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Content Based Image Retrieval Using Singular Value Decomposition

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***Abstract* – A computer application which automatically identifies or verifies a person from a digital image or a video frame from a video source, one of the ways to do this is by com-paring selected facial features from the image and a facial database. Content based image retrieval (CBIR), a technique for retrieving images on the basis of automatically derived features. This paper focuses on a low-dimensional feature based indexing technique for achieving efficient and effective retrieval performance.**

An appearance based face recognition method called singular value decomposition (SVD) is proposed in this paper and is different from principal component analysis (PCA), which effectively considers only Euclidean structure of face space for analysis which lead to poor classification performance in case of great facial variations such as expression, lighting, occlusion and so on, due to the fact the image gray value matrices on which they manipulate are very sensitive to these facial variations. We consider the fact that every image matrix can always have the well known singular value decomposition (SVD) and can be regarded as a composition of a set of base images generated by SVD and we further point out that base images are sensitive to the composition of face image.

Finally our experimental results show that SVD has the advantage of providing a better representation and achieves lower error rates in face recognition but it has the disadvantage that it drags the performance evaluation. So, in order to overcome that, we conducted experiments by introducing a controlling parameter ‘α’, which ranges from 0 to 1, and we achieved better results for α=0.4 when compared with the other values of ‘α’.

***Key words*: singular value decomposition (SVD), Euclidean distance, original gray value matrix (OGVM).**

I. Introduction

The past few years have seen many advanced techniques evolving in Content Based Image Retrieval (CBIR) systems. Applications like art, medicine, entertainment, education, manufacturing, etc. make use of vast amount of visual data in the form of images. This envisages the need for fast and effective retrieval mechanisms in an efficient manner.

A major approach directed towards achieving this goal is to use low-level visual features of the image data to segment, index and retrieve relevant images from the image database. Recent CBIR systems based on features like color, shape, texture, spatial layout, object motion, etc., and are cited. Of all the visual features, color is the most dominant and distinguishing one in almost all applications. Hence, our approach is to segment out prominent regions in the image
based on color and pick out their features. We then use shape features of these regions to obtain shape index used for retrieving based on shape matching.

Content Based Image Retrieval (CBIR) has gained more and more attention in the last few years. The main aim of CBIR is to search for similar images in a given database based on an expressive representation of its images. The process of finding this expressive information is known as “Feature Extraction”. It is known that no single descriptor is powerful enough to en-compass all aspects of image content; each feature extraction method has its own view of the image content. A possible approach to cope with that fact is to get a whole view of the image (object).

In this paper we are trying to replicate a computer application for automatically identifying or verifying a person from a digital image or video frame from a video source. One of the ways to do this is by comparing selected facial features of the image from a facial database. It is typically used in security systems and smart cards and so on. The places where we can apply our work are briefly explained with the following example: In confidential places such as bank lockers, in automatic door opening systems. In bank lockers, the existing system has a fault that the unknown person can easily open the locker if he gets the key. So, to avoid this we can use the person’s face as the password for opening the locker, by which we can easily avoid cheating. Some facial recognition algorithms identify faces by extracting landmarks, or features, from an image of the subjects face. For example, an algorithm may analyze the relative position, size, and or shape of the eyes, nose, cheekbones, and jaw. These features are then used to search for other images with matching features.

Other algorithms normalize a gallery of face images and then compress the face data, only saving the data in the image that is useful for face detection. A probe image is then compared with the face data.

Recognition algorithms can be divided into two main approaches, geo-metric, which look at distinguishing features, or photometric, which is a statistical approach that distills an image into values and comparing the values with templates to eliminate variances. Popular recognition algorithms include principal component analysis with Eigen face, Linear Discriminate analysis, singular value decomposition (SVD) and fractional order singular value decomposition (FSVD). The present paper uses an Eigen face and singular value decomposition approach as in [1]. Eigen faces and Eigen vectors of co-variance matrix are represented given image space. Any new face image can then be represented as a linear combination of these Eigen faces. This makes it easier to match any two images and thus proceeds face recognition process. Another method which is an appearance based face recognition method called the singular value decomposition (SVD) approach. In this method, SVD is employed to each OGVM to obtain

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singular values (SVs) to represent this face image, and then to perform classification based on these SVs and these SVs are used as an IR, and then an optimal discriminant transformation is employed to transform the SVs into a new space for subsequent classification. We point out that the SVs contained little useful information for face recognition and attributed the good performance in case of small testing database. The other method FSVDR is proposed with SVs it is clear that the two methods are quite different. The representation by SVs only employs the SVs, while our FSVDR utilizes not only the SVs, the left and right transformation matrices but also a parameter α to yield the so-needed IR.

