video frame from a video source. One of the ways to do this is by comparing selected facial features from the image and a facial database. It is very important for these systems to be able to locate or detect a face in a field of vision so that it is only the image pattern of the face (and not the background "noise") that is processed and analyzed. Face Recognition (FR) is an emerging field of research with many challenges such as large set of images, improper illuminating conditions. Eigen face approach is one of the simplest and most efficient methods to overcome these obstacles in developing a system for Face Recognition. Eigen faces are eigenvectors of covariance matrix, representing given image space. Any new face image can be then represented as a linear combination of these Eigen faces. This makes it easier to match any two given images and thus face recognition process. The report gives a basic knowledge of Eigen values and Eigenvectors. It covers various steps involved in face recognition using Eigen face approach along with its significance and some results. It mainly focuses on Eigen face approach for Face Recognition.

It is a very challenging task because the Face detection systems are very sensitive: These are shown in figure 1.1 and 1.2 Pose Variation , Illumination conditions ,Partial or full occlusions ,Image Orientation ,Facial Expressions .

**Figure 1.1: Same image in two different illumination conditions**

**Figure 1.2: Images of two persons with varying facial expressions**

Facial recognition is a visual pattern recognition task. The three-dimensional human face, which is subject to varying illumination, pose, expression etc., has to be recognized. This recognition can be performed on a variety of input data sources such as: A single 2D image, Stereo 2D images (two or more 2D images), 3D laser scans. Also, soon Time of Flight (TOF) 3D cameras will be accurate enough to be used as well. The dimensionality of these sources can be increased by one by the inclusion of a time dimension. A still image with a time dimension is a video sequence. The advantage is that the identification of a person can be determined more precisely from a video sequence than from a picture since the identity of a person cannot change from two frames taken in sequence from a video sequence.

### 1.1 General Difficulties

Face recognition is a specific and hard case of object recognition. The difficulty of this problem stems from the fact that in their most common form (i.e., the frontal view) faces appear to be roughly alike and the differences between them are quite subtle. Consequently, frontal face images form a very dense cluster in image space which makes it virtually impossible for traditional pattern recognition techniques to accurately discriminate among them with a high degree of success.

Furthermore, the human face is not a unique, rigid object. Indeed, there are numerous factors that cause the appearance of the face to vary. The sources of variation in the facial appearance can be categorized into two groups: intrinsic factors and extrinsic ones. A) Intrinsic factors are due purely to the physical nature of the face and are independent of the observer. These factors can be further divided into two classes: intrapersonal and interpersonal. Intrapersonal factors are responsible for varying the facial appearance of the same person, some examples being age, facial expression and facial paraphernalia (facial hair, glasses, cosmetics, etc.). Interpersonal factors, however, are responsible for the differences in the facial appearance of different people, some examples being ethnicity and gender. B) Extrinsic factors cause the appearance of the face to alter via the interaction of light with the face and the observer. These factors include illumination, pose, scale and imaging parameters (e.g., resolution, focus, imaging, noise, etc.).

### 1.2 Face Recognition Design

Eigen space-based approaches approximate the face vectors (face images) with lower dimensional feature vectors. The main supposition behind this procedure is that the face space (given by the feature vectors) has a lower dimension than the image space (given by the number of pixels in the image), and that the recognition of the faces can be performed in this reduced space. This approach considers training, where the face database is created and the projection matrix, the one that achieve the dimensional reduction, is obtained from all the database face images. Also mean face is calculated and the reduced representation of each database image with respect to mean face.

To obtain a super resolute image for face recognition the query image has to pass through some processing steps. Facial recognition systems usually consist of four steps, as shown in Figure face detection (localization), face preprocessing (face alignment/normalization, light correction and etc.), feature extraction and feature matching . These steps are described in the following sections and shown in figure 1.3.

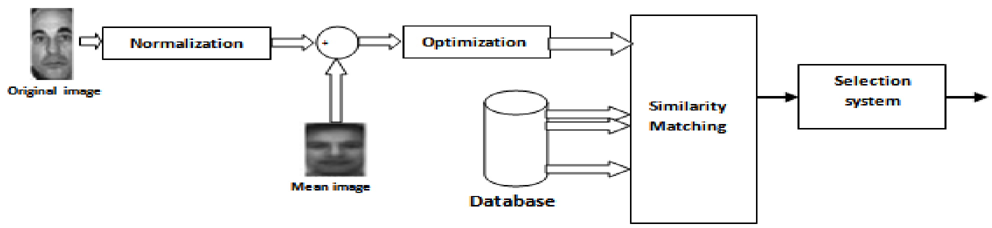



Figure 1.3: Face Recognition System

The Eigen faces approach for face recognition involves the following initialization operations:

1. Acquire a set of training images.

2. Calculate the eigen faces from the training set, keeping only the best M images with the highest Eigen values. These M images define the “face space”. As new faces are experienced, the eigen faces can be updated.

