IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 17, Issue 5, Ver. III (Sep. – Oct. 2015), PP 01-14
www.iosrjournals.org

Normalized Feature Representation with Resolution Mapping For Face Image Recognition

1Raghavendra Kulkarni,
Research Scholar, Mewar University, Rajasthan,

Abstract: *This paper develops an approach for face feature representation under variant resolution condition with normalized face distribution. In the approach of face feature extraction, SVD based approach for Eigen space representation is been used. To optimize the feature representation under various input conditions, a novel approach for feature representation under variant scales and its recognition is proposed. The effect of scaling over different resolutions and variation in face feature distribution is evaluated. A normalization approach to face feature representation with scale mapped feature is presented. The simulation observations under variant scaling condition on YALE face dataset is carried out. An improvement in the recognition accuracy under these variant conditions was observed.*

Index Term – *Face Recognition, Feature representation, Normalization, Scale mapped coding.*

I. Introduction

Face recognition is an area of study from a long time. Various approach of face recognition and its enhancements were proposed in past to achieve the objective of optimal face recognition. Input face images with different real- time parameters of the face recognition systems with a set of trained data is often observed to be reduced. This is a major problem for automated face recognition system. Limited accuracy of existing algorithms and real-time image capture devices are usually effective in face recognition. In various applications of face recognition, to train and test samples, images are not maintained to a common scale. Therefore, to improve the recognition performance under scale variation of similar samples is required in face recognition applications. In various usage faces from the camera where the field of view is quite small, such as security surveillance, images are captured at lower scale. In this paper, to develop a recognition system, focusing on improving the performance under scaling is proposed. Researchers in machine learning community are focusing on advanced classifiers, in order to increase the recognition rate of lower quality inputs to achieve better performance. In the work proposed in June Liu [11], defines that face always are represented by a well-known singular value decomposition of image matrix with variation all elements such as illumination, expression, etc, which are more sensitive and highly variant from face to face variations [1].Kwak & Pedrycz developed an independent component analysis (ICA) and presented a technique for face recognition related to their application. In the ICA modeling, face is represented by unsupervised learning and use higher-order statistics[2] to perform face recognition. To optimize the face recognition more effectively, a Fuzzy clustering and parallel ANN based approach of face recognition was developed by Jianming Li[3].In such approach Face patterns are divided into many small-scale NN units with fuzzy clustering and obtained recognition are combined to achieve the result. The most commonly used fuzzy clustering algorithm FCM algorithm is a clustering algorithm been associated with dataset with a membership function for each feature point. This technique measures the difference in different scale groups and process the cost function to minimize it. The approach divides the data points into clusters, defined by its center in each group so as the data points could be split into group of collection. The Independent component analysis in such system, perform a linear transformation of the data point to maximize the statistical independence. A new data analysis tool using such Independent analysis was outlined in [4].In the approach of face recognition under different image scaling; a vector is represented as a projecting coefficient using standard linear algebra to make the operation effective under stand alone operation. In [17] a practical model for face representation using rectangular graph design is proposed. Based on the coefficient matching approach face recognition is proposed in [18].To overcome the drawback of conventional method a new algorithm is designed. In this paper to achieve this objective, a new coding approach for scale mapped features for training and testing feature is developed. These features is called as Scale-mapped Feature (SMF), which is applied to extract mapped features that have maximal correlation between the training original and scaled similar features. In order to directly connect the scaled similar features to their original counterparts, a feature mapping approach is employed to construct the nonlinear mappings between the features in the mapped subspaces. Given an input scaled similar face image, the mapped original feature is obtained by mapping the scaled similar feature with the trained features. The distribution of face image with respect to illumination and expression variation is also considered. Where a normalized singular distribution is proposed for image uniformity. To present the stated approach, this paper is organized as follows. In Section II, we briefly review related works on original for face recognition and applications of SMF and SVM model. In Section III, the framework of our method is introduced. Section IV gives the details of our method, and is followed by experimental results in Section V. Section VI gives the conclusion for the presented approach.

II. Face Recognition System

Galton proposed a face recognition approach based on photos alignment from human faces. The main problem, not able to describe personal similarities, the types of faces and personal characteristics. Biometric features of facial images are extracted to overcome the above problem and processes for face recognition. For new face images we need to match existing face to perform face recognition making use of Eigen faces Approach. New face image having high dimension. For given new face image, it becomes very difficult to recognize this face with existing face. So Eigen Face approach is used to simplify this problem. So instead of considering whole face space, it is better to consider only a subspacewith lower dimensionality. The Eigen Face approach gives us efficient way to find this lower dimensional space. Eigen faces are the Eigenvectors, which are representative of each of the dimensions of this face space, and they can be considered as various face features. It means that all images projected in this direction lie close to each other and so do not represent much face variation. The eigenvectors in some sense represent the features of face. So this Eigen Face approach helps in extracting various useful features essential for face recognition. So this Eigen Face Approach can be used for Face Recognition. This is very simple and efficient method of face recognition.The primary reason for using fewer Eigen faces is computational efficiency. The most meaningful M Eigen faces span an M-dimensional subspace "face space" of all possible images. The Eigen faces are essentially the basis vectors of the Eigen face decomposition.The idea of using Eigen faces for efficiently representing faces images using principal component analysis.It is argued that a collection of face images can be approximately reconstructed by storing a small collection of weights for each face and a small set of standard images. Therefore, if a multitude of face images can be reconstructed by weighted sum of a small collection of characteristic images.Eigen space-based approaches approximate the face images with lower dimensional feature vectors. The main idea behind this procedure is that the face spacehas a lower dimension than the image space, and that the recognition of the faces can be performed in this reduced space. Also mean face is calculated and the reduced representation of each database image with respect to mean face.These representations are the ones to be used in the recognition process. The Eigenfaces approach for face recognition involves the following initialization operations:

