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A Combination Approach to Human Face Recognition

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Abstract

In this paper, we propose a combination approach for face recognition based on combination of two features extractor schemes named Singular Value Decomposition and Gabor filters. Singular value decomposition (SVD) is a good method to extract image features because it has invariance for the rotation and mirroring transformation, and also has better robustness for noise and light intensity transform. Gabor filters produce perfect localization features in frequency and spatial domains. From theexperimental results, the suggested approach obtains a good recognition rate. A recognition rate of more than 98% has been achieved on the ORL database.The proposed approach has also been compared to some existing techniques and the results obtained by the proposed method are far better than these techniques.

Keywords: Pattern recognition, Face Recognition, Singular Value Decomposition (SVD),Gabor filters

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الخلاصة

اقترحنا في هذا البحث طريقه مدمجة لتمييز الوجه بالاعتماد على طريقتين لاستخلاص المميزات وهي تحليل القيمة المفردة و موجات غابور. ان تحليل القيمة المفردة هيطريقة جيدة لاستخلاص المميزات من الصورة لانها تملك ثبات للدوران و التحويل المنعكس وايضا لها متانة افضل للضوضاء وتحويل شدة الاضاءة. تنتج مرشحات غابور مميزات مركزه ودقيقة في المجالين الحيزي والترددي. من النتائج التجريبية، فان النهج المقترح يحصل على معدل اعتراف جيد ، معدل الاعتراف كان اكثر من 98% على قاعدة البيانات (ORL). كما تم مقارنة النهج المقترح مع بعض التقنيات الموجوده فكانت النتائج التي تم الحصول عليها من خلال النهج المقترح افضل بكثير من تلك التقنيات.

كلمات البحث: تمييز الانماط ، تمييز الوجه ، تحليل القيمة المفردة ، مرشحات غابور.

1- Introduction

Face recognition has become very important gradually due to its wide range of commercial and law enforcement applications such as access control, forensic identification,human interactions, border surveillance and availability of low cost recording devices and so on[1]. Generally, There are three methodologies forface recognition: holistic methodswhere whole faceregion is used as raw input for the system.Feature-basedmethods use local features such as the nose, eyes, mouth .etc.Hybrid methods uses both local features and the whole face region to recognize a face.In literature workseveral face recognition systems have been suggested[2].Jin Zhang et al. introduced the novel chaotic neural network mimicking olfactory system and use its characters on the face recognition. Based on the idea of image partition, the features are extracted by using SVD and Discrete Cosine Transform DCT [3].Chou-Hao Hsu proposed a new feature extraction method based onSVD and Principal Component Analysis (PCA)for classifyingfacial images [4]. Fusion of some selected left and right singular vectors of SVD and DCT-RLDA is capable of generating the superior results on face images as compared to their individual counterpart [5].Fredy Purnomo et al. developed a hybrid method from Gabor Wavelet and Non-negative Matrix Factorization(NMF) [6]. Xiaohong Hu proposed a new method for face recognition system combined Gabor with sparse representation [7]. H. Yan et al. proposed a novel idea based on Gabor wavelet transform and modular Two-principal component analysis for face recognition[8].

This paper is organized in the following sequence. In Section 2 the Singular Value Decompositionis described. Next, the Gabor filtersintroduced in section 3.Section 4 describes the dissimilarity measurements. Section 5describes the proposed approach. Experimental results ispresented on section 6 and conclusion is drawn on section 7.

2- Singular Value Decomposition

The Singular Value Decomposition (SVD) is an algebraic technique for factoring any rectangular matrix into the product of three other matrices.If $A \in R^{m\times n}$ is a gray level facial image and$\mathrm{rank}(A) = r$, then there exist two orthogonal matrices

$$U = [u_1, \dots, u_m] \in R^{m\times m}, U^t U = I \qquad V = [v_1, \dots, v_n] \in R^{n\times n}, V^t V = I$$

and diagonal matrix

$$\Sigma = \mathrm{diag}(\lambda_1, \lambda_2, \dots, \lambda_r, 0, \dots, 0) \in R^{m\times n}, \ \lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_r \geq 0$$

such that

$$A = U\Sigma V^t = \sum_{i=1}^{r} \lambda_i u_i v_i{}^t \qquad (1)$$

where λ_i^2 is the eigenvalue of $A^t A$ as well as $A A^t$, λ_i is singular value (SV) of facial image A, u_i, v_i, are column eigenvectors of $A^t A$ and $A A^t$ corresponding to eigenvalue λ_i^2, respectively[9]-[11].SVD has the following important properties. In [12] these important properties were proved. Now we list these properties as follows: stability, transposition invariance, rotation invariance, proportion invariance, mirror transform invariance.