3. Calculate the corresponding distribution in M-dimensional weight space for each known individual (training image), by projecting their face images onto the face space.

Having initialized the system, the following steps are used to recognize new face images:

Given an image to be recognized, calculate a set of weights of the M eigen faces by projecting the it onto each of the eigen faces.

4. Determine if the image is a face at all by checking to see if the image is sufficiently close to the face space.

5. If it is a face, classify the weight pattern as Eigen a known person or as unknown.

## II. EIGEN FEATURES ESTIMATION

Each face image in the training set can be represented exactly in terms of a linear combination of the eigenfaces. The number of possible eigenfaces is equal to the number of face images in the training set. However, the faces can also be approximated using only the “best” eigenfaces those that have the largest eigen values, and which therefore account for the most variance within the set of face images. The primary reason for using fewer eigenfaces is computational efficiency. The most meaningful M eigenfaces span an M-dimensional subspace “face space” of all possible images. The eigenfaces are essentially the basis vectors of the Eigen face decomposition.

### 2.1 Procedure of Recognition system

❖ **Eigenfaces Initialization**

1. Acquire an initial set of face images (the training set)
2. Calculate the Eigenfaces from the training set, keeping only the M images that correspond to the highest eigenvalues [44]. These M images define the face space. As new faces are experienced, the Eigenfaces can be updated or recalculated
3. Calculate the corresponding distribution in M dimensional weight space for each known individual, by projecting their face images onto the "face space."

❖ **Eigenfaces Recognition**

1. Calculate a set of weights based on the input image and the M Eigenfaces by projecting the input image onto each of the Eigenfaces.
2. Determine if the image is a face at all by checking to see if the image is sufficiently close to "face space."
3. (Optional) Update the Eigenfaces and/or weight patterns.
4. If it is a face, classify the weight pattern as either a known person or as unknown.

To summarize whole process of Face Recognition using Eigenface approach from the above diagram, the training set of images are given as input to find eigenspace. Using these images, the average face image is computed. The difference of these images is represented by covariance matrix. This is used to calculate Eigenvectors and Eigenvalues. These are the Eigen faces which represent various face features. Sort the eigenvalues, and consider higher of them since they represent maximum variations. This becomes Eigen space spanned by the Eigen faces, Which has lower dimension than original images.

Now given two test images are projected onto this Eigen space to give the weight vector also known as Face key for that image. The Euclidean distance between these two face key vectors is calculated. If this is below some threshold value, then two images are said to be matching that means they belong to same person. Depending on this result, False Acceptation Rate (FAR) and False Rejection Rate (FRR) are found. These are used to change value of Threshold. In this way Face Recognition is carried out using Eigen face Approach.

