Super Resolution Technique for Face Recognition using SVD

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***Abstract*—Super Resolution method produces a high resolution image at the output from multiple numbers database images which may be blurred or aliased low resolution images as input to get an efficient face recognition method. It produces a super resolution image using various methods like super resolution method, morphological method, two dimensional principal component analysis method with reduced memory. We propose face recognition scheme using singular value decomposition. The two orthogonal matrices obtained from singular value decomposition contain the leading information of a face image. Principal component analysis method is implemented on the two orthogonal matrices to recognize the face. Eigen transformation of feature based super resolution method by 2DPCA retains the same combination of weights but low resolution samples are substituted with the corresponding high resolution face samples. The earlier methods suffer from pose, alignment, facial expression and illumination variations. This paper proposes a better method to overcome these problems for recognition of face images**

Keywords— Super resolution, Singular value decomposition, two-dimensional principal component analysis.

I. INTRODUCTION

Super resolution image reconstruction is a process of recreating high resolution image from one or more low resolution images of the same image. It extracts all the required image details needed for recognition process. It restores high resolution images from degraded i.e., blurred or aliased image. A software resolution enhancement technique called super resolution is applied in almost all imaging applications such as medical imaging, video surveillance, high definition TV broadcasting, satellite imaging, pattern recognition.

Feature based super-resolution method used for biometric recognition of face [1][2][6][7]. Human face recognition is an active biometric recognition scheme along with finger print recognition and iris recognition. It recognizes the face from the database based on the weighted coefficients [3]of the database face and the input face considered for recognition purpose. It determines whether it a known or unknown face from the database. It has various applications for security purposes like airport terminals, participation identification in meeting, smart card, recognition of criminals by scanning. The problems that arise because of the variations in facial expression, head position, alignment, illumination variations, and blurred face are overcome. The hallucinating faces also recognized [4][5][6] which occurs due to the large distance of the image and camera.

We apply singular value decomposition to image processing technique for face recognition. It decomposes or represents the digital image into three matrices U,S,V using which we can represent images with smaller set of values, thereby preserving all the features of original image [8][9]. The two orthogonal matrices of each image is determined. Only one orthogonal matrix is considered instead of the whole matrix. We then consider two dimensional Principle component analysis (2DPCA) technique to get 2D matrix which can be transformed into covariance matrix result smaller than that obtained from PCA analysis. The weighted coefficients are calculated from the eigen vectors and eigen values obtained in 2DPCA method [13][14][15]. It is a image compression method occupying less memory space. The weighted coefficients of the database is calculated and stored. Then the weighted coefficient of the input image is compared with that of the database based on the Euclidian distance to recognize the face. The one with the smallest Euclidian distance determines the recognized face.

The paper is organized in the following manner. The general idea about the system and its functioning is in section 2. In the next, section3 a mathematical study of the singular value decomposition (SVD) method is done.

It also explains the two orthogonal matrix method with its respective outputs. Section 4 presents the procedure of 2DPCA over PCA, considering the eigen vectors and eigen values. Section5 shows the face recognition experimental results. The last section6 concludes the paper with the proposed method.

II. SYSTEM OVERVIEW

In this technique, we derive a face recognition technique.

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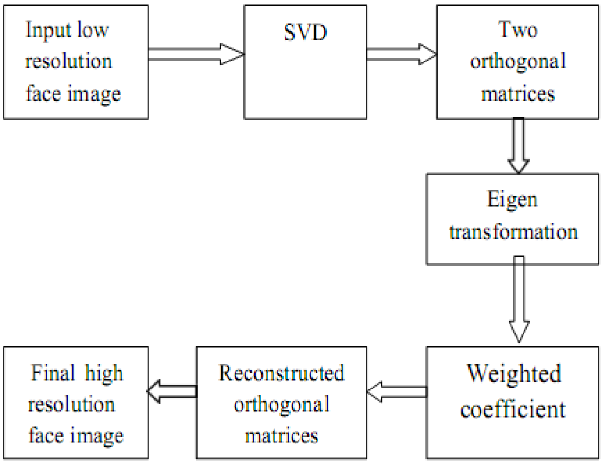

Figure.1 Flowchart of super resolution technique for face recognition using SVD

This proposed recognition algorithm consists of multiple stages. The first stage generates two orthogonal matrices by applying singular value decomposition method on the low resolution input images. In the second stage the face features are extracted from two dimensional PCA using Eigen transformation. the weighted coefficients are calculated to compare with the weighted coefficient of the original face images from the database. The smallest Euclidian distance from database images, is the recognized face.

