2016 International Conference on Computer Communication and Informatics (*ICCCI* -2016), Jan. 07 – 09, 2016, Coimbatore, INDIA

Performance analysis of different Matrix decomposition methods on Face Recognition

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Abstract—**Applications using face biometric are ubiquitous in various domains. We propose an efficient method using Discrete Wavelet Transform (DWT), Extended Directional Binary codes (EDBC), three matrix decompositions and Singular Value Decomposition (SVD) for face recognition. The combined effect of Schur, Hessenberg and QR matrix decompositions are utilized with existing algorithm. The discrimination power between two different persons is justified using Average Overall Deviation (AOD) parameter. Fused EDBC and SVD features are considered for performance calculation. City-block and Euclidean Distance (ED) measure is used for matching. Performance is improved on YALE, GTAV and ORL face databases compared with existing methods.**

Keywords — Biometrics; City-block distance; Euclidean distance; Extended directional binary codes; Matrix decomposition.

I. INTRODUCTION

Human recognition requirement has rationale in the present scenario. People use family names, ancestral or ethnic names, father / mother name, siblings name, nature of work, external virtue / factors such as how he/she looks, speaks?, how he/she walks (gait)?, what he/she eats? What assets he/she has? Qualification? and so on to identify and verify humans manually. Critical problems occur in recognising when two different persons have similarities in the above mentioned personal details.Physical access control, background checking, digital rights management, medical diagnosis and defense [1] applications use biometrics data. Real time tracking is a vital step in applications like traffic monitoring, video surveillance, motion based recognition, and Human computer interaction. The validation of a person results in verification / authentication and identification/ recognition. Verification proves the genuinity of a person by comparing a real time (probe) image with stored (authorised) images of same person [2]. Recognition compares probe image with all authorised persons repository to produce the result. Challenges in physical appearance of face / race [3] verification across the people of different territories is attracting researchers.

Various factors affect the accuracy of overall validation process of face, i.e. from the image acquisition step to till the results are produced. In between these two steps the acquired image is refined / made smooth against noise or degradation and reduced in dimension for processing time improvement such that the demarcation between different persons is faster. Conventional methods using Principal Component Analysis (PCA) and its variants offer data reduction by extracting distinct features [4]. Comparison between unknown real time image and known stored images in terms of dimension reduced images is made to declare identity of a person. It is proved that the recognition accuracy is improved by converting the images with variation in expression to neutral images [5] and using image fusion with light field camera for image capturing [6]. Maintaining robustness in recognition accuracy is elusive for key factors such as pose [7], back view [8], illumination variation [9] and others. Developing illumination invariant image representation with textures is a difficult task and pre-processing methods for mitigating the illumination effect are discussed in future sections of this work. Representing images using illumination and reflectance parameters documents edge details. Normalizing the Singular Value Decomposition (SVD) [9] coefficients has potential to overcome the illumination sensitivity problem and even it reduces the dimension of input. The matrix decompositions of an input image has the ability to make computation simpler [10], hence three different types of matrix decompositions are utilized and described later part this work. Conferencing applications do not cater higher storage capacity; hence single image registration [11] has to serve the purpose. Scaling and speed factors are critical in dealing with web scale datasets [12] in internet applications. Seamless applications are deployed using face recognition for various purposes.

Organization: Rest of the paper is organized as follows; related work is reviewed in section II; FRMD model and algorithm is in section III and IV respectively. Performance is discussed in section V and inferred in section VI.

II. REVIEW OF RELATED WORK

Zhuolin Jiang et al., [13] introduced label consistent K-SVD algorithm uses sparse coding for face, action, scene, and object recognition. Objective function is the integration of discriminative sparse codes and single predictive linear classifier for dictionary learning. Experimental results on Extended Yale-B and AR face databases with two object category datasets such as Caltech101, Caltech256, a scene category dataset and a realistic action dataset proves the performance is better compared with other sparse-coding techniques. Yin Zhouand Kenneth E Barner [14] presented locality constrained dictionary learning algorithm for handling large dataset problem. The locality-preserving landmark points based learning is employed. Computational complexity is greatly reduced as applied on synthetic dataset, Extended Yale-B Database and CMU PIE Database. Yi-Fu Hou et al., [15] proposed Eigen face based sparse representation classification method for face detection and recognition. It extracts histogram of orientated gradient features and Eigen faces for each class face images. Better results are reported on ORL and Yale face database.

Chandan Singh et al., [16] presented Local Binary Pattern (LBP) / Local Ternary Pattern (LTP) and Zernike moments (ZMs) descriptors with fusion for face recognition. The ZM descriptor has good global image representation capabilities against image rotation and noise, while the LBP / LTP descriptors capture the innate details which are insensitive to illumination variations. Recognition rates on FERET, Yale, and ORL face databases found better when single image per person used for training.