3- Gabor filters

Gabor filters are also called Gabor kernels or Gabor wavelets in some documents . Gabor filters are widely used to represent the face image because the kernels of Gabor filters are similar to two-dimensional receptive field profiles of the mammalian cortical simple cells, which captures the properties of spatial localizations, orientation selectivity, and spatial frequency selectivity to cope with the variations in illumination and facial expressions [13].The 2D Gabor filters in the spatial domain is [14][15]:

$$\psi_{u,v}(x,y) = \frac{f^2}{\pi\gamma\eta} e^{-\left(\frac{f^2}{\gamma^2}\acute{x}^2+\frac{f^2}{\eta^2}\acute{y}^2\right)} e^{j2\pi f\acute{x}} \qquad (2)$$

$$\acute{x} = x\cos\theta + y\sin\theta \qquad (3)$$

$$\acute{y} = -x\sin\theta + y\cos\theta \qquad (4)$$

where (x, y) denote the pixel position in the spatial domain , f is the central frequency of the filter , θ the rotation angle of the Gaussian major axis and the plane wave (anti-clockwise orientation of a Gabor filter) , γ the sharpness along the major axis , and η the sharpness along the minor axis (perpendicular to the wave). f is defined as

$$f = \frac{f_{max}}{(\sqrt{2})^u} \qquad (5)$$

where u defines as the scale of the Gabor filters . θ is defined as

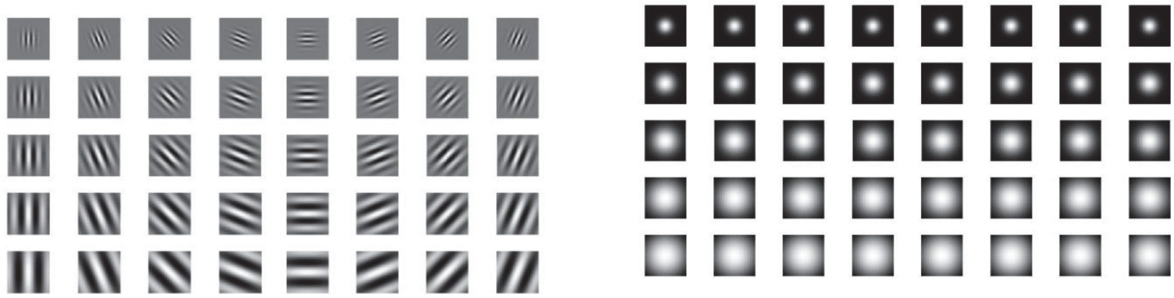
$$\theta = \frac{v}{8}\pi \qquad (6)$$

where v defines as the orientation of the Gabor filters. Gabor filters with 5 scales $(u = 0, \dots ,4)$ and 8 orientations $(v = 0, \dots ,7)$ are commonly used in face recognition applications [16]. For example, the real parts and the magnitude responses of Gabor filters with 5 scales and 8 orientations are shown in figure (1) , with the following parameter : $f_{max} = 0.25$, $\gamma = \sqrt{2}$ and $\eta = \sqrt{2}$.