II. Proposed Method

In this paper, proposed experimental study on content based image retrieval is performed using the three methods PCA, SVD, FSVD.

2.1 Principal Component Analysis

CBIR is discriminating the images from image database into several categories. The database images belonging to same category may differ in lighting conditions, noise etc., but are not completely random and in spite of their differences, there may present some patterns. Such patterns could be referred as principal components. Principal Component Analysis (PCA) is a mathematical tool used to extract principal components of original image data. These principal components may also be referred as Eigen images. PCA is generally used for face recognition. The idea of using principal components to represent human faces was developed by Sirovich and Kirby [17] in 1987 and used by Turk and Pentland [18] in 1991 for face detection and recognition. The Eigen face approach is considered by many to be the first working facial recognition technology. PCA can be used to transform each original image from database into its corresponding Eigen image. An important feature of PCA is that any original image from the image database can be reconstructed by combining the Eigen images. Even only some part of Eigen image can be used to reconstruct an approximate of the original image. PCA can do the jobs like prediction, redundancy removal, feature extraction, data compression, etc. So using PCA for image retrieval becomes obvious.

In statistics, principal components analysis (PCA) is a technique that can be used to simplify a dataset as mentioned in the book [4] more formally it is a transform that chooses a new coordinate system for the data set such that the greatest variance by any projection of the data set comes to lie on the first axis (then called the first principal component), the second greatest variance on the second axis, and so on. PCA can be used for reducing dimensionality in a dataset while retaining those characteristics of the dataset that contribute most to its variance by eliminating the later principal components. PCA aims at

1) Reducing the dimensionality of the data set.
2) Identifying new meaningful underlying variables.

2.1.1 Finding Principal Components

Principal Component Analysis is traditionally done as in [5, 8, 10] on a square symmetric covariance or correlation matrix obtained from the given m x n data matrix. A covariance matrix is obtained by mean centering the data across the origin and then taking the dot products.

A correlation matrix is obtained by normalizing the covariance matrix. This normalization is required because; in statistical data it is very natural to have data spread out over wide ranges. If normalizations were not done, it would be difficult to assess the contributions of various components to the principal component. Principal components are the Eigen vectors of the square symmetric correlation matrix. The Eigen vector with the maximum Eigen value is the first principal component, the one with next largest Eigen value is the second principal component and so on.

To understand this better, we take an example. Suppose we have data for marks of n students in 2 subjects.

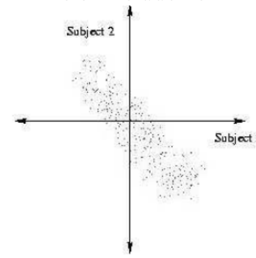

Fig.1. Centered Marks of Students in 2 Subjects

Centering of data is done by subtracting the mean from the data points. It should be noted that although the position of the points in the space has changed, the relationships between them are preserved. Further, even if we rotate the axes, the pattern in the underlying data remains the same.

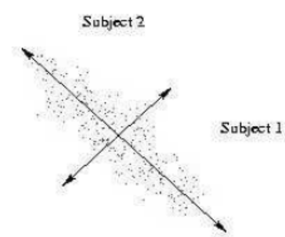

Fig.2. Axes rotated to get Principal Components.

The Principal Components are just linear combinations of the original axes but they define the directions in which the variability of given data set is maximum. This is useful in case we want to retain some and not all values; the projection of the data points on the first k principal components retains maximum information in the data.

2.2 Singular value decomposition

Singular value decomposition (SVD) provides a new way for extracting algebraic features from an image. SVD has been used in many fields such as data compression, signal processing and pattern analysis [4]. The main theoretical properties of SVD relevant to face image recognition are 1) The SVD of a face image has good stability. When a small perturbation is added to face image, large variance of its SVs does not occur. 2)

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Singular values represent algebraic properties of an image to some extent; SV features possess algebraic and geometric invariance. Singular Value Decomposition (SVD) is said to be significant topic in linear algebra by renowned mathematics.SVD has many practical and theoretical values; special features of SVD is that it can be performed on any real (m,n) matrix. Let's say we have a matrix A with 'm' rows and 'n' columns, with rank 'r' and $r \leq n \leq m$. Then the A can be factorized into three matrices:

Mathematically, every r×c (rxc without loss of generality) OGVM A can always have the SVD as

$$\mathbf{A=USV^T} \quad \mathbf{(1)}$$

Where Matrix U is an mxm orthogonal matrix

$$U= [u_1,u_2,\ldots\ldots, u_r ,u_{r+1}\ldots\ldots.,u_m]$$

Column vectors u_i, for i=1,2,3,………,m, form an orthogonal set :

$$u_i^T u_j = \begin{cases} 1,,,,,,i=j \\ 0,,,,, i\neq j \end{cases}$$

And matrix V is an nxn orthogonal matrix

$$V= [v_1, v_2,\ldots\ldots\ldots,v_r ,v_{r+1} ,\ldots\ldots\ldots,v_n]$$

Column vectors vi for i=1,2,……..,n form an orthogonal set:

$$v_i^T v_j = \begin{cases} 1,,,,,,,,i=j \\ 0,,,,,,,,,i\neq j \end{cases}$$

Here, S is an mxn diagonal matrix with singular values (SV) on the diagonal. The matrix S can be shown as follows

$$S = \begin{bmatrix} S_1 & 0 & 0 & . & . & . & . & 0 & 0 & 0 \\ 0 & S_2 & 0 & . & . & . & . & 0 & 0 & 0 \\ 0 & 0 & S_3 & . & . & . & . & 0 & 0 & 0 \\ . & . & . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . & . & . \\ 0 & 0 & 0 & . & . & S_r & . & 0 & 0 & 0 \\ . & . & . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . & . & . \\ 0 & 0 & 0 & . & . & . & . & 0 & 0 & S_i \end{bmatrix} \quad \mathbf{(2)}$$

For i =1, 2,………..,n, S_i are called Singular Values of matrix A .It can be proved that

$$S_1>S_2>\ldots\ldots>S_r>0, \text{ and}$$
$$S_{r+1}=S_{r+2}=\ldots=S_n=0.$$

For i=1, 2,…………….n, Si are called singular values (SVs)of matrix A. The v_i 's and u_i's are called right and left singular vectors of A[15].

2.3 Fractional order singular value decomposition

To alleviate the facial variations on face images, we propose a novel FSVDR, whose underlying ideas are that (1) the weights of the leading base images u_i,v^T_i 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^T_i corresponding to relatively small i's should be inflated, since they may be less sensitive to the facial variations within A, which can be read from [11,12,13] the order of the weights of the base images $u_iv^T_i$ in formulating the new representation B should be retained. More specifically, for each face image matrix A which has the SVD in Eq. (2), its FSVD B is defined as

$$\mathbf{B = U\ S^{\alpha}\ V^T} \quad \mathbf{(3)}$$

Where U, S and V are the corresponding matrices in Eq. (2), and in order to achieve the above underlying ideas, α is a fractional parameter that satisfies: 0< α< 1. FSVDR employs the well-known singular value decomposition (SVD) and it needs to tune a parameter α to yield an IR and the choice of the parameter is both database and DR method dependent.

III. Architecture of CBIR System

In this section, an overview of the face recognition models that introduce some notation that will help to unify the idea developed.

Image processing starts with image acquisition, yielding a digital image that is to be preprocessed to accentuate some visual information. The basic stages for object recognition are demonstrated in fig 3.1.

After image acquisition stage, various methods of preprocessing can be applied to the image to produce an output which in some way represents an 'improvement' to original image. This stage may remove noise, increase the contrast of the image, remove blurring caused by movement of the camera during image acquisition etc.

Usually, next stage is extracting the features of images by using PCA or SVD.These features are in the form of vectors .The similarity match is performed in order to retrieve the similar images in the database for a given query image and gives the most similar images as output.

Face recognition and retrieval applications generally use different techniques and give different emphasis on subjects of image analysis. In a typical recognition problem, we expect a comparison to be successful for images very close to the model and unsuccessful for images different from the query. Image retrieval applications require a similarity distance that accurately measure perceptual similarity for all shapes in database, reasonably similar to the query.