III. SINGULAR VALUE DECOMPOSITION (SVD)

Singular value decomposition (SVD) method is transformation of the variables which are correlated into uncorrelated variable set considering the original data sets. The maximum variable dimensions are identified and the best approximation of the uncorrelated data points. Considering few dimension SVD helps in data reduction. . SVD applies the theories of from linear algebra which breaks down a rectangular matrix 'A' into three matrices as an orthogonal matrix 'U', a diagonal matrix 'S', and the transpose of an orthogonal matrix 'V' . It is expressed as

Axy = Uxx Sxy VT (1)

where, **U =**[p1,p2,…ph] is an orthogonal matrix of *x X x*

i.e U.UT = I. **VT** is the transpose (Conjugate transpose if V is complex), where V=[q1,q2,…qh] is the orthogonal matrix of *y X y* i.e V.VT = I. **S=(D 0)T** is a diagonal matrix of *x X y* which is the square roots of eigen values obtained from U or V in descending order. D=diag(λ1,λ2,…,λr), λ1≥ λ2≥….≥ λr≥0.

So above expression can be represented as

$$A = \sum_{i=1}^{r} \lambda_i p_i q_i^T \quad (2)$$

where λ_i2 is the eigenvalue of AAT and A^TA, pi and qi are eigenvectors of AA^T and A^TA. The *x* columns of U are called the **left-singular vectors** and the *y* columns of V are called **right- singular vectors** of A.

A. *Two Orthogonal Matrices (TOMs)*

SVD generates two orthogonal matrices (TOMs) which contain all the leading information for face recognition. four high-resolution faces are denoted as A_1,A_2,A_3,A_4 respectively. Every face image can be represented as

$A_n = U_n S_n V_n$, n=1, 2, 3, 4.. .considering two input image below.

Swapping of TOMs between two different high resolution images, we get eight different combinations of $U_1.S_1.V_1$, $U_1.S_1.V_2$, U2.S1.V1, U2.S1.V2, $U_1.S_2.V_1$, $U_1.S_2.V_2$, $U_2.S_2.V_1$ and $U_2.S_2.V_2$

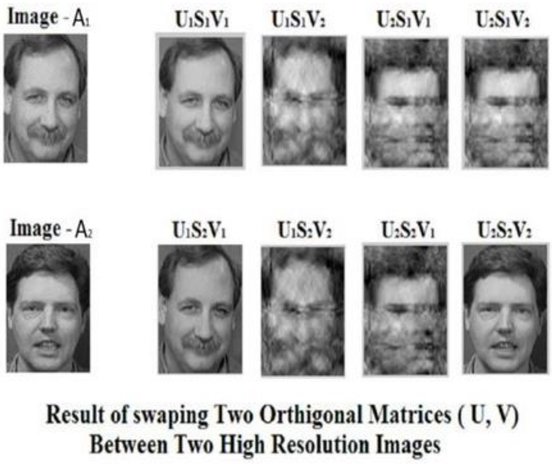

Figure.2 Two high resolution input images and corresponding result of swapping of orthogonal matrices

The above figure shows the results of swapping of two orthogonal matrices between two high resolution images. When we are changing one orthogonal matrix of the image-1 with image-2 it shows a new image that completely changes from its original image. On the other hand if we are swapping the diagonal matrix between these two images keeping the TOMs constant the image property doesn't change. By doing this swapping of TOMs concludes that TOMs carry significant and leading information of the image. This is a great cause for us as we took only the orthogonal matrices instead of the whole image matrix for our next step i.e for face recognition.