1. Acquire a set of training images.
2. Calculate the Eigenfaces from the training set, keeping only the best M images with the highest Eigenvalues. These M images define the "face space". As new faces are experienced, the Eigenfaces 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.
4. Having initialized the system, the following steps are used to recognize new face images:
5. Given an image to be recognized, calculate a set of weights of the M Eigen faces by projecting it onto each of the Eigen faces.
6. 4. Determine if the image is a face at all by checking to see if the image is sufficiently close to the face space.
7. 5. If it is a face, classify the weight pattern as either a known person or as unknown.

a) Eigen Face Estimation

Let the training set of face images be Γ_1, Γ_2, Γ_3, …, Γ_M. The average face of the set if defined by $\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n$. Each face differs from the average by the vector $\Phi_n = \Gamma_n - \Psi$. This set of very large vectors is then subject to principal component analysis, which seeks a set of M orthonormal vectors, μ_n, which best describes the distribution of the data. The kth vector, μ_k is chosen such that

$$\lambda_k = \frac{1}{M}\sum_{n=1}^{M}(\mu_k^T\Phi_n)^2 \quad (1)$$

is a maximum, subject to

$$\mu_l^T\mu_k = \begin{cases} 1, & l = k \\ 0, & otherwise \end{cases} \quad (2)$$

The vectors μ_k and scalars λ_k are the eigenvectors and eigenvalues, respectively, of the covariance matrix

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T = AA^T \quad (3)$$

Where the matrix $A = [\Phi_1 \Phi_2 ... \Phi_M]$. The matrix C, however, is N^2 by N^2, and determining the N^2 eigenvectors and eigenvalues is an intractable task for typical image sizes. A computationally feasible method is needed to find these eigenvectors.If the number of data points in the image space is less than the dimension of the space ($M < N^2$), there will be only $M - 1$, rather than N^2, meaningful eigenvectors (the remaining eigenvectors will have associated eigenvalues of zero). Fortunately, we can solve for the N^2-dimensional eigenvectors in this case by first solving for the eigenvectors of and M by M matrix e.g., solving a 16 x 16 matrix rather than a 16,384 x 16,384 matrix—and then taking appropriate linear combinations of the face images Φ_n. Consider the eigenvectors v_n of $A^T A$ such that

$$A^T A v_n = \lambda_n v_n \qquad (4)$$

Pre-multiplying both sides by A, we have

$$AA^T A v_n = \lambda_n A v_n \qquad (5)$$

from which we see that $A v_n$ are the eigenvectors of $C = AA^T$.

Following this analysis, we construct the M by M matrix $L = A^T A$, where $L_{mn} = \Phi_m^T \Phi_n$, and find the Meigenvectors v_n of L. These vectors determine linear combinations of the M training set face images to form the eigenfaces μ_n:

$$\mu_n = \sum_{k=1}^{M} v_{nk} \Phi_k = A v_n,\ n = 1, \dots \dots, M \qquad (6)$$

With this analysis the calculations are greatly reduced, from the order of the number of pixels in the images (N^2) to the order of the number of images in the training set (M). In practice, the training set of face images will be relatively small ($M < N^2$), and the calculations become quite manageable. The associated eigenvalues allow us to rank the eigenvectors according to their usefulness in characterizing the variation among the images.

b) Face Image Classification

The Eigenface images calculated from the eigenvectors of L span a basis set with which to describe face images. As mentioned before, the usefulness of eigenvectors varies according their associated eigenvalues. This suggests we pick up only the most meaningful eigenvectors and ignore the rest, in other words, the number of basis functions is further reduced from M to M' (M'<M) and the computation is reduced as a consequence. Experiments have shown that the RMS pixel-by-pixel errors in representing cropped versions of face images are about 2% with M=115 and M'=40.

In practice, a smaller M' is sufficient for identification, since accurate reconstruction of the image is not a requirement. In this framework, identification becomes a pattern recognition task. The eigenfaces span an M' dimensional subspace of the original N^2 image space. The M' most significant eigenvectors of the L matrix are chosen as those with the largest associated eigenvalues.

A new face image Γ is transformed into its eigenface components (projected onto "face space") by a simple operation

$$w_n = \mu_n (\Gamma - \Psi) \qquad (7)$$

for n=1,……,M'. This describes a set of point-by-point image multiplications and summations.

The weights form a vector $\Omega^T = [\omega_1, \omega_2, ..., \omega_{M'}]$ that describes the contribution of each Eigen face in representing the input face image, treating the Eigen faces as a basis set for face images. For each new face image to be identified, calculate its pattern vector Ω, the distance ε_k to each known class, and the distance ε to face space. If the minimum distance $\varepsilon_k < \theta_\varepsilon$ and the distance $\varepsilon < \theta$, classify the input face as the individual associated with class vector Ω_k. If the minimum distance $\varepsilon_k > \theta_\varepsilon$ but $\varepsilon < \theta$, then the image may be classified as "unknown", and optionally used to begin a new face class. If the new image is classified as a known individual, this image may be added to the original set of familiar face images, and the eigenfaces may be recalculated (steps 1-4). This gives the opportunity to modify the face space as the system encounters more instances of known faces.