III. PROPOSED WORK

Proposed Face Recognition based on Matrix Decompositions (FRMD) model is in Figure 1and explanation for the same is discussed below.

A. Databases

YALE database [17] consists of totally 165 Graphics Interchange Format (GIF) images of 15 individuals, with 11 images per subject. Each image has variation in facial expressions or configurations such as left-light, center-light, right-light, wearing glasses, without wearing glasses, neutral, happy, sleepy, surprised, sad, and wink. All images are with dimension 243*320 and 24 bit pixel depth. The pixels are arranged with 96 dpi. The GIF images are converted to JPEG format in our work.

GTAV (Audio Visual Technologies Group)Face database [18],has been created for the purpose of evaluating robustness of any face recognition algorithm over illumination and pose variations. It includes total 44 persons with 27 images per person. Many images are captured under three different illuminations such as light source at an angle 45º, natural light, and frontal strong light source. Other few images are acquired at 0º, ±30º, ±45º, ±60º and 90º pose variations. Remaining images are captured with different facial expressions and occlusions. Resolution of each image is 240 320 and all are in Bit Map (BMP) format. The pixel depth is 24 bits.

The ORL face database [19], has a total of 400 images of 40 different subjects. Ten images per person are acquired at different times by varying lighting intensities. Different facial expressions such as smiling or non-smiling face and images with opening or closing of eyes are acquired. It includes facial images of wearing glasses or without wearing glasses also. All the subjects are in frontal, up-right position with a dark homogeneous background. All images have 92*112 size and represented by 8-bit grey levels in JPEG format. Each image has 96 dpi of horizontal and vertical resolution.

B. Pre-processing

The Illumination Normalization techniques for robust Face recognition (IN-Face) toolbox [20], [21] are used to perform preprocessing, which contains fourteen different photometric normalization techniques.

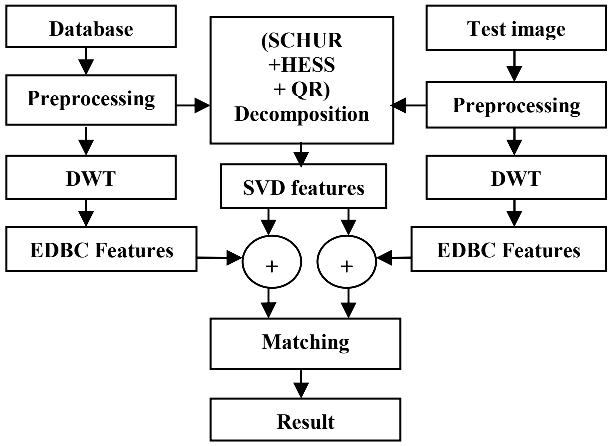

Figure 1. Block diagram of the proposed FRMD model

The grey scale images with size 128*128 pixels are used to implement all techniques in the toolbox. Three methods such as Single Scale Retinex (SSR) algorithm, Multi Scale Retinex (MSR) algorithm and Single scale Self Quotient image (SSQ) are used to process input images in the proposed work.SSR algorithm [22] is based on Retinex theory [23], which uses flux independent image representation. The word Retinex is a combination of words Retina and Cortex. The theory considers three individual cone systems such as short, middle and long wavelength regions of the visible spectrum. It computes lightness values for each pixel in the image and uses thresholding operation to reduce the non uniform illumination effects. Retinex theory has the major advantage of representing the image details independent of ambient light`s spectral power distribution and surface reflectance of the objects in a scene. MSR algorithm [24] is an extension of SSR algorithm, both uses the Gaussian smoothing filters. The default sizes of Gaussian filters are 15 and [7 15 21] for SSR and MSR respectively. Self Quotient Image (SQI) [25] is defined as the ratio of original image and smoothened image. Gaussian filters are used for smoothing with size 7 and the bandwidth parameter is 1.SQI representation is illumination free and has invariant properties for shadow, shading and edge regions.