We have taken two version of a same image to get another result. One is the high resolution image and the other one is the low resolution image of the corresponding high resolution image. After performing the singular values decomposition (SVD) we have swapped TOMs between these two images and as a result we conclude that TOMs carry leading information of an image. The result of swapping is shown below.

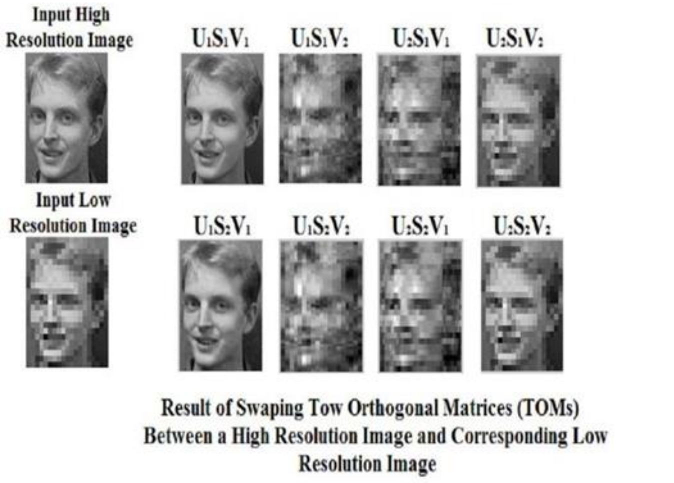

Figure.3 One high and one low resolution input images from database and corresponding result of swapping of orthogonal matrices

B. 2D-PCA (Two Dimensional Principal Component Analysis)

Two-dimensional principal component analysis (2DPCA) is an image processing technique for feature extraction. It can construct a two dimensional matrix which is transformed into covariance matrix. The covariance matrix from 2D matrix is smaller compared to the covariance matrix derived from 1D matrix in PCA technique, thereby reducing the memory space. It can also be termed as image compression technique. The weighted coefficients are calculated from the Eigen vectors and Eigen values obtained in 2DPCA method.

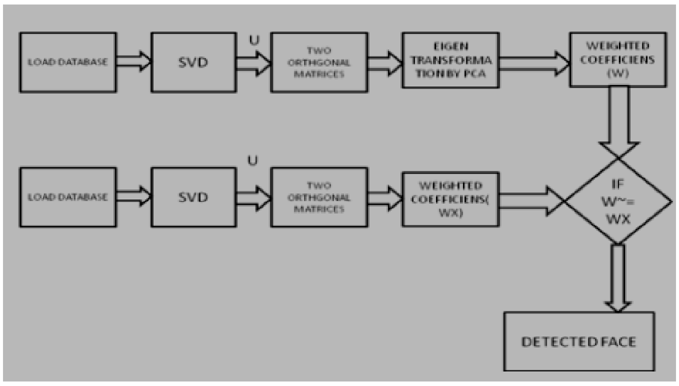

Figure.4 Block diagram of the methodology

Hence 2DPCA determines accurately the covariance matrix in less time. It also takes less time to get the eigenvectors from the covariance matrix.

2DPCA [15] evaluate the covariance matrix accurately than PCA. It consumes less time to determine the corresponding eigenvectors from covariance matrix. So this method i.e., 2DPCA decomposes the face images into weighted coefficient combination of eigen-vectors to form the eigen faces. Suppose M training samples in total, the *j*th training image is denoted by a matrix mXn.