III. Face Feature Normalization

The singular value decomposition is a outcome of linear algebra. It plays an interesting, fundamental role in many different applications. On such application is in digital image processing. SVD in digital applications provides a robust method of storing large images as smaller, more manageable square ones. This is accomplished by reproducing the original image with each succeeding nonzero singular value. Furthermore, to reduce storage size even further, images may approximated using fewer singular values.

a) Singular Value Decomposition

The singular value decomposition of a matrix A of m x n matrix is given in the form,

$A = U\Sigma V^T$ (8)

Where U is an m x m orthogonal matrix; V an n x n orthogonal matrix, and $\sum$ is an m x n matrix containing the singular values of A.

$\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_n \geq 0$ (9)

along its main diagonal.

A similar technique, known as the eigenvalue decomposition (EVD), diagonalizes matrix A, but with this case, A must be a square matrix. The EVD diagonalizes A as;

$A = VDV^{-1}$ (10)

Where D is a diagonal matrix comprised of the eigenvalues, and V is a matrix whose columns contain the corresponding eigenvectors. Where Eigen value decomposition may not be possible for all facial images SVD is the result.

These SVD features are used for facial feature decomposition to represent an image in dimensionality reduction (DR) factor.

An SVD operation breaks down the matrix A into three separate matrices.

$A = U\Sigma V^T$ (11)

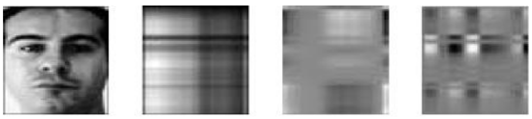
$$= [u_1, \dots, u_n] \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \dots. & 0 \\ 0 & 0 & \sigma_n \end{bmatrix} \begin{bmatrix} v_1^T \\ : \\ v_n^T \end{bmatrix}$$

$$= [u_1, \dots, u_n] \begin{bmatrix} \sigma_1 v_1^T \\ : \\ \sigma_n v_n^T \end{bmatrix}$$

$= \sigma_1 u_1 v_1^T + \cdots . + \sigma_n u_n v_n^T$ (12)

$= \sigma_1 u_1 v_1^T + \cdots . + \sigma_r u_r v_r^T$ (13)

because$\sigma_{r+1} .. \sigma_n$are equal to zeros.



(a) (b) (c) (d)

Fig 1: (a) original face image, (b) SV at (1), (c) SV at (2), (d) SV at (3)

Figure above illustrates the obtained Singular values at each iteration.

(1) at 1st iteration SV values the facial information provided is given by

$A = \sigma_1 u_1 v_1^T$ (14)

(2) After n=2 iteration the facial approximation is given by,

$A = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T$ (15)

(3) after n=3 iteration the facial approximation is given by,

From the above observations it could be observed that the facial information's are though presented in high leading images such as the eye, mouth and nose regions they are less definitive to facial expressions. So a same face image with facial variation may not be predicted in such SV approach. To overcome this limitation the SVD based face recognition approach is modified to SDM approach as presented below.

b) Singular Distribution Normalization (SDM)

To alleviate the facial variations on face images, a novel Singular Distribution Normalization (SDM) approach is suggested.The main ideas of SDM approach are that;

(1) The weights of the leading base images $u_i v_i^T$ should be deflated, since they are very sensitive to the great facial variations within the image matrix A itself.
(2) the weights of base images $u_i v_i^T$ corresponding to relatively small σ_i 's should be inflated, since they may be less sensitive to the facial variations within A.

The order of the weights of the base images $u_i v_i^T$ in formulating the new representation of SVD should be retained. More specifically, for each face image matrix A which has the SVD, its SDM 'B' can be defined as,

$$B = U \sum^{\alpha} V^T \quad (16)$$

Where U, Σ and V are the SV matrices, and in order to achieve the above underlying ideas, α is a Normalizing parameter that satisfies:

$$0 \leq \alpha \leq 1 \quad (17)$$

it is seen that the rank of SDM 'B' is r, i.e., identical to the rank of A as the B matrix isNormalizing raised the values are inflated retaining the rank of the matrix constant.
The $u_i v_i^T$, i = 1, 2, . . . , r form a set of uv^Twhich are similar to the base images for the SVD approach. It is observed that the intrinsic characteristic of A, the rank, is retained in the SDM approach. In fact it has the same uv^T like base images as A, and considering the fact that these base images are the components to compose A and B, the information of A is effectively been passed to B. As SDM approach uses a Normalizing parameter, α which inflates the lower SV, the effect of α on the above-illustrated image is been presented below,

(a) (b) (c) (d)

Fig 2: Face image under variation of Normalizing factor (a) α = 1, (b) α = 0.7, (c) α = 0.4, (d)α = 0.1

From the observation it could be observed that:
(1) The SDM is still like human face under lower SV.
(2) The SDM deflates the lighting condition in vision. Taking the two face images (c) and (d) under consideration, when α is set to 0.4 and 0.1, from the SDM alone, it is difficult to tell whether the original face image matrix A is of left light on or right light on.
(3) The SDM reveals some facial details. In the original face images (a) presented, neither the right eyeball of the left face image nor the left eyeball of the right face image is visible, however, when setting α to 0.4 and 0.1 in SDM, the eyeballs become visible.
In the case of SDM thus the Normalizing parameter and it's optimal selection is an important criterion in making the face recognition process more accurate.

c) Normalization Parameter 'α'