Gabor facial feature is extracted from an image through convolution between facial image and Gabor filters as defined in Eq.(7) where $I(x, y)$ represent grey-scale face image, $\psi_{u,v}(x, y)$ represent the Gabor filters and convolution is denoted by $*$ operator [17].

$$G_{u,v}(x,y) = I(x,y) * \psi_{u,v}(x,y) \qquad (7)$$

For example, The real parts and magnitude responses of the convolution outputs for a sample image shown in figure (2) with Gabor filters with 5 scales and 8 orientations are shown in figure (3).(a) and (b) , respectively

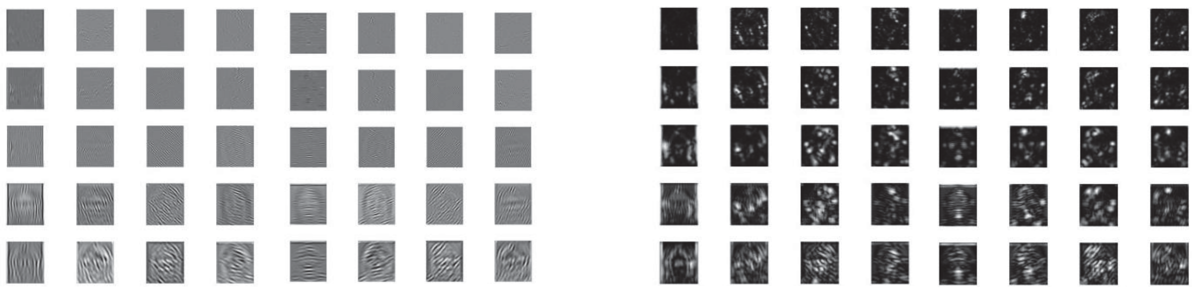


[(a) (b)

Figure 1: (a) Real Parts (b) Magnitude Responses of Gabor filters with 5 scalesand 8 orientations

.

Figure 2: Sample image



(a) (b)

Figure 3: (a) Real parts and (b) Magnitude Responses of the convolution output for image in figure (2)

4- Dissimilaritymeasurements

In our study we are interested to three distance measurements , mathematical description of these measurements is given below [18] :

(a) Euclidean distance : It is the most commonly used metric based on the Pythagorean formula. If $u = (u_1 , u_2 , \dots , u_N)$ and $v = (v_1 , v_2 , \dots , u_N)$ are two feature vectors, the Euclidean distance is given by :

$$D_{Euc}(u, v) = \sqrt{\sum_{i=1}^{N} (u_i - v_i)^2} \quad (8)$$

(b) City block distance : It is also known as Manhattan distance . In this metric, the distance between two vectors is the sum of the absolute differences of their elements. Mathematically, the distance between two vectors u and v is given by:

$$D_{Ctb}(u, v) = \sum_{i=1}^{N} |u_i - v_i| \tag{9}$$

(c) Cosine distance : Cosine similarity is measure of similarity based on the cosine of the angle between two vectors. Two vectors of same orientation has a cosine similarity value of 1 which reduces to -1 as the angle between the vectors increase to 180°. The mathematical expression is shown in Eq. (10) where a minus sign is introduced to convert the measure to dissimilarity metric in line with the other metrics here. Hence the cosine distance between two vector u and v is given by:

$$D_{Cos}(u,v) = -\frac{u \cdot v}{\|u\|\|v\|} = -\frac{\sum_{i=1}^{N} u_i \; v_i}{\sqrt{\sum_{i=1}^{N} u_i^{\;2}} \cdot \sqrt{\sum_{i=1}^{N} v_i^{\;2}}} \tag{10}$$

5- The Proposed Approach

In this section we present our methodology for face recognition.Figure (4) shows the block diagram of the proposedapproach. It is composed of the following steps:

1-Pre-processing: First, the image from the database is obtained and converted to gray scale. Then we resized the images in database to HxW (the size 92×92 is used in our experiments) in order to additional reduction in memory consumption and computational complexity.

2-Feature Extraction based on SVD: The SVD-Based Features Extraction form training images and test image is described as follows:

Given M training face images, denoted by m×n matrices Xk (k = 1, 2, ⋯, M), we first compute the mean face image.

$$\overline{X} = \frac{1}{M}\sum_{k=1}^{M} X_k \tag{11}$$

Then, we use SVD to decompose the matrix $\overline{X}$into three simple matrices as fellow:

$$\overline{X} = U\Sigma V^t \tag{12}$$

After that, each face image Xkis transformed into a face feature matrix Fk by:

$$F_k = U_r^t X_k V_c \tag{13}$$

where$U_r = [u_1, u_2, \dots, u_r]$, $V_c = [v, v_2, \dots, v_c]$, we have used 7 leftsingular vectors and 3 right singular vectors (r=7, c=3)because this configuration gives the best results.The size of F_k is r×c (Total features are 7*3=21 features).