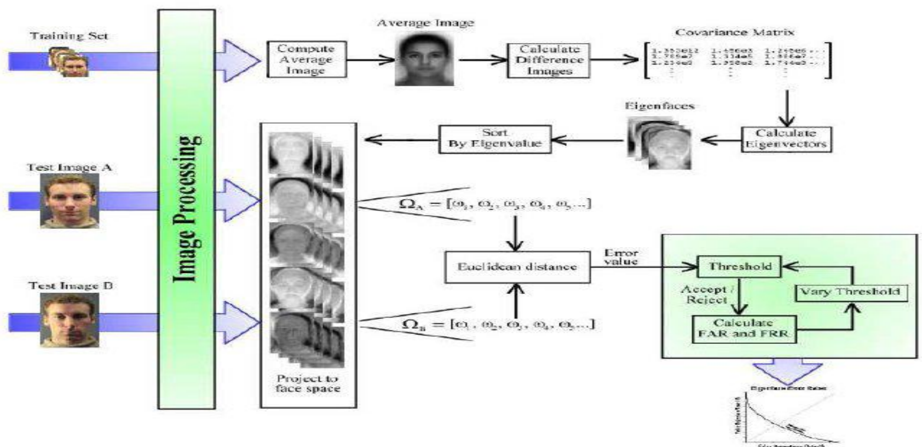



**Figure 2.1: Eigen face method for Face Recognition**

### 2.2 PCA Algorithm

The algorithm for the facial recognition using eigenfaces is basically described in figure 2.2. First, the original images of the training set are transformed into a set of eigenfaces *E*. Afterwards; the weights are calculated for each image of the training set and stored in the set *W*. Upon observing an unknown image *X*, the weights are calculated for that particular image and stored in the vector *WX*. Afterwards, *WX* is compared with the weights of images, of which one knows for certain that they are facing (the weights of the training set *W*).

One way to do it would be to regard each weight vector as a point in space and calculate an average distance *D* between the weight vectors from *WX* and the weight vector of the unknown image *WX*. If this average distance exceeds some threshold value , then the weight vector of the unknown image *WX* lies too "far apart" from the weights of the faces. In this case, the unknown *X* is considered to not a face. Otherwise (if *X* is actually a face), its

weight vector *WX* is stored for later classification. The optimal threshold value has to be determined empirically. By means of PCA one can transform each original image of the training set into a corresponding eigenface.
An important feature of PCA is that one can reconstruct any original image from the training set by combining the eigenfaces. Remember that eigenfaces are nothing less than characteristic features of the faces. Therefore one could say that the original face image can be reconstructed from eigenfaces if one adds up all the eigenfaces (features) in the right proportion.

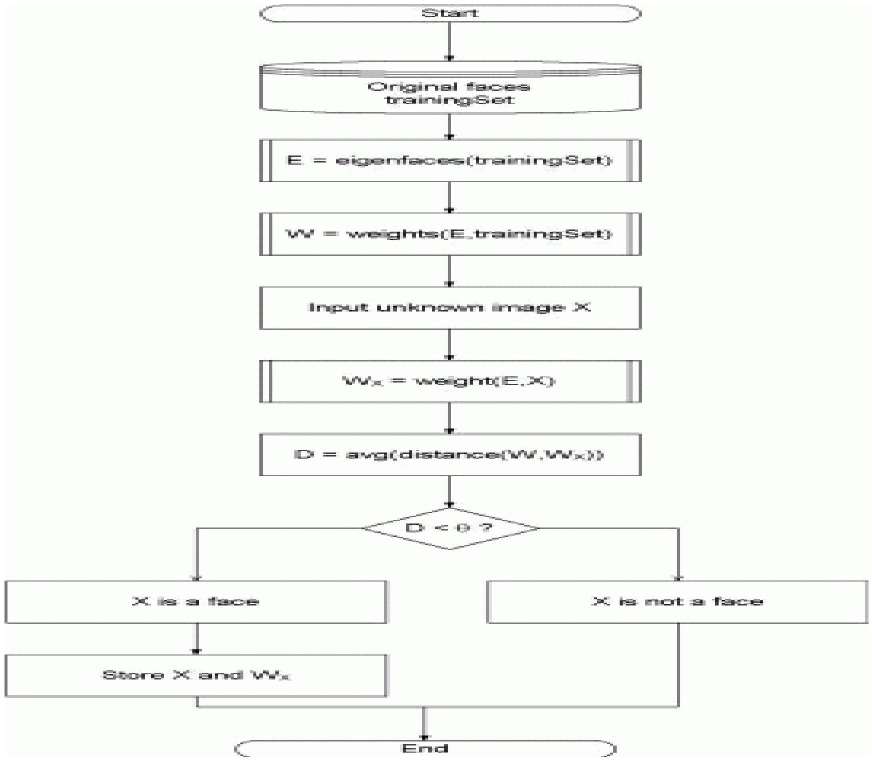



**Fig 2.2: Flow Chart for PCA Algorithm**

## III. PCA BASED FACE RECOGNITION

The proposed method is implemented in 3 sections. Training, Testing, Classification. The block diagram is shown in below figure 3.1