In SDM, **α** is a key parameter that should be tuned. On a suitable selectivity of α parameter the recognition system can achieve superior performance to existing recognition performance. Further, in images (which are sensitive to facial variations) are deflated but meanwhile the discriminant information contained in the leading base images may be deflated. Some face images have great facial variations and are perhaps in favor of smaller **α**'s, while some face images have slight facial variations and might be in favor of larger **α**'s. The **α** learned from the training set is a tradeoff among all the training samples and thus is only applicable to the unknown sample from the similar distribution. each DR method has its specific application scope, which leads to the difficulty in designing a unique **α** selection criterion for all the DR methods. As a result, the criterion for automatic choosing **α** should be dependent on the training samples, the given testing sample and the specific DR method. To optimally choose the **α**value minimum argument MSV criterion is used.Mean square variance (MSV) criterion state that,

$$MSV = \frac{1}{C}\sum_{i=1}^{C} SV_i, \quad (18)$$

whereSV_i is the standard variance of the i^{th} class defined as

$$SV_i = \frac{1}{d}\sum_{k=1}^{d}\sqrt{\frac{1}{N_i - 1}\sum_{j=1}^{N_i}(x_{jk}^i - m_{ik})^2}, \quad (19)$$

Where x^i_{jk} and m_{ik}, respectively, denote the k^{th} element of the d-dimensional samples x^i_j and class mean m_i, C is the number of classes, and N_i is the number of training samples contained in the i^{th}class. For an optimal selection of **α** value the MSV value must be optimally chosen. The smaller MSV value represents, compact the same class samples are, and on the contrary, the bigger MSV is, the looser the same class samples. When the

same class samples are very loose, these samples will lead to biased estimation of the class mean, within class and between-class scatter matrices, while on the contrary, when the same class samples are compact, the estimation of the class mean, within-class and between-class variance matrices may be much more reliable. When the same class samples are compact, it is more likely that these samples can nicely depict the Gaussian distribution from which they are generated and considering the fact it is essential for the same class samples to be compact, namely MSV to be small in the recognition methods. Based on the above argument, a heuristic criterion to automatically choose an adequate $\boldsymbol{\alpha}$ for the recognition method is given as,
$\alpha_{opt} = arg \min_{\alpha} MSV(\alpha)$(20)

d) SDM-Algorithm

Let the face image in the data Base be represented as F(i)K , where i represent the total number of samples for Kth class face image. Then the SVD feature for the given face image is calculated as,

1. Apply SVD on each of the face image for each class in the database, such that $\Psi i = UiSiVi^t$. where, $U = [u_1, u_2, \ldots, u_m]$, $V = [v_1, v_2, \ldots, v_n]$, and $S = [0\ X_i\ 0]$, X_i=diag (s_i), s_i are the computed Singular vector for each face image.
2. (2) The obtained Singular Vector is applied with the Normalizing value of αand a modified SVD values are obtained as, $Bi=Ui\ Si^{\alpha}Vi^t$
3. Each training face image $F_i^{(k)}$ is then projected using the these obtained face feature image.
4. For the obtained representing image apply a DR method PCA, where the eigen features are computed and for the maximum eigen values eigen vectors are located and normalized for this projected image.
5. A test face image $Tr \sim \epsilon R^{m\times n}$ is transformed into a face feature matrix $Yr\ \epsilon R^{r\times c}$ by
6. $Yr = UrSrVr^t$.
7. For the developed query feature a image representation is developed and passed to the PCA.
8. For the computed face feature the distance between a test face image T and a traning face images $X_i^{(j)}$ is calculated by $R_{ji} = \delta(Y,X_i^{(j)}) = \left\|Y - X_i^{(j)}\right\|_F$, , a Frobenius norm.

(9) Retrieve the top 8 subjects of the database according to the rank of Rji given byarg Rank $_j\{R_{ji} = \delta(Y,X_i^{(j)}), 1 \le i \le N_j\}$. the image with the highest Rank is obtained as the recognized image.However under scaled image of same two face images the feature may deviate, to overcome this problem, a scale map coding is proposed.

IV. Scale Map-Coding

In this section, we present the detailed procedure of our algorithm. Different from the mixture models, SMF just works with a single PCA. It is an extension of PCA to non-linear distributions. Instead of directly doing a PCA, the n data points x_i are mapped into a higher-dimensional (possibly infinite-dimensional) feature space [12].As stated, the problem of original of feature domain for face recognition is formulated as the inference of the original domain feature c_o from an input scaled similar image I_s , given the training sets of original and scaled similar face images, $I^o=\{I_i^o\}_{i=1}^m$and $I^L=\{I_i^s\}_{i=1}^m$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 eigenfaces. We define;
$x_i^o = (B^o)^T(I_i^o - \mu^o)$ (21)

where$\mu^H$is the corresponding mean face of original training face images and $x_i^o$is the feature vector of face image I_i^o. B^o is the feature extraction matrix obtained by the original training face images and is made up of orthogonal eigenvectors of$(\hat{I}^o)^T\times\hat{I}^o$corresponding to the Eigen values being ordered in descending order. Similarly, the feature of scaled similar face image is represented as
$x_i^s = (B^s)^T(I_i^s - \mu^s)$ (22)

Where B^L and $\mu^L$are the feature extraction matrix and the mean face obtained by scaled similar training face images, respectively. Then, we have the PCA feature vectors of original and scaled similar training sets. The following process of our algorithm is based on these SMF feature vectors.