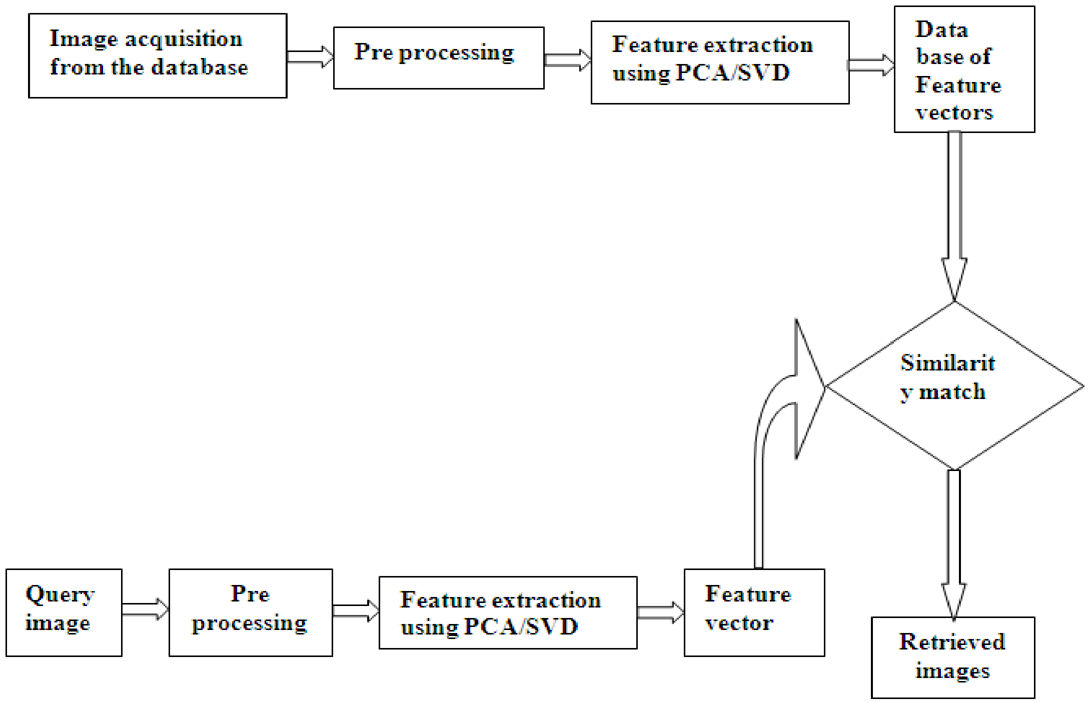

Fig.3.1. Architecture of CBIR system

IV. Result Analysis

Experiment conducted with some classes of images in face database. Each class contains 10 images which are varied in terms of expressions. These features for the images in the database are computed and stored. Take a query image, the same features of the query images is compared with the features of same class images in data base using distance metric function. If the distance is minimum then the query image belongs to that class. Database consists of 100 images from 10 classes. Each class has 10 different versions. The retrieval rate is measured precision. The query image, it is matched with all the images in database and the top 15 most nearer images are retrieved from the database as shown below

In this section, we carry out experiments to show that, FSVD can yield significantly better classification performance than SVD and it can significantly improve the classification performance of quite dimensionality reduction (DR) methods such as PCA, SVD.

Furthermore, we experimentally visualize the samples by SVD, PCA to the benefit brought by FSVD.

Results for the query 39 are shown below

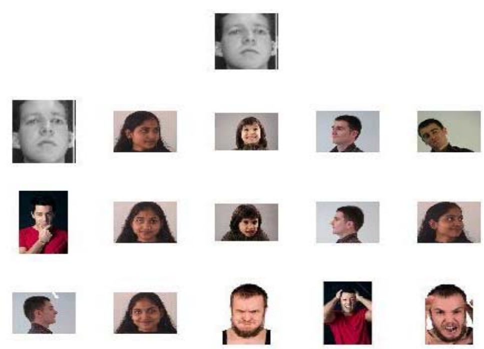

Fig.1. PCA

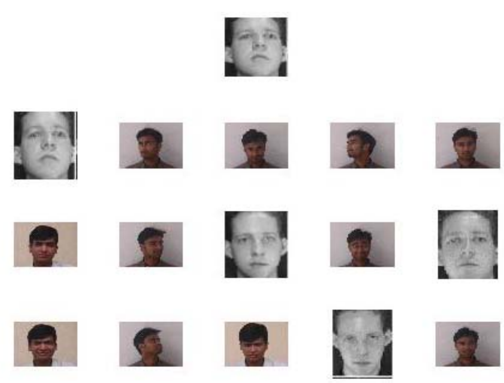

Fig.2. SVD

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Fig.3. FSVD

Firstly, we look at the best 15 matches presented in the fig-(1) from which we see that, when employing PCA, the samples from the same class are wide in distance, and the samples from different classes are not faraway.