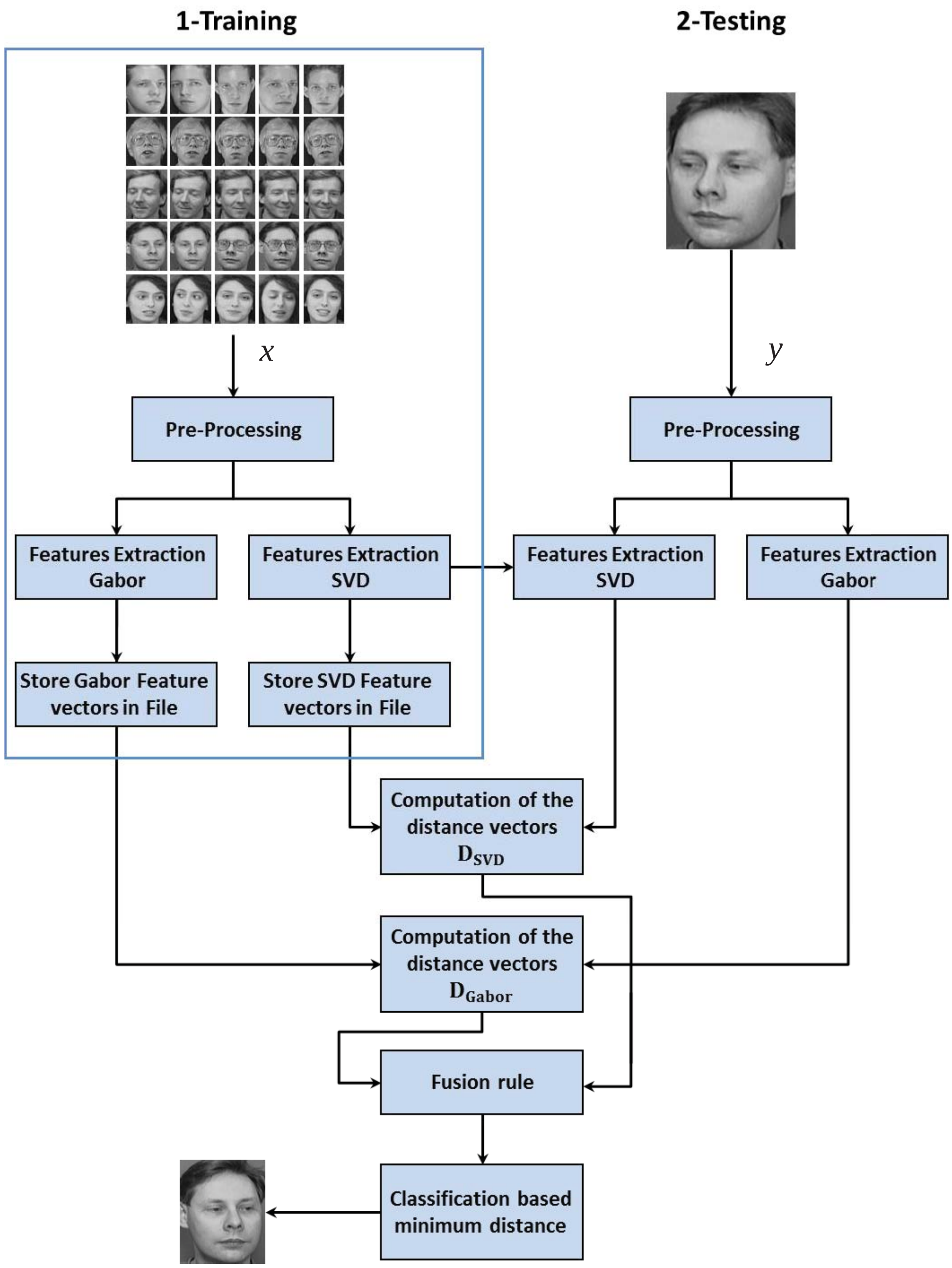


Figure 4 : Block diagram of the proposedapproach

then a test face image T is transformed into a face feature matrix Tp by

$$T_p = U_r^t \, T \, V_c \quad (14)$$

Finally, we compute the distance between a test face image$T_p$and all the training faces imagesF_k .