Scaled Mapping analysis has been used to study the correlations between two sets of variables. In our study of feature-domain original for scaled similar face recognition, the relationship between original and scaled similar feature vectors should be learned by the training sets. Thus, given an input scaled similar face features, the corresponding original features can be obtained for recognition. In the existing methods, this relationship is directly obtained by the SMF features of scaled similar and original face images. Corresponding original and scaled similar images of the same face have differences only in resolution, thus, they are mapped through their intrinsic structures. In order to learn the relationship between original and scaled similar feature vectors more exactly, we apply SMF to incorporate the intrinsic topological structure as the prior constraint. In the mapped subspace obtained by SMF transformation, the solution space of original feature corresponding to a given scaled similar image is reduced. Then, the more exact mapped original features can be obtained for recognition in the mapped subspace.

Specifically, from the PCA feature training sets X^o and X^s, we first subtract their mean values X^o and X^s, respectively, which yields the centralized data sets. SMF finds two base vectors V^H and V^L for datasets X^o and X^s in order to maximize the correlation coefficient between vectors C^o and C^s. The correlation coefficient is defined as;

$$\rho = \frac{E[C^o C^s]}{\sqrt{E[(C^o)^2]E[(C^s)^2]}} \qquad (23)$$

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

$$R_1 = C_{11}^{-1} C_{12} C_{22}^{-1} C_{21} \qquad (24)$$

$$R_2 = C_{22}^{-1} C_{21} C_{11}^{-1} C_{12} \qquad (25)$$

V^o is made up of the eigenvectors of R1 when the eigenvalues of R1 are ordered in descending order. Similarly, the eigenvectors of R2 compose V^s. We obtain the corresponding projected coefficient sets C^o and C^s of the SMF feature sets X^o and X^s projected into the mapped sub spaces using the following base vectors:

$$C_i^H = (V^o)^T X_i^o \qquad (26)$$

$$C_i^L = (V^s)^T X_i^s \qquad (27)$$

As there exists a mapped intrinsic structure embedded in the original and scaled similar feature sets X^o and X^s, the correlation between the two sets C^o and C^s is increased and their topological structures are more mapped after the transformation. Then, the relationship between original and scaled similar features is more exactly established in the mapped subspace.

a) Mapping approach

As the mapped subspace is obtained, the nonlinear mapping relationship between the mapped features of original and scaled similar will be learned by the training features. This problem can be formulated as finding an approximate function to establish the mapping between the mapped features of original and scaled similar face images. Radial kernels are typically used to build up function approximations. So, we apply radial kernel to construct the mapping relationship. Radial kernel uses radial symmetry function to transform the multivariate data approximation problem into the unary approximation problem, and can interpolate no uniform distribution of high-dimensional data smoothly. The form of radial kernel used to build up function approximations is

$$f_i(.) = \sum_{j=1}^{m} wj(\| t_i) - t_j \|) (28)$$

where the approximating function $f_i(\cdot)$ is represented as a sum of m-kernels $fi(.)$, each associated with a different center t j, and w_j is the weighting coefficient. The form has been particularly used in nonlinear systems. In our implementation, we apply multi quadric basis function

$$\varphi(.) = \sqrt{\| t_i - t_j \|^2 + 1} \qquad (29)$$

In order to apply radial kernels, first, we train the weighting coefficients by training mapped features of original and scaled similar face images. The approximate value we want to obtain is the mapped original features, while the input value is the mapped features of scaled similar face images. So, in the training stage, we substitute the mapped features of scaled similar face images C_i^l and C_j^L for t_i and t_j, and the mapped original feature C_L^H corresponding to C_i^L for f_i. The aim of radial kernels is to establish the nonlinear mappings between C_L^H and C_H^L.

b) Feature mapping for Recognition

We feed the mapped features super-resolved from the features of scaled similar faces to an SVM classifier to achieve the face recognition. In the testing phase, given an scaled similar face image Il ,theSMF feature vector xl of the input face image is computed as

$$x_i = (B^s)^T (I_l - \mu^s) \qquad (30)$$

In our algorithm, we execute our recognition process in the mapped subspaces. So, the PCA feature vector X_s is transformed to the mapped subspace using

$$c_i = (V^s)^T(x_i - x^{-s}) \qquad (31)$$

The mapped original feature c_h is obtained by feeding the mapped feature of the scaled similar face image c_l to the trained radial kernel mapping. We will get

$$c_h = w.[\varphi(c_1^s, c_i), \ldots \ldots \ldots \varphi(c_m^s, c_i)]^T \qquad (32)$$

Finally, we apply the mapped feature c_h and $C^H = \{c_i^H\}_{i=1}^m$ for recognition based on the SVM classification with L2 norm

$$g_k(c_o) = \min(\| C_h - C_{ik}^o \| 2) \quad i=1,2,\ldots\ldots m \qquad (33)$$

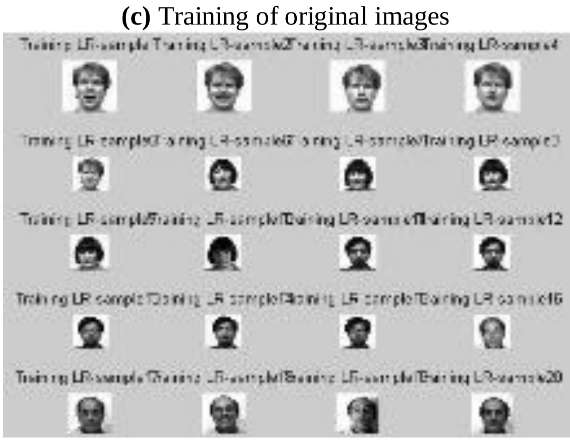
Where C_{ik}^o represents the i^{th} sample in the k^{th} class in C^o.