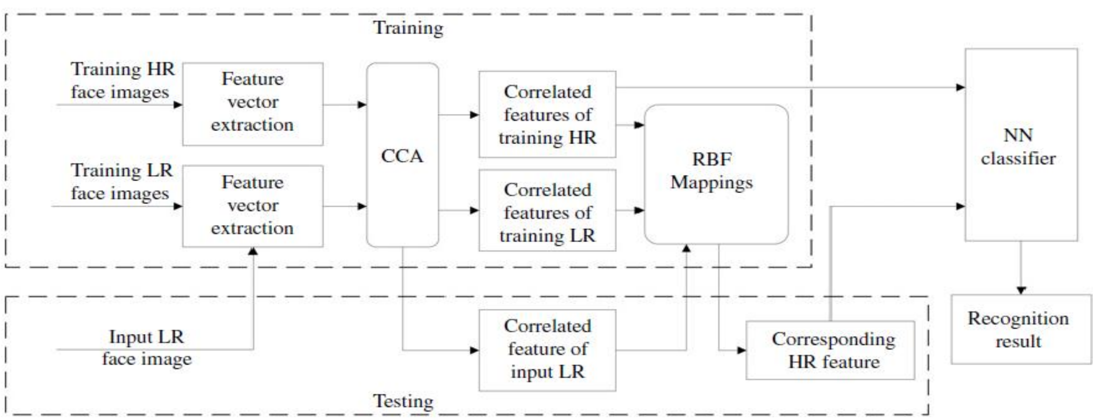



**Fig. 3.1: Block diagram of proposed method.**

**SR Algorithm**

In this section, we present the detailed procedure of our algorithm. As stated, the problem of SR of feature domain for face recognition is formulated as the inference of the HR domain feature $c_h$ from an input LR image $I_l$, given the training sets of HR and LR face images, $I^H=\{I_i^H\}_{i=1}^m=[I_1^H,I_2^H,\ldots I_m^H]$ and $I^L=\{I_i^L\}_{i=1}^m=[I_1^L,I_2^L,\ldots I_m^L]$ where m denotes the size of the training sets. The dimension of the image data, which is much larger than the number of training images, leads to huge computational costs. So, the holistic features of face images are obtained by classical PCA, which represents a given face image by a weighted combination of Eigen faces. We define as in equation 3.19

$$x_i^H = (B^H)^T (I_i^H - \mu^H) \quad \ldots\ldots (3.19)$$

where $\mu^H$ is the corresponding mean face of HR training face images and $x\ Hi$ is the feature vector of face image $I_i^H$. $B^H$ is the feature extraction matrix obtained by the HR training face images and is made up of orthogonal eigenvectors of $(\hat{I}^H)^T \times \hat{I}^H$ corresponding to the eigenvalues being ordered in descending order, where $\hat{I}^H = [\,(I_1^H - \mu^H), (I_2^H - \mu^H), \ldots, (I_m^H - \mu^H)]$. Similarly, the feature of LR face image is represented as in equ 3.20.

$$x_i^L=(B^L)^T (I_i^L - \mu^L) \quad \ldots\ldots (3.20)$$

Where $B^L$ and $u^L$ are the feature extraction matrix and the mean face obtained by LR training face images, respectively. Then, we have the PCA feature vectors of HR and LR training sets as $X^H= \{x_i^H\}_{i=1}^m \in R^{p\times m}$ and $X^L=\{x_i^L\}_{i=1}^m \in R^{q\times m}$. The following process of our algorithm is based on these PCA feature vectors.

## IV. COHERENT FEATURES

In our study of feature-domain SR for LR face recognition, the relationship between HR and LR feature vectors should be learned by the training sets. Thus, given an input LR face features; the corresponding SR features can be obtained for recognition. In the existing methods, this relationship is directly obtained by the PCA features of LR and HR face images. Corresponding HR and LR images of the same face have differences only in resolution, thus, they are coherent through their intrinsic structures. In order to learn the relationship between HR and LR feature vectors more exactly, we apply CCA to incorporate the intrinsic topological structure as the prior constraint. In the coherent subspace obtained by CCA transformation, the solution space of HR feature corresponding to a given LR image is reduced. Then, the more exact coherent SR features can be obtained for recognition in the coherent subspace.