C. Feature extraction

The details of DWT, EDBC and SVD [26] are utilized from our previous work. The details of three matrix decompositions such as Schur, Hessenberg and QR are as follows. Schur decomposition is computationally efficient and numerically stable [27]. Schur decomposition of a square matrix A is given in Equation 1.

$$[U, S_c, U^T] = \text{Schur}(A) \tag{1}$$

Where, U is unitary matrix, S_c is a block upper quasi-triangular matrix with 1*1 and 2*2 blocks in the diagonals. These diagonal elements represented as $\lambda_1, \lambda_{2..}\ \lambda_n$ are Schur values. The diagonal elements of S_c are sorted so that we have optimality in the reconstruction with respect to a little loss of face image information. Schur vectors are the columns of orthogonal matrix U for each Schur value λ_i in matrix S_c. The output matrix S_c is considered in our work contains Eigen values of input matrix. Hessenberg decomposition [28] produces zero below the first sub-diagonal of a matrix, which consists of Eigen values and/or Eigenvectors. It has good performance for dense non-symmetric matrices. QR decomposition converts the input matrix to unitary and upper triangular components using Householder transformation. The QR decomposition [29] works better with singular scatter matrices for large sizes.SVD is applied on the resultant matrix of three decompositions addition. Fusion of EDBC and SVD features are considered as final features.

D. Matching

Conventional methods for the comparison of database and query image features are Mahalanobis, Hamming, Correlation, City block, Minkowski, Euclidean Distance (ED) and others. In our work the City block and ED measure is considered for calculating results. The results are computed for correct matching of a person under consideration. The general equation for Minkowski distance calculation is given in Equation 2.

$$D(P, Q) = \sqrt[x]{\sum_{i=1}^{n} |Pi - Qi|^x} \qquad (2)$$

Where P and Q are any two vectors and 'n' is the total values of P and Q. The variable 'x=1' for City block distance, x=2 for ED and x=∞ for Chebychev distance measures.

IV. ALGORITHM

Problem definition: Face Recognition with Matrix Decompositions (FRMD) model is used to identify a person. Algorithm of the proposed FRMD model is described in Table I. The objectives are:

- To get better Recognition Rate (RR)
- To obtain lesser False Rejection Rate (FRR) and False Acceptance Rate (FAR) values.

TABLE I. ALGORITHM OF PROPOSED FRMD MODEL

Input: Database and query images of face Output: Recognition / Refutation of a person. 1. Preprocessing is performed using SSR, MSR and SSQ methods, then resized to 100*100 dimension. 2. DWT is applied and Approximate band (LL) of 50*50 size is considered. 3. LL image matrix is converted to 100 cells, where individual cell size is 5*5. 4. Eight directional derivatives (EDBC) are computed for each cell. 5. From each cell a 9-bit code is generated in 8- directions, and then its decimal equivalent is calculated. 6. One hundred features from each direction are generated and respectively averaged with all 8-directions to constitute 100-EDBC features. 7. Schur, Hessenberg and QR matrix decompositions are applied on preprocessed image separately and added linearly. 8. SVD is computed on the output of step 7 to elicit 100 singular values & fused with 100 EDBC features of step 6. 9. City-block / Euclidean Distance measures are computed between database and test image feature vectors. 10. Matching is decided for an image with minimum distance.

V. PERFORMANCE ANALYSIS

The performance is evaluated on three databases such as YALE, GTAV and ORL face databases. The proposed FRMD model is tested using SSR, MSR and SSQ pre-processing methods with City- block and Euclidean matching methods.

A. Performance on YALE database

The YALE database images of faces for ten persons each with nine images per person is used for database. First image is used as the test image for FRR calculation and fifth out of database image of five persons is used for FAR calculation. Performance is verified for individual matrix decompositions such as Schur, Hessenberg and QR with MSR preprocessing. It is observed that each of the three matrix decompositions yields maximum recognition accuracy of 80% with the proposed work. When all these matrices are arithmetically added the recognition rate is improved by 10% as compared to individual performances.% FRR, %FAR and %RR are computed to justify the effect of preprocessing techniques used in the proposed work. From Table II, the maximum %RR resulted for three preprocessing methods are 80, 90, and 90 respectively for SSR, MSR, and SSQ with the proposed algorithm. The City-block or Minkowski distance measure for x=3 in Equation 2 yielding better results than Euclidean distance on YALE face database.

B. Performance on GTAV database

The GTAV database images of faces for thirty persons each with sixteen images per person is used for database. One image is used as the test image for FRR calculation and tenth out of database image of ten persons is used for FAR calculation. The performance of with SSR, MSR, and SSQ pre-processing methods is in Table III. The Maximum %RR of 90, 90, and 93.33is obtained for SSR, MSR, and SSQ pre-processing methods respectively. ED is used to compute the results on GTAV face database.

C. Performance on ORL database

ORL database images of faces for twelve persons each with eight images per person is used for database. One image is used as the test image for FRR calculation and ninth out of database image of twenty eight persons is used for FAR calculation. Performance of the proposed algorithm with pre-processing methods such as SSR, MSR, and SSQ is in Table IV. The Maximum %RR attained is 100 for all the three pre-processing methods. ED is used to compute the results on ORL face database.