3-Feature Extraction based on Gabor : The Gabor features are computed as a convolution of the input image with the average Gabor filteras fellow:

$$G(x, y) = I(x, y) * \psi(x, y) \qquad (15)$$

where$I(x,y)$is training imageor test image and $\psi(x,y)$ is the average Gabor filters. Then we downsample output by a factor (d=10is used in our experiments) to reduce the dimensionality of the original vector spaceas fellow:

$$X^{(d)} = G^{(d)^t}(16)$$

then normalize it to zero mean and unit variance, which is a common normalization procedure in face recognitionas fellow:

F = (X-mean(X))/std(X) (17)

these steps apply on training images and test image .Total featuresbased on Gabor are 100 features($(f(w/d) * f(h/d) * \text{filter} = (f(92/10) * f(92/10) * 1) = 100$ features), wheref(x) rounds each element of x to the nearest integer greater than or equal to that element).

Finally, we compute the distance between a test face imageand all the training faces images .

4-Computation of Dissimilarity Measure:In SVD-Based Features Extraction, we have a vector v which contains the features corresponding to the test face and a matrix $F_k(k = 1, 2, \cdots, M)$, such as M represents the number of training faces, The comparison between $F_k$and v is done by calculating the distances between them, we obtained a distance vector $D_{SVD} = (d_1, d_2, \dots, d_M)$ which represents the score to be combined with Gabor .

In Gabor-Based Features Extraction, we have a vector v which contains the features corresponding to the test face and a matrix $F_k(k = 1, 2, \cdots, M)$, such as M represents the number of training faces, The comparison between $F_k$and v is done by calculating the distances between them, so we obtained a distance vector $D_{Gabor} = (d_1, d_2, \dots, d_M)$ which represents the score to be combined with SVD .

5- Fusion Method: After computethe two distance vectors, we combine the two resulting vectors D_{SVD} and D_{Gabor} in order to find the combined vector D_{Fusion}. we calculate D_{Fusion} as the multiplication of the two distance vectors. We choose the corresponding class according to the smallest value of D_{Fusion}.

$$D_{Fusion} = \left(\left(D_1^{SVD} . D_1^{Gabor}\right), \left(D_2^{SVD} . D_2^{Gabor}\right), \dots, \left(D_M^{SVD} . D_M^{Gabor}\right)\right) \qquad (18)$$

6- Experiment results

The standard database Olivetti Research Laboratory (ORL) [19] is selected to evaluate the recognition accuracy of the proposed approach.In the ORL database, there are 10 different images for each of the 40 distinct subjects. There are variations in facial expression (open/closed eyes, smiling/non-smiling), and facial details (glasses/no glasses). All images were taken against a dark homogeneous background with the subjects in an up-right, frontal position, with tolerance for some tilting and rotation of up to about 20°. Sample images from ORL databaseare shown in Figure (5). Hence, there are 400 face images in the database. The resolution of all images is 112×92, 8-bit grey levels.

Figure 5 :Sample images from ORL database

The recognition performance is evaluated in term of Recognition Rate (RR). Recognition rate is the percentage of the number of correct label over the total number of testing image. The formula of recognition rate is as follow:

$$\text{Recognition Rate} = \frac{\text{Number of test images recognized correctly}}{\text{total number of testing images}} \times 100$$

The recognition performance is affected by the selection of training and testing images, so the results on a number of differently selected training and test sets are conducted. To evaluate the performance of proposed method against the pose variation, the experimental setup designed for the ORL database is as the first set, namely Set1, has first five images as training and remaining five as test images. Set2, Set3, Set4, Set5 and Set6 consists of randomly five images as training images and the remaining images as testing images. Thus, the total number of training image and testing is 200 for both of all the Sets . The six training sets are list in table (1) which shows which images are used in different training sets.