More significantly, out of the ten training samples from the given query class, only one sample of the same query class is retrieved, but the other nine training samples from the given query class are faraway from the retrieved sample.

The above given experimental results show that when performing PCA on original gray value matrix (OGVM), 1) we cannot come to the objective that the samples from the same class are compact and meanwhile the samples from different classes are faraway in case of great facial variations. 2) We can observe that retrieval efficiency is very poor.

Secondly, we look at the testing samples presented in fig-(2) from which we can clearly see that the testing samples from the same class are not compact too and meanwhile the samples from different classes are not faraway. More specifically, out of the ten training samples from the given query class, only four samples of the same query class are retrieved and the remaining relevant samples are faraway from the obtained samples from the given query class, only four samples of the same query class are retrieved and the remaining relevant samples are faraway from the obtained samples.

The results presented in the fig-(2) witness similar phenomenon as fig-(1).the reason behind this in fig-(1) and fig-(2) is: based on original gray value matrix, the methods PCA,SVD are unable to compactly under the same class samples, which are under severe facial variations such as lighting, expression and occlusions.

Finally, we turn to the experimental results with FSVDR as an IR (α =0.4, alpha is set to 0.4), from which we can clearly see that (refer fig-(3)): 1) the images belonging to the same class become very compact. 2) The images belonging to different classes are well separated from each other.3) the testing images from the same class are compact with each other. 4) Generally speaking, these testing samples do not locate very near to the training samples of the same classes, which attributes to the fact that our proposed FSVDR does not remove the occlusions such as glasses and scarves and on the contrary it just alleviates the influence of such occlusions. 5) Despite that the testing samples do not locate very near to the training samples in the same classes, the testing samples can all be correctly classified, which attributes to the fact the testing samples are farther away from the training samples of different classes compared to those of the same class.

Similar observations can be obtained from the training samples of queries as shown below