Table V compares the Maximum %RR of other algorithms with proposed work on YALE database. It is justified that our work is outperforming in terms of Maximum %RR compared to [30] and [31], but comparable with [32], which has marginal difference of 0.67.It is justified from Table VI that the Maximum %RR is higher compared to [33]on GTAV face database. Table VII Compares the Maximum %RR of other algorithms such as [31], [32], [34], and [35] with proposed work on ORL database, which proves by attaining the maximum value.

TABLE II. PERFORMANCE ON YALE DATABASE WITH PREPROCESSING METHODS

Threshold	SSR			MSR			SSQ		
	% FRR	% FAR	% RR	% FRR	% FAR	% RR	% FRR	% FAR	% RR
0.0	100	0	0	100	0	0	100	0	0
0.1	80	0	20	90	0	10	90	0	10
0.2	30	0	60	20	0	70	40	0	60
0.3	10	20	70	10	20	80	20	0	80
0.4	10	80	70	10	80	80	0	80	80
0.5	0	100	80	0	100	90	0	100	90
0.6	0	100	80	0	100	90	0	100	90
0.7	0	100	80	0	100	90	0	100	90
0.8	0	100	80	0	100	90	0	100	90
0.9	0	100	80	0	100	90	0	100	90
1.0	0	100	80	0	100	90	0	100	90

TABLE III. PERFORMANCE ON GTAV DATABASE WITH PREPROCESSING METHODS

Threshold	SSR			MSR			SSQ		
	% FRR	% FAR	% RR	% FRR	% FAR	% RR	% FRR	% FAR	% RR
0.0	100	0	0	100	0	0	100	0	0
0.1	63.33	0	33.33	70	0	30	86.67	0	13.33
0.2	10	30	86.67	13.33	40	86.67	23.33	10	70
0.3	0	70	90	0	70	90	3.33	60	90
0.4	0	90	90	0	90	90	0	80	93.33
0.5	0	100	90	0	100	90	0	90	93.33
0.6	0	100	90	0	100	90	0	100	93.33
0.7	0	100	90	0	100	90	0	100	93.33
0.8	0	100	90	0	100	90	0	100	93.33
0.9	0	100	90	0	100	90	0	100	93.33
1.0	0	100	90	0	100	90	0	100	93.33

TABLE IV. PERFORMANCE ON ORL DATABASE WITH PREPROCESSING METHODS

Threshold	SSR			MSR			SSQ		
	% FRR	% FAR	% RR	% FRR	% FAR	% RR	% FRR	% FAR	% RR
0.0	100	0	0	100	0	0	100	0	0
0.1	75	0	25	100	0	0	83.33	0	16.67
0.2	41.67	0	58	83.33	0	16.67	41.67	0	58.33
0.3	8.33	21.42	91.67	50	0	50	16.67	17.85	83.33
0.4	0	39.28	100	25	7.14	75	0	42.85	100
0.5	0	82.14	100	8.33	39.28	91.67	0	82.14	100
0.6	0	96.42	100	0	82.14	100	0	96.42	100
0.7	0	96.42	100	0	100	100	0	96.42	100
0.8	0	100	100	0	100	100	0	100	100
0.9	0	100	100	0	100	100	0	100	100
1.0	0	100	100	0	100	100	0	100	100

TABLE V. MAXIMUM %RR COMPARISION ON YALE DATABASE

Method	Maximum % RR
ALBP +BCD [30]	71.9
WM(2D)^{2}PCA[31]	80.77
GABOR +DTW [32]	90.67
Proposed FRMD model	90

TABLE VI. MAXIMUM %RR COMPARISIONON GTAV DATABASE

Method	Maximum % RR
P^{2}CA [33]	78
Proposed FRMD model	93.33

TABLE VII. MAXIMUM %RR COMPARISION ON ORL DATABASE

Method	Maximum % RR
WM(2D)^{2}PCA [31]	74.06
GABOR +DTW [32]	86.38
OOLPP2+SVM2 [34]	94
BTSS [35]	99.5
Proposed FRMD model	100

The plot of FAR and FRR versus Threshold on YALE, GTAV and ORL databases using MSR, SSQ and SSR pre-processing is in Figure 2, 3 and 4 respectively.