V. Simulation Result

Experiments are performed on the YALE face database. In order to demonstrate the effectiveness of our algorithm, we compare the face recognition rate of our method with other methods.The developed system is evaluated for various effects of illumination, expression and wearing glass effects. For the robustness of the developed system the Yale Database is trained and evaluated for various classes of face information with the variation effects of improved parameter **α.** The effect of retrieval on the value of **α** and number of training sample per class is evaluated.

(a) Mean image of original **(b)** Mean image of scaled similar

(c) Training of original images



(d) Training of scaled similar images

Fig.3 (a) Mean image of original (b) Mean image of scaled similar(c) Training of original images d) Training of scaled similar images

CASE 1:
Image having right side light ON

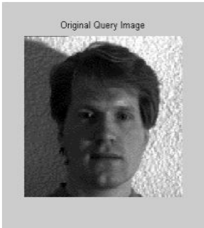


Fig: 4. Original image considered for the testing with left side light off

SVD based outputs

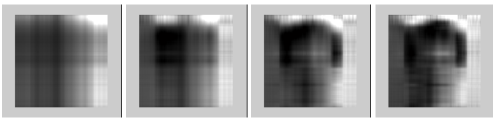


Fig:5 obtained SVD results for the given query for 1-8 iteration

SDM based results

At α = 0.5

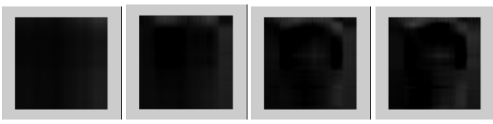


Fig:6 SDM based retrieval for the same input image after 1-8 iteration at α = 0.5

At α = 0.8

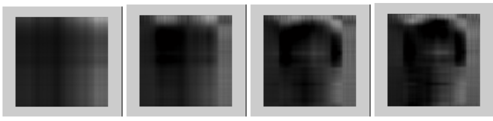


Fig:7 SDM based retrieval for the same input image after 1-8 iteration at α = 0.8

At α = 1

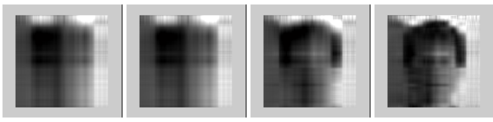


Fig:8 SDM based retrieval for the same input image after 1-8 iteration at α = 1

RETRIEVAL OPERATION:
CASE 2:
Image Having Left side Light ON

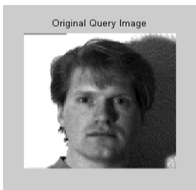


Fig:9 Original image considered for the testing with left side light ON

SVD based outputs

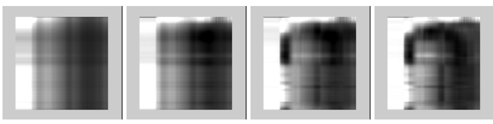


Fig:10 obtained SVD results for the given query for 1-8 iteration

SDM based results
At α = 0.5

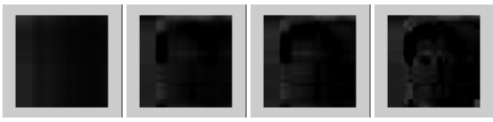


Fig:11 SDM based retrieval for the same input image after 1-8 iteration at α = 0.5

At α = 0.8

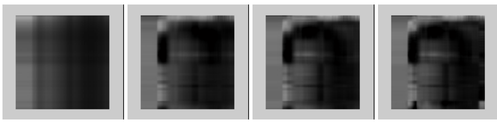


Fig:12 SDM based retrieval for the same input image after 1-8 iteration at α = 0.8