Table 1: Filenames of different training sets

Set1	1.pgm, 2.pgm, 3.pgm, 4.pgm, 5.pgm
Set2	1.pgm, 2.pgm, 3.pgm, 9.pgm, 10.pgm
Set3	1.pgm, 2.pgm, 4.pgm, 7.pgm, 9.pgm

Set4	2.pgm, 4.pgm, 5.pgm, 6.pgm, 10.pgm
Set5	1.pgm, 3.pgm, 4.pgm, 5.pgm, 8.pgm
Set6	2.pgm, 5.pgm, 6.pgm, 7.pgm, 8.pgm

Various experiments performed on this database and the obtained results are shown in Table(2). It is clear from the experiments carried out on all the sets of training and test images that the recognition rate obtained by the proposed method is butter that the result that obtained by the individual Gabor and SVD approaches. The mean recognition rates of Gabor, SVD and Proposed methods are 82.25%, 95.17% and 98% respectively with Euclidean distance classification method . The recognition rate of proposed method is higher than Gabor and SVD method. Moreover, for every training set and the corresponding testing set, the accuracy of Proposed method is never worse than individual Gabor and individual SVD. Also, amongst the classification methods , Euclidean Distance performs better than the other two methods (Manhattan Distance and Cosine Distance) .

Table (2): Recognition results on ORL database

Classification method	Method	Experiment performed on						Mean accuracy (%)
		Set1	Set2	Set3	Set4	Set5	Set6	
Euclidean Distance	Gabor	78	79.5	83	84	83.5	85.5	82.25
	SVD	92.5	94.5	95.5	95.5	97.5	95.5	95.17
	Proposed method	**97.5**	**98.5**	**98**	**97**	**99**	**98**	**98**
Manhattan Distance	Gabor	83	85.5	90.5	89	88	91	87.83
	SVD	91.5	97.5	95.5	96.5	96.5	97	95.75
	Proposed method	**96.5**	**99.5**	**97**	**97**	**99**	**97**	**97.67**
Cosine Distance	Gabor	78	79.5	83	84	83.5	85.5	82.25
	SVD	90.5	96	95	94.5	96.5	95.5	94.67
	Proposed method	**94**	**98**	**97**	**95.5**	**97.5**	**97**	**96.5**

the performance of the proposed method is analysed against some of the recent available methods. Table (3) shows the recognition accuracy of some well known face recognition methodson ORLdatabase wherein first five images of each person are taken in the training set and allremaining are kept in the test set.

Table 3: Performance comparison of various face recognition approaches(sorted based years).

Paper	Approach	Database	Recognition rate(%)
Jin Zhang et al.(2006)[3]	SVD and DCT	ORL	91.5%
Chou-Hao Hsu (2006)[4]	SVD and PCA	ORL	95%
Messaoud Bengherabi et al.(2008)[5]	SVD and DCT-RLDA	ORL	95%
Fredy Purnomo et al.(2008)[6]	Gabor and NMF	ORL	95%
Xiaohong Hu (2014)[7]	Gabor and Sparse Representation	ORL	92.31%
H. Yan et al.(2015)[8]	Gabor andmodular 2DPCA	ORL	96.5%
The proposed system	**Gabor and SVD**	**ORL**	**97.5%**

7- Conclusion

In this paper, we have proposed face recognitionapproachbased on combination of two features extractor schemes named Singular Value Decomposition and Gabor filters. This method led to robust face recognition under extreme facial expression change, illumination change, multi-poses as frontal, where this method achieved excellent recognition rate reach to 98%.The accuracy of proposed method is never worse than individual Gabor method and individual SVD method.Amongst the classification methods , Euclidean Distance performs better than the other two methods (Manhattan Distance and Cosine Distance).The recognition accuracy of the proposed approach has also been compared to some existing techniques, the recognition accuracy of the proposed method is better than the accuracy of these well-known face recognition methods.

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