Specifically, from the PCA feature training sets $X^H$ and $X^L$, we first subtract their mean values $\bar{x}^H$ and $\bar{x}^L$, respectively, which yields the centralized data sets $\widehat{X}^H=[\hat{x}_1^H, \hat{x}_2^H, \ldots\ldots, \hat{x}_m^H]$ and $\widehat{X}^L=[\hat{x}_1^L, \hat{x}_2^L, \ldots\ldots, \hat{x}_m^L]$. CCA finds two base vectors $V^H$ and $V^L$ for datasets $X^H$ and $X^L$ in order to maximize the correlation coefficient between vectors $C^H = (V^H)^T \widehat{X}^H$ and $C^L = (V^L)^T \widehat{X}^L$. The correlation coefficient is defined as in equation 3.21.

$$\rho = \frac{E[C^H C^L]}{\sqrt{E[(C^H)^2]E[(C^L)^2]}} \quad \ldots\ldots (3.21)$$

$$= \frac{E[(V^H)^T X^H (X^L)^T V^L]}{\sqrt{E[(V^H)^T X^H (X^H)^T V^H] E[(V^L)^T X^L (X^L)^T V^L]}}$$

Where $E[C^H C^L]$ denotes mathematical expectation. To find the base vectors $V^H$ and $V^L$ we define $C_{11} = E[\widehat{X}^H (\widehat{X}^H)^T]$ and $C_{22} = E[\widehat{X}^L (\widehat{X}^L)^T]$ as the within-set covariance matrices of $\widehat{X}^H$ and $\widehat{X}^L$, respectively, while $C_{12} = E[\widehat{X}^H (\widehat{X}^L)^T]$ and $C_{21} = E[\widehat{X}^L (\widehat{X}^H)^T]$ as their between-set covariance matrices. Then, we compute equations 3.22.

$$R_1 = C_{11}^{-1} C_{12} C_{22}^{-1} C_{21}$$

$$R_2 = C_{22}^{-1} C_{21} C_{11}^{-1} C_{12} \quad \ldots\ldots (3.22)$$

$V^H$ is made up of the eigenvectors of $R1$ when the eigenvalues of $R_1$ are ordered in descending order. Similarly, the eigenvectors of $R_2$ compose $V^L$. We obtain the corresponding projected coefficient sets $C^H=$

$\{c_i^H\}_{i=1}^m \in \mathrm{R}^{p\times m}$ and $C^L=\{c_i^L\}_{i=1}^m \in \mathrm{R}^{q\times m}$ of the PCA feature sets $X^H$ and $X^L$ projected into the coherent sub spaces using the following base vectors as shown in equation 3.23:

$$c_i^H = (V^H)^T X_i^H$$

$$c_i^L = (V^L)^T X_i^L \quad \ldots\ldots (3.23)$$

As there exists a coherent intrinsic structure embedded in the HR and LR feature sets $X^H$ and $X^L$, the correlation between the two sets $C^H$ and $C^L$ is increased and their topological structures are more coherent after the transformation. Then, the relationship between HR and LR features is more exactly established in the coherent subspace.

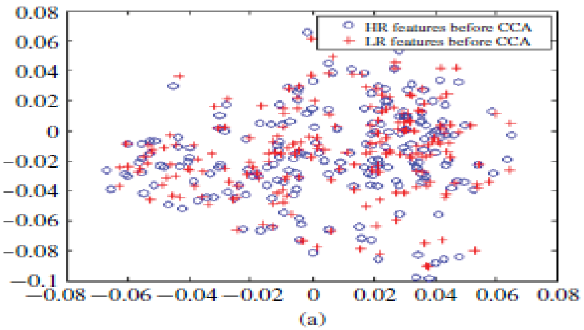



Fig 3.2. First two dimensions of the features of HR and LR face images (a) before CCA transformation, and (b) after CCA transformation

## V. RESULTS AND ANALYSIS

The experiments are performed on the Yale face database, the UMIST database, and the ORL database. In order to demonstrate the effectiveness of Proposed SR algorithm, we compare the face recognition rate of proposed method with that of the CLPM method which applies RBF to study the relationship between training LR/HR PCA coefficient pairs and then based on the relationship obtain the interpolated PCA coefficient of the input LR images for recognition; Wang's method, which applies RBF to study the relationship between training LR/HR PCA coefficient pairs and then based on the relationship obtain the interpolated PCA coefficient of the input LR images for recognition; Gunturk's method, which applies RBF to obtain the interpolated HR face image of the input LR face image and extracts the feature of the interpolation image for recognition.