R_j(j=1,2,..., *M*) , and $\bar{R}$ be the average image. Then the image covariance matrix C_j can be expressed as

$$C_t = \frac{1}{M}\sum_{j=1}^{M}(R_j - \bar{R})^T\,(R_j - \bar{R}) \qquad (3)$$

The criterion J(X) can be represented as $J(X)=X^TC_tX$

Corresponding to the largest Eigen values, the optimal projection axes are the orthonormal eigenvectors of *C*. Considering a face image f_R , principal component vectors Q_K can be calculated by projecting it onto the orthonormal eigenvectors X_K : $Q_K=f_RX_K$, k=1,2, …., d Then we can get each Q of M training image samples by projecting them onto *X* :

$$\begin{cases} Q_j = R_jX \quad j = 1,2,\ldots.M \\ X^T = \frac{1}{M}\sum_j^M Q_j^T R_j \end{cases} \qquad (4)$$

$Q = [q1\ q2\ ..qm]T$ an m-component vector variable and denoted by

$$Q = \begin{bmatrix} q11 & q12 & \ldots.q1n \\ q21 & q22 & \ldots.q2n \\ qm1 & qm2 & \ldots.qmn \end{bmatrix} \qquad (5)$$

the sample matrix of q, where q_i^j , q=1,2,…..,n, are the discrete samples of variable q_i , i=1,2,….,m. The i^{th} row of sample matrix Q, denoted by

$Qi = [q^1\ \ q^2\ \ \ldots..\ \ q^n]$ (6)

is called the sample vector of qi. The mean value of Qi is calculated as

$$\mu = \frac{1}{n}\sum_{j=1}^{n} Qi(j) \qquad (7)$$

And the sample vector Qi is centralized matrix of Q is

$\bar{Q}i = [\bar{q}\,1\ \ \bar{q}\,2\ \ \ldots..\ \bar{q}\,n]$ (8)

Where $\bar{q}\,j = q\,j - \mu i$. Therefore, the centralized matrix of Q is

$\bar{Q} = [\bar{Q}\,T\ \ \bar{Q}\,T\ \ \ldots\ldots..\ \ \bar{Q}\ \ T\,]T$ (9)

The final co-variance matrix is calculated as

$$б = \frac{1}{N}\overline{QQ}^T \qquad (10)$$

PCA finds an orthonormal transformation matrix P that is used to $\bar{Q}$, i.e. $\bar{Z}$ =P$\bar{Q}$ so that Z is diagonal of the co-variance matrix. As the covariance matrix б is symmetrical, it is expressed as

$$б=\omega\ \Lambda\ \omega^T \qquad (11)$$

where $\omega = [\omega_1 \ \omega_2 \ \ldots\ldots \ \omega_m]$ is the $\times m$ orthonormal eigenvector matrix and the diagonal eigenvalue matrix $\Lambda = \mathrm{diag}\{\lambda_1, \lambda_2, \ldots \lambda_m\}$ is with $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_m$. The terms $\omega_1, \omega_2, \ldots, \omega_m$ and $\lambda_1, \lambda_2, \ldots \lambda_m$ are the eigenvectors and eigenvalues of б. substituting $P = \omega^T$

$\bar{Q}$ can be de-correlated as follows

$$\bar{Z} = P\bar{Q} \quad (12)$$

$$\Lambda = \frac{1}{N}\bar{Q}\bar{Q}^T \quad (13)$$

In PCA separates the signal from the noise. the signal energy will concentrate on a small subset of the PCA transformed dataset and the noise energy will spread evenly over the whole dataset separating signal from noise.

IV. EXPERIMENTAL RESULTS

We have taken the ORL data base for our experiment which is given below.

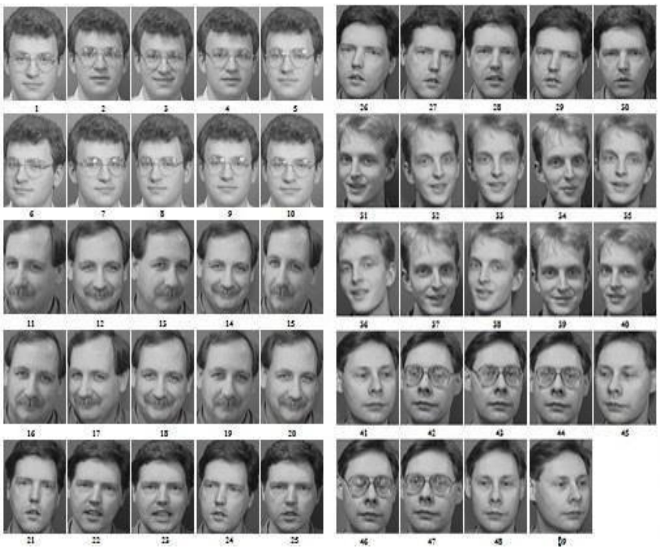

Fig.5 ORL database

The mean face for the above ORL data base was determined as below.