TABLE VIII. AOD COMPARISION OF FUSED FEATURES ON THREE DATABASES

Database	Between Two images of Person1	Between Two images of Person2	Between Person2 and Person1
YALE	53.36	34.15	61.59
GTAV	40.39	47.91	70.91
ORL	63.5	66.5	95.88

Average Overall Deviation (AOD) is computed for different image combinations using Equation 3 and is defined as the ratio between the sum of elementary differences of two image matrices and total number of elements in each image.

$$\text{AOD} = \sum_{i,j=1}^{N} [X(i,j) - Y(i,j)]/\text{N} \qquad (3)$$

Where, X, and Y are any two image matrices and N is total number of elements in each matrix. It is observed that the image details and the decomposition coefficients have linear correspondence across different images of same person, but they are not correlated across the similar image of other person. The AOD for YALE, GTAV, and ORL databases is compared in Table VIII.

The reasons for results improvement are; SSR, MSR, and SSQ preprocessing methods reduce the nonlinear effect of image details. Irrespective of the image information contained before preprocessing, the output image is normalized using Gaussian filters, to yield smooth image. The Approximate band of DWT has linear relationship with the input image, but neglects the edge information. EDBC extracts directional information related to high frequency details of the image. Schur, Hessenberg and QR matrix decompositions are individually nonlinear in nature, but have less number of nonzero coefficients when all are combined. It is found by analysis that the matrix decompositions are able to discriminate different persons efficiently. Singular values of SVD have bounded good energy, as the ratio of input and output is 10:1. Fusing EDBC and SVD features has good discrimination ability between two different persons and it is justified from Table VIII, in terms of AOD. Minimum AOD value of 34.15 is observed between two images of same person on Yale database, and maximum AOD value of 95.88 is reported for the images of two different persons of ORL database.

VI. CONCLUSION

The proposed FRMD method has good demarcation ability between different persons efficiently. The AOD parameter computation justifies the same. Tools such as DWT, EDBC Schur, Hessenberg and QR matrix decompositions combination with SVD have key role in improving performance. EDBC and SVD features fusion contributed for overall performance. Results are produced based on city block and ED measure. The performance on YALE, GTAV and ORL face datasets is higher compared with existing algorithms.

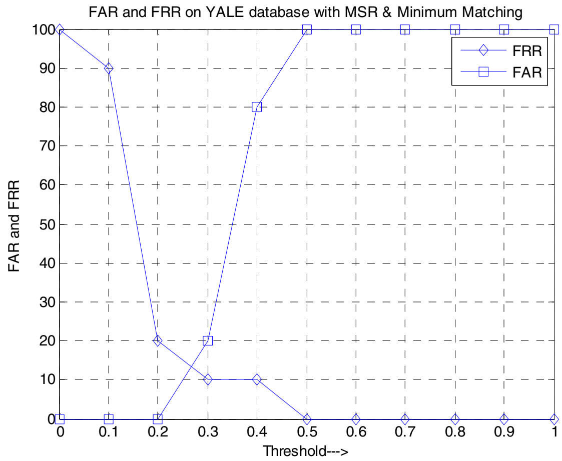

Figure 2. FAR and FRR versus Threshold on YALE database

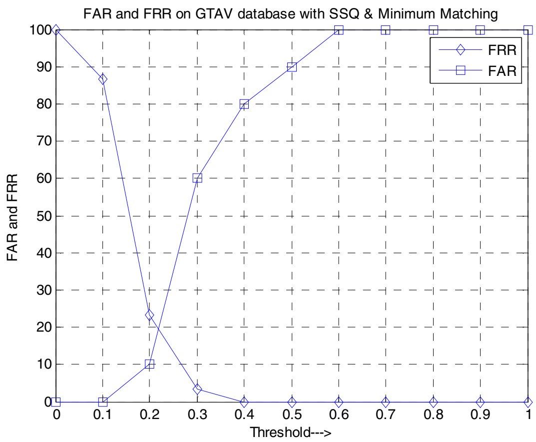

Figure 3. FAR and FRR versus Threshold on GTAV database

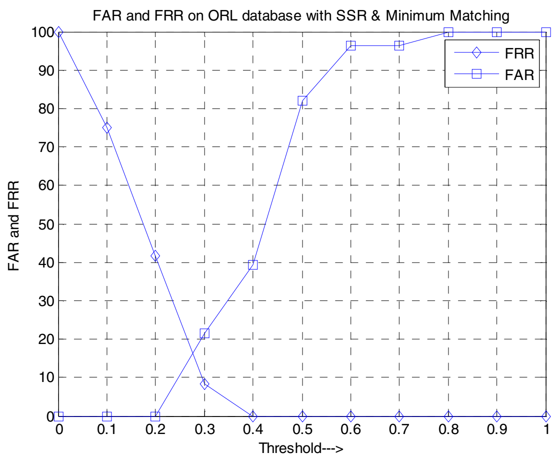

Figure 4. FAR and FRR versus Threshold on ORL database

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