Results for the query 36 are shown below

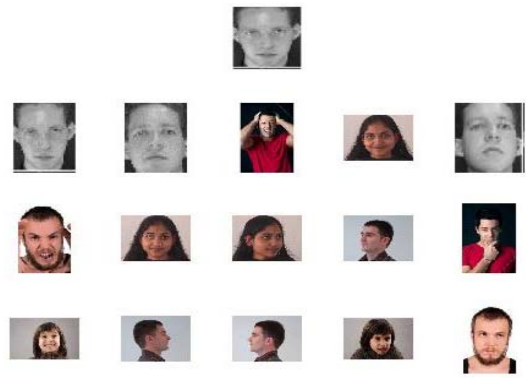

Fig.4. PCA

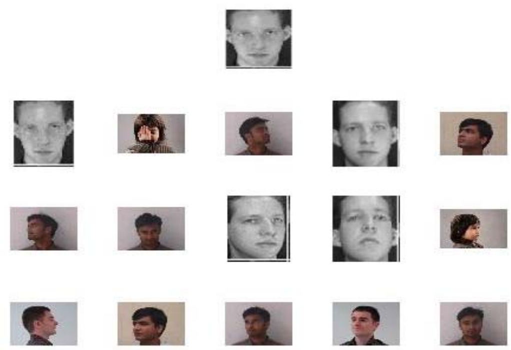

Fig.5. SVD

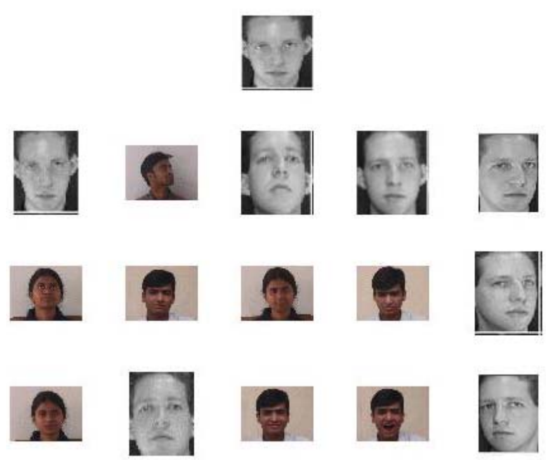

Fig.6. FVSD

Results for the query18 are shown below

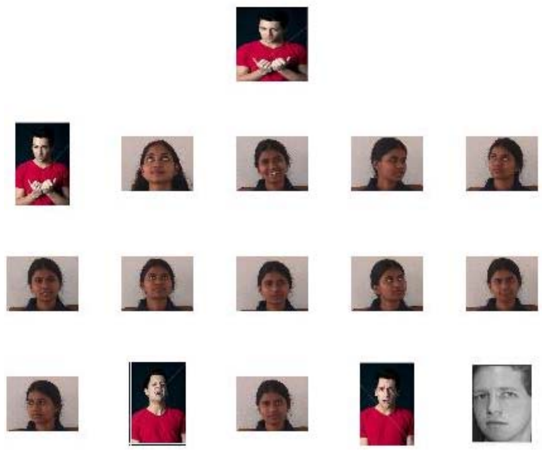

Fig.7. PCA

Fig.8. SVD

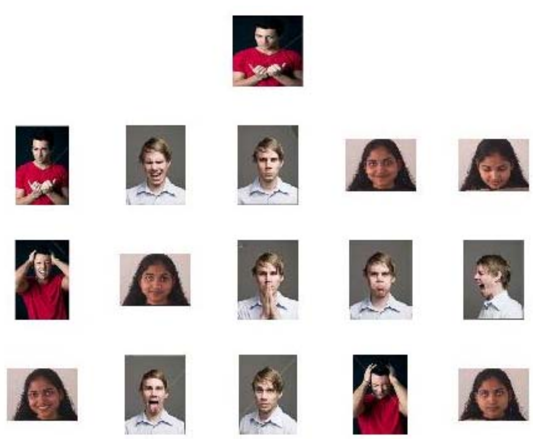

Fig.9. FSVD

Comparing the results presented in above figures, we can clearly see that, FSVD's alleviation of facial variations can help PCA, SVD achieve its objective (namely, samples from the same class are compact and samples from the different classes are faraway) and as a result can help improve the classification performance.

The parameter α :

In FSVD, α is the key parameter that should be tuned. Generally speaking, in designing automatic criterion for choosing adequate parameter alpha, one should consider the following factors: 1) the smaller α is, the more the leading base images (which are sensitive to facial variations) are deflated. 2) Some face images have great facial variations and are perhaps in favor of smaller α' s