**Face image one individual in face Database**

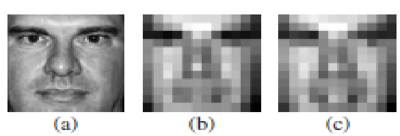
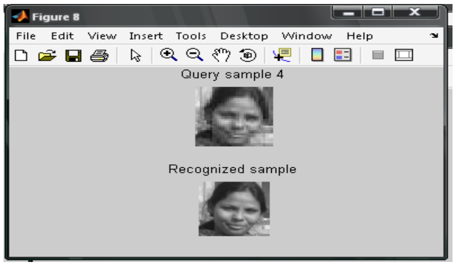
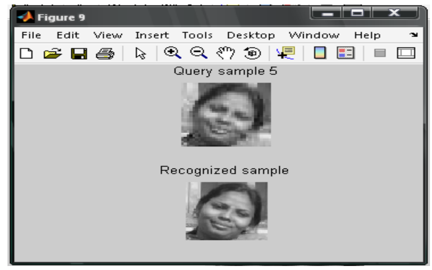



**Figure 4.1: (a) HR training face with size 128x128. (b) LR face image for trainig with size 16x16. (c) LR input face image for testing with size 16x16 from testing image set**

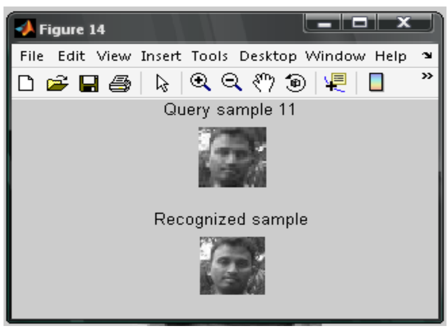
❖ **Recognition results with query images**



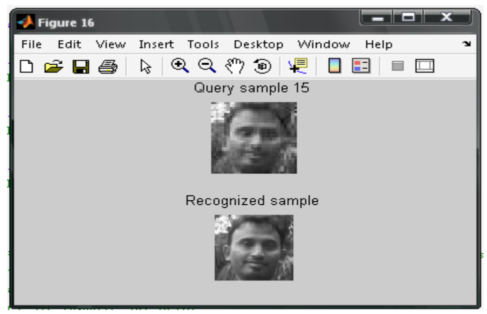

**(a)**



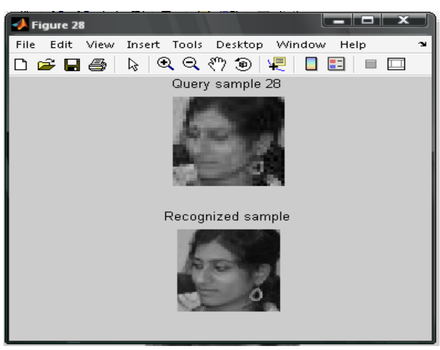

**(b)**



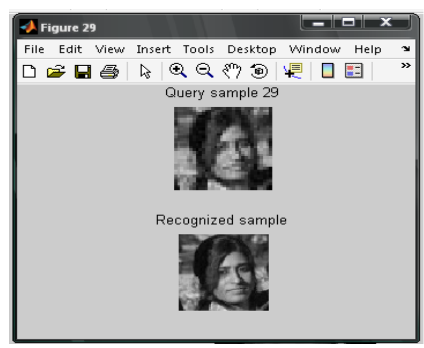

**(c )**




**(d)**




**(e)**




**(f)**

- ❖ **Recognition rate with tested images**

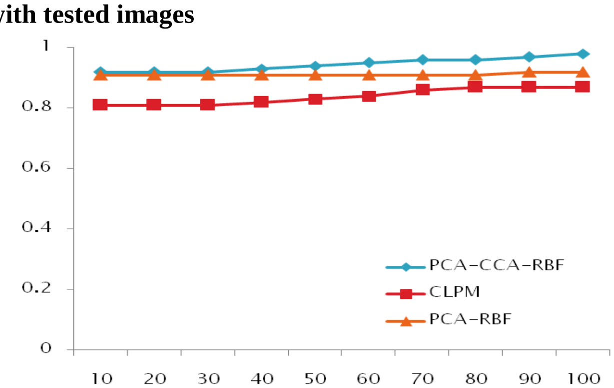



**Fig 4.2: Recognition rate with tested images**

| Query images | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Pca-CCA-RBF** | **0.92** | **0.92** | **0.92** | **0.93** | **0.94** | **0.94** | **0.95** | **0.96** | **0.97** | **0.98** |
| **CLPM** | **0.81** | **0.81** | **0.81** | **0.82** | **0.83** | **0.86** | **0.87** | **0.87** | **0.87** | **0.87** |
| **PCA-RBF** | **0.91** | **0.91** | **0.91** | **0.91** | **0.91** | **0.91** | **0.91** | **0.91** | **0.92** | **0.92** |