At α = 1

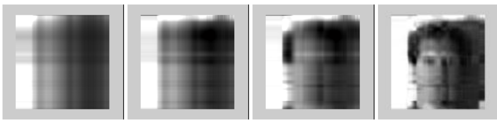


Fig:13 SDM based retrieval for the same input image after 1-8 iteration at α = 1

Case 3:
Image with wearing glasses

Fig:14 Original image considered for the testing with Spectacles on

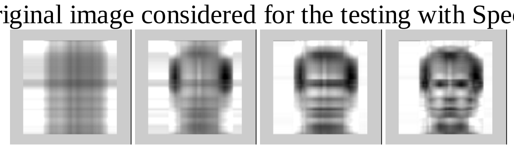


Fig:15 SVD result obtained for given query after 1-8 iterations

SDM based results
At α = 0.5

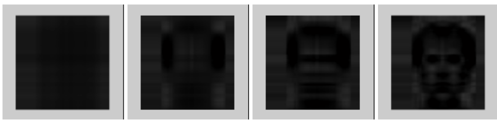


Fig:16 SDM based results obtained after 1-8 iteration at α = 0.5

At α = 0.8

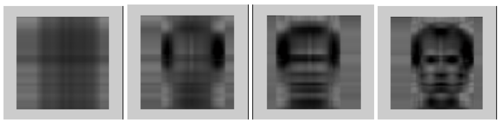


Fig: 17 SDM based results obtained after 1-8 iteration at α = 0.8

At α = 1

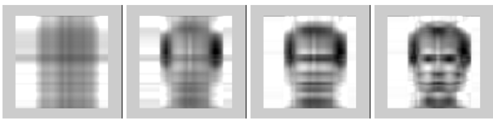


Fig: 18 SDM based results obtained after 1-8 iteration at α = 1

CASE 4: Image with facial expression variation

Fig: 19 Original Image with facial expression variation

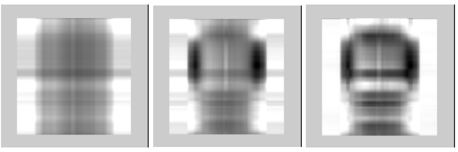


Fig:20 SVD based results for given query

SDM based results

At α = 0.5

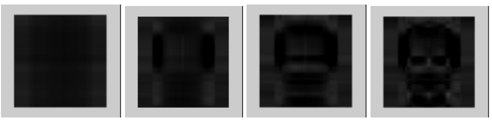


Fig:21 SDM results after 1-8 iteration at α = 0.5

At α = 0.8

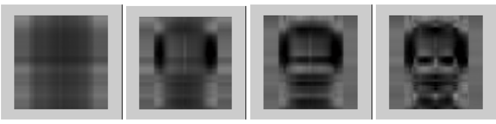


Fig:22 SDM results after 1-8 iteration at α = 0.8

At α = 1

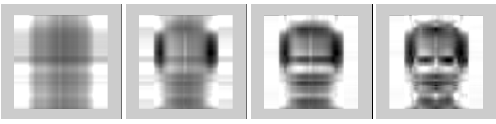


Fig:23 SDM results after 1-8 iteration at α = 1

(e) Testing input scaled similar image (f) Recognized image by SDM-SMF approach

Fig:24 Observations and dataset Face images in Yale Database

The proposed algorithm undergoes 3 phasesi.e training, testing and classification. The figures (a)-(d) are training images, the figure (e) is the testing stage input image and the figure (f) is the recognized result.

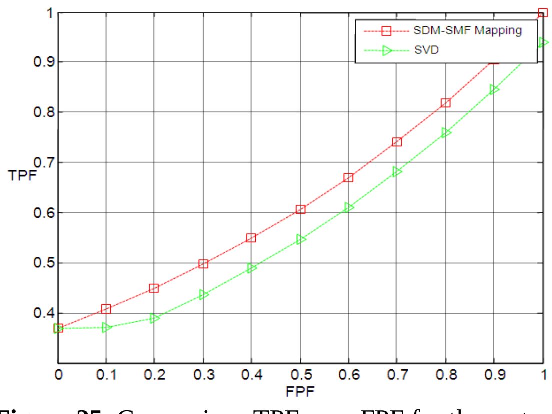


Figure 25. Comparison TPF over FPF for the system

Figure 25 shows the comparison of recognition rate of proposed method with other methods. From the results the proposed method achieves higher recognition rate. Table 1 shows that cumulative results for Yale database. From the table it is clear that the recognition rate for SMF method is higher than the other methods. So compared to other methods, SMF method achieves the good recognition result.

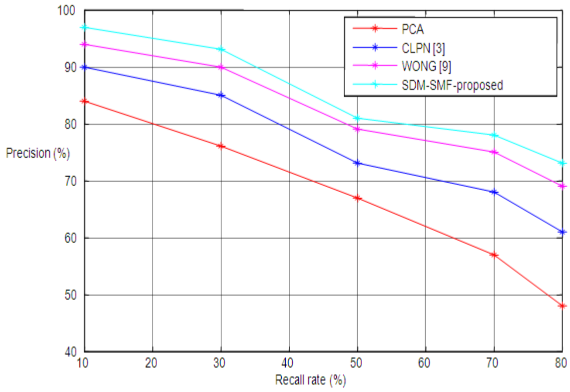


Figure 26: System precision over recall rate

To evaluate the retrieval efficiency of the developed approach, the performance measures of recall and precision is made. Where the recall is defined as a ratio of number of relevant image retrieved over, total number of relevant image present. The Precision is derived as a ratio of number of relevant images retrieved to the total number of images retrieved. The recall and the precision factor is defined as;

$$\text{Precission} = \frac{\text{No .of relevant images retreived}}{\text{No .of images retreived}} \qquad (34)$$

$$\text{Recall} = \frac{\text{No .of rel evant images retreived}}{\text{No .of relavent images present}} \quad (35)$$

Table 1 Cumulative Recognition Results for ORL database

Rank	1	2	3	4	5
SDM-SMF METHOD	0.95	0.965	0.98	0.985	0.99
PCA METHOD	0.935	0.94	0.96	0.9	0.98
CLPM [3]	0.915	0.93	0.955	0.96	0.965
Wong's method [9]	0.91	0.93	0.945	0.95	0.975

a) Impact of down sampling Rate

In this experiment, we study the impact of dowmsampling rate on each SR recognition method. When the downsampling rate is 4, 5, 6, 7, and 8, all methods were applied to the relatively large YALE database to study the impact of the downsampling rate. Table 2 gives the corresponding results. We can see that, basically, the larger the downsampling rate, the lower the recognition rate for every method. At all downsampling rates, our method obtains the highest recognition rate. With the downsampling rate changing from 4 to 8, the changing range of recognition rate, which is obtained by the maximum minus the minimum, of our method is only 0.058 (i.e., 0.844 minus 0.786), which shows that our method is very stable. And the range of CLPM, Wang's, Gunturk's, and LR-PCA methods, respectively, is 0.220, 0.179, 0.228, and 0.198. Thus, our method is the best, considering both stability and effectiveness.