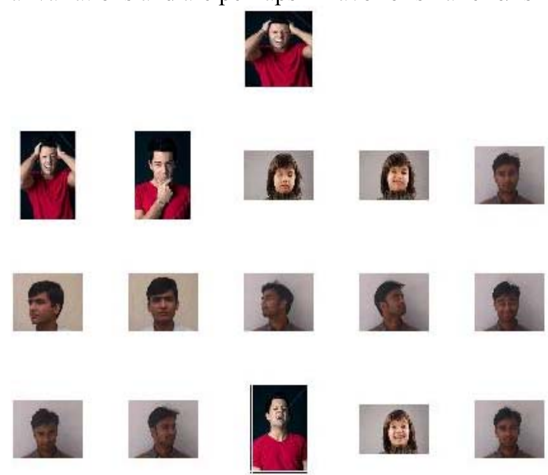

Fig.10. α=0

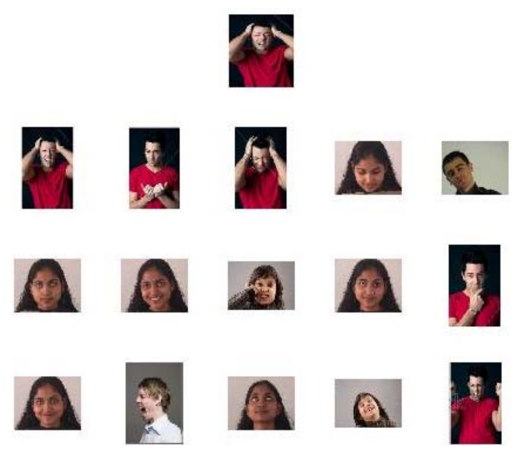

Fig.11. α=0.4

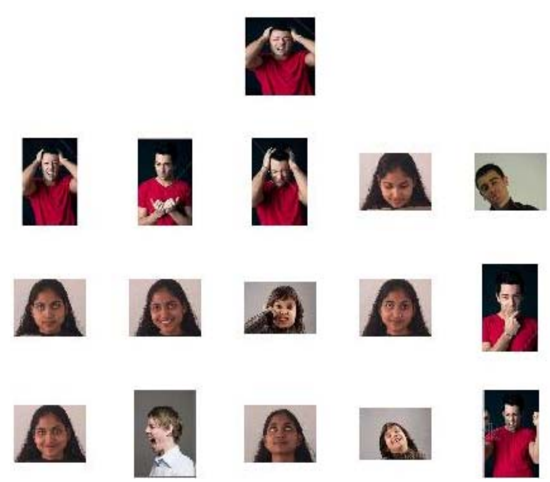

Fig.12. α=0.8

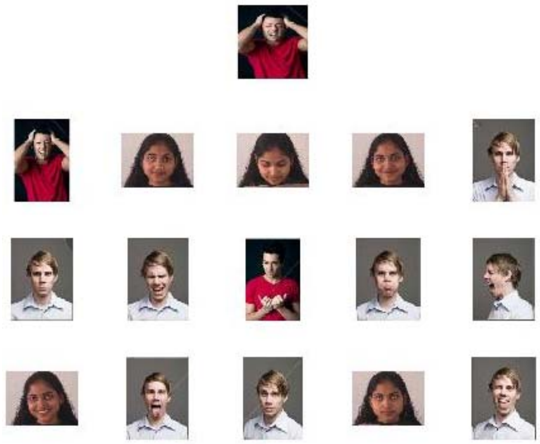

Fig.13. α=1

We just varied the values of α from 0 to 1.and it is observed that for α=0.4 and 0.5 the results obtained are same as we prefer to work with smaller α's, α=0.4 is considered as the optimum value if α = 1 the result obtained is same as that for SVD.

Many different measures for evaluating the performance of image retrieval systems have been proposed. The measures require a collection images in database and a query image. The retrieval performance is measured in terms of precision and recall.

Precision:

Precision is defined as the number of relevant images retrieved divided by the total number of images retrieved.

$$\text{Precision} = \frac{\text{No of relevant images retrieved}}{\text{Total no of images retrieved}} \times 100$$

Recall: Recall is defined as the number of relevant images retrieved by a search divided by the total number of existing relevant images.

$$\text{Recall} = \frac{\text{No of relevant images retrieved}}{\text{Total No. of relevant images in the database}} \times 100$$

Table for Precision and recall rates is as shown below
Total retrieved images =15
Total relevant images = 10
Total images in the database=100

query	**retrieved relevant images**			**Precision (%)**			**Recall (%)**		
	PCA	SVD	FSVD	PCA	SVD	FSVD	PCA	SVD	FSVD
18	4	3	5	26.6	20	33	40	30	50
20	1	2	5	6.6	13	33	10	20	50
36	3	4	7	20	26	46	30	40	70
39	1	4	6	6.6	26	46	10	40	60
44	7	10	10	46	66	66	70	100	100
45	6	10	10	40	66	66	60	100	100
81	1	4	7	66	26	46	10	40	70
90	4	5	7	26	33	46	40	50	70

4.1 Table for Precision and recall rates

The above table ensures that the precision and recall rates are high when FSVD is employed as compared with those of PCA, SVD

V. Conclusion & Future Work

In this paper, we show that the face image matrix *A* can be viewed as a composition of a set of base images generated by their SVD per se, where the leading base images on one hand dominate the composition of *A* and on the other hand are sensitive to the great facial variations within the image matrix *A*. Based on these observations, we propose a novel FSVDR *B*, which is a transformed version of OGVM *A* by SVD and the fractional parameter α and can alleviate facial variations for face recognition. When directly employing FSVDR for classification, it can yield significantly higher classification accuracies than both OGVM and SVs; and as an intermediate representation, the FSVDR can significantly improve the classification performance than by using PCA, SVD.

In this paper, we have proposed SVD method for face verification. Real-time face identification is necessary in most practical applications. The proposed method can process face images (including training and identifying) in high speed and obtain good results. Its effectiveness and good performance has been proven by experiments. The

SVD based verification method achieves good results in the database because the training and testing images have been normalized. The proposed identification technique improves the correct verification rates.

In our point of view, there are the following aspects that are worthy of further studies:(1) carry out research to set sample dependent parameter α, since different face samples are affected by facial variations differently (note that, in our FSVDR, we set a universal value for all the face samples); (2) set different 'α' values for different singular values in order to suppress noise.

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