**Table 4.1 Recognition rate with tested images**

### 4.3 APPLICATIONS

There are numerous application areas in which face-recognition can be exploited are .Security (access control to buildings, airports/seaports, ATM machines and border checkpoints; computer/network security; email authentication on multimedia work stations),Surveillance (a large number of CCTVs can be monitored to look for known criminals, drug offenders, etc. and authorities can be notified when one is located; for example, this procedure was used at the Super Bowl 2001 game at Tampa, Florida; in another instance, according to a CNN report, two cameras linked to state and national databases of sex offenders, missing children and alleged abductors have been installed recently at Royal Palm Middle School in Phoenix, Arizona).General identity verification (electoral registration, banking, electronic commerce, identifying newborns, national IDs, passports, drivers' licenses, employee IDs).Criminal justice systems (mug-shot/booking systems, post-event analysis, forensics).Image database investigations (searching image databases of licensed drivers, benefit recipients, missing children, immigrants and police bookings)."Smart Card" applications (in lieu of maintaining a database of facial images, the face-print can be stored in a smart card, bar code or magnetic stripe, authentication of which is performed by matching the live image and the stored template).Multi-media environments with adaptive human computer interfaces (part of ubiquitous or context aware systems, behavior monitoring at childcare or old people's centers, recognizing a customer and assessing his needs).Video indexing (labeling faces in video).Witness faces reconstruction.

In addition to these applications, the underlying techniques in the current face recognition technology have also been modified and used for related applications such as gender classification, expression recognition and facial feature recognition and tracking; each of these has its utility in various domains: for instance, expression recognition can be utilized in the field of medicine for intensive care monitoring while facial feature recognition and detection can be exploited for tracking a vehicle driver's eyes and thus monitoring his fatigue, as well as for stress detection. Face recognition is also being used in conjunction with other biometrics such as speech, iris, fingerprint, and ear and gait recognition in order to enhance the recognition performance of these methods.

## VI. CONCLUSION

Face recognition is a challenging problem in the field of image analysis and computer vision that has received a great deal of attention over the last few years because of its many applications in various domains. Research has been conducted vigorously in this area for the past four decades or so, and though huge progress has been made, encouraging results have been obtained and current face recognition systems have reached a certain degree of maturity when operating under constrained conditions; however, they are far from achieving the ideal of being able to perform adequately in all the various situations that are commonly encountered by applications utilizing these techniques in practical life.

The ultimate goal of researchers in this area is to enable computers to emulate the human vision system and, as has been aptly pointed out by Torres, "Strong and coordinated effort between the computer vision, signal processing, and psychophysics and neurosciences communities is needed" to attain this objective.

For the problem of LR face images resulting in low recognition rate, an SR method in the feature domain for face recognition was proposed in this technique. CCA was applied to obtain the coherent subspaces between the holistic feature of HR and LR face images, and RBF model was used to construct the nonlinear mapping relationship between the coherent features. Then, the SR feature in the HR space of the single-input LR face image will obtain for recognition. Experiments show that even the simple NN classifier can implement high recognition rates in the coherent subspaces.

The SR algorithm is implemented using PCA features. To improve the recognition rate further SR algorithm is also implemented using Kernel PCA features. Compared to most neural network type generalizations of PCA, kernel-PCA moreover has the advantage that it provides a better understanding of what kind of nonlinear features are extracted: they are principal components in a feature space which is fixed a priori by choosing a kernel function. In this sense, the type of nonlinearities that we are looking for are already specified in advance, however this specification is a very wide one, it merely selects the (high dimensional) feature space, but not the relevant feature subspace: the latter is done automatically. The conventional PCA allows only linear dimensionality reduction. However if data has more complicated structure which cannot be simplified in a linear subspace, PCA is invalid. The limitations of PCA can be overcome by kernel PCA in the SR algorithm. Kernel PCA allows generating conventional PCA to nonlinear dimensionality reduction. Kernel PCA is advantageous in following aspects, Computational Complexity, Dimensionality Reduction.Kernel PCA will have all the advantages of the regular PCA, as well as the implicit nonlinear mapping to a feature space where the features representing the structure in the data may be better extracted. The drawbacks of KPCA are not easy for low rank approximations and also computing Eigen values in kernel space when there is highly sophisticated transformations are required.

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