Figure.6 Mean face

A good resolution image is given as input to the system and as a result the image is recognized from our database. The result is shown below

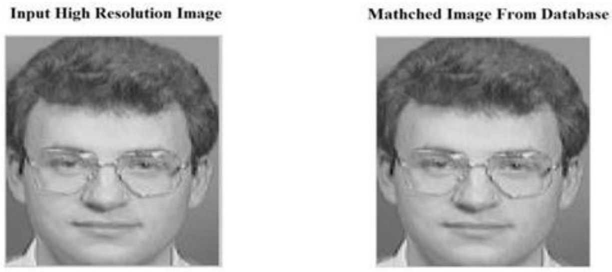

Figure.7 Input face with corresponding recognized face.

A very low resolution image is given as input to the system and as a result the image is recognized from our database.

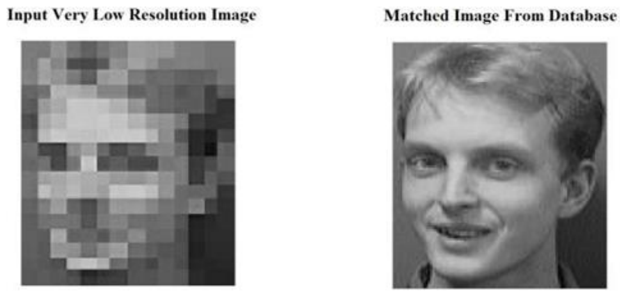

Figure.8 Input face with corresponding recognized face

A color inverted low resolution image is given as input to the system and as a result the image is recognized from our database.

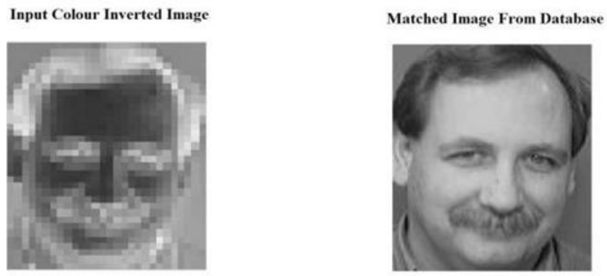

Figure.9 Input face with corresponding recognized face

A blurred image is given as input to the system and as a result the image is recognized from our database.

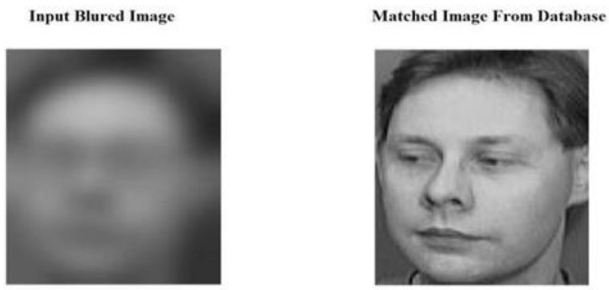

Figure.10 Input face with corresponding recognized face

VI. CONCLUSION

This paper proposed a face recognition TECHNIQUE using super resolution technique. We performed singular value decomposition (SVD) of an image and proved two orthogonal matrices (TOMs) carry leading information of an image. Furthermore we have done principal component analysis by taking only orthogonal matrices instead of the whole image matrix for the face recognition. We have recognized face images by changing their different features and characteristics successfully in our method. the signal to noise ratio (SNR) value which is very high that proves the efficiency and error free capacity of our method very well.

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