Table 2 Recognition Results with Different Dimensions for the Yale Database

Down sampling rate	4	5	6	7	8
SDM-SMF METHOD	0.835	0.844	0.841	0.786	0.803
PCA METHOD	0.818	0.825	0.826	0.762	0.796
CLPM	0.802	0.701	0.674	0.674	0.582
Wong's method	0.696	0.693	0.699	0.52	0.52

b) Discussion

The SDM based recognition approach is observed to be more effective in face recognition compared to the existing approach due to the fact that the SDM approach works on the simple principle of deflating the more dominant leading base image (i.e. the higher order SV) and inflating the lower SV's. As these lower SV's are content of low variations which are facial expressions in the given face image. As SDM inflate these SV's the expression or illumination, which are completely neglected in previous, approach resulting in lower estimation accuracy are overcome in SDM approach. The proposed SDM based recognition approach is found to be very effective in case of intermediate feature extraction for face recognition. This feature extraction could then be used as a information for recognition systems such as PCA, LDA, SVM etc. The SDM based recognition approach is focused to overcome the effects of various real time factors in face image. Though this technique is found to inflate the low SV so as to reveal the expression affects this method is found to be of same computation time as compared to the existing recognition system. When employing SDM as a recognition approach for face recognition method, the time complexities in training and testing are almost the same as the existing methods. The time complexity for training N samples with dimensionality d = rxc is $T(N^2d)$, and the time complexity in testing any given unknown sample is T(dC), where C is the number of classes. For and SDM based system it consumes T(Nd max(r, c)) in computing the SDM for N samples where max(r,c) is usually smaller than N, and thus the time complexity in training is still $T(N^2d)$, as with the original recognition system, on the other hand, for any unknown sample, it takes T(max(r, c)d) in computing SDM, and thus the time complexity in testing is also T(dC) since max(r, c) is usually comparable to or less than C.

VI. Conclusion

For the problem of scaled similar face images resulting in lower recognition rate, an original method in the feature domain for face recognition was proposed in this paper. SMF was applied to obtain the mapped subspaces between the holistic features of original and scaled similar face images, and radial kernel was used to construct the nonlinear mapping relationship between the mapped features. Then, the original feature in the original space of the single-input scaled similar face image was obtained for recognition. Experiments show that even the simple SVM classifier can implement high recognition rates in the mapped subspaces. Compared to other feature-domain original methods, our method is more robust under the variations of expression, pose, lighting, and down sampling rate and has a higher recognition rate.

References

[1]. S.-W Lee. and J. Park, "Low resolution face recognition based on support vector data description," Pattern Recognit., vol. 39, no. 9, pp. 1809–1812, Sep. 2006.

[2]. O. Sezer, Y. Altunbasak, and A. Ercil, "Face recognition with independent component-based super-resolution," in Proc. SPIE Visual Commun. Image Process., vol. 6077. San Francisco, CA, 2006, pp. 52–66.

[3]. J. Lu, X. Yuan, and T. Yahagi, "A method of face recognition based on fuzzy c-means clustering and associated sub-NNs," IEEE Trans. Neural Netw., vol. 18, no. 1, pp. 150–160, Jan. 2007.

[4]. K.-C. Kwak and W. Pedrycz, "Face recognition using an enhanced independent component analysis approach," IEEE Trans. Neural Netw., vol. 18, no. 2, pp. 530–541, Mar. 2007.

[5]. F. Lin, J. Cook, V. Chandran, and S. ORidharan, "Face recognition from super-resolved images," in Proc. 8th Int. Symp. Signal Process. Appl., vol. 2. Sydney, NSW, Australia, Aug. 2005, pp. 667–670.

[6]. S. Zhou, V. Krueger, and R. Chellappa, "Probabilistic recognition of human faces from video," Comput. Vis. Image Understanding, vol. 91, nos. 1–2, pp. 214–245, Jul.–Aug. 2003.

[7]. H. Hotelling, "Relations between two sets ofvariates," Biometrika, vol.28, nos. 3–4, pp. 321–377,1936.,http://en.wikipedia.org/wiki/Kernel_principal_component_analysis

[8]. T.-K. Kim, S.-F.Wong, and R. Cipolla, "Tensor mapped correlation analysis for action classification," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Minneapolis, MN, Jun. 2007, pp. 1–8.

[9]. J. Moody and C. Darken, "Fast learning in networks of locally-tuned processing units," Neural Comput., vol. 1, no. 2, pp. 281–294, 1989.

[10]. Z. Hong, Algebraic feature extraction of image for retrieval, Pattern Retrieval 24 (1991) 211–219.

[11]. J. Liu, S. Chen, Discriminant common vecotors versus neighbourhood components analysis and laplacianfaces: a comparative study in small sample size problem, Image Vision Comput. 24 (3), 249–262, 2006.

[12]. J. Liu, S. Chen, Resampling lda/qr and pca+lda for face retrieval, in: The 18th Australian Joint Conference on Artificial Intelligence, pp. 1221–1225, 2005.

[13]. J. Ye, Q. Li, A two-stage linear discriminant analysis via qrdecomposition, IEEE Trans. Pattern Anal. Mach. Intell. 27 (6), 929–941, 2005.

Authors Detail

1) **Mr. Raghavendra Kulkarni**
Scholar,Mewar University,Rajasthan.
e-mail: raghavendrakulkarni444@gmail.com

Raghavendra Kulkarni received B. Tech. (ECE) from Gulbarga University, M. Tech Degree in DSCE from JNTU Hyderabad. He is pursuing Ph.D from MEWAR UNIVERSAITY, RAJASTHAN. He is having 21 years of experience .He has authored and coauthored 28 research papers in National and International Conferences & Journals.