Global Journal of Computer Science and Technology: F
Graphics & Vision
Volume 16 Issue 1 Version 1.0 Year 2016
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals Inc. (USA)
Online ISSN: 0975-4172 & Print ISSN: 0975-4350

Face Recognition using Fused Diagonal and Matrix Features

By Jagadeesh H S, Suresh Babu K & K B Raja
APS College of Engineering, India

Abstract- Face recognition with less information availability in terms of the number of image samples is a challenging task. A simple and efficient method for face recognition is proposed in this paper, to address small sample size problem and rotation variation of input images. The robert`s operator is used as edge detection method to elicit borders to crop the facial part and then all cropped images are resized to a uniform 50*50 size to complete the preprocessing step. Preprocessed test images are rotated in different angles to check the robustness of proposed algorithm. All preprocessed images are partitioned into one hundred 5*5 equal size parts. The matrix 2-norm, infinite norm, trace and rank are elicited for each of 5*5 part and respectively averaged to yield on hundred matrix features. Another one hundred diagonal features are extracted by applying a 3*3 mask on each image. Final one hundred features are obtained by fusing averaged matrix and diogonal features. Euclidian distance measure is used for comparision of database and query image features. The results are comparitively better on three publically availabe datasets compared to existing methods.

Keywords: cropping, edge detection, rotation variation, small sample size problem.

GJCST-F Classification: I.4.8 I.7.5

FACERECOGNITIONUSINGFUSEDDIAGONALANDMATRIXFEATURES

Strictly as per the compliance and regulations of:

Face Recognition using Fused Diagonal and Matrix Features

Jagadeesh H S [α], Suresh Babu K [σ] & K B Raja [ρ]

Abstract- Face recognition with less information availability in terms of the number of image samples is a challenging task. A simple and efficient method for face recognition is proposed in this paper, to address small sample size problem and rotation variation of input images. The robert`s operator is used as edge detection method to elicit borders to crop the facial part and then all cropped images are resized to a uniform 50*50 size to complete the preprocessing step. Preprocessed test images are rotated in different angles to check the robustness of proposed algorithm. All preprocessed images are partitioned into one hundred 5*5 equal size parts. The matrix 2-norm, infinite norm, trace and rank are elicited for each of 5*5 part and respectively averaged to yield on hundred matrix features. Another one hundred diagonal features are extracted by applying a 3*3 mask on each image. Final one hundred features are obtained by fusing averaged matrix and diogonal features. Euclidian distance measure is used for comparision of database and query image features. The results are comparitively better on three publically availabe datasets compared to existing methods.

Keywords: cropping, edge detection, rotation variation, small sample size problem.

I. Introduction

Prevailing of a single technology over a long period of time is difficult. Many approaches provided solution to issues related to cognitive detection and recognition of human. The assumptions are deciding factors in most of approaches, because of flaws in predicting the sources of errors for real-time situations. Recognizing humans using faces has many influencing parameters, which are categorized under constrained and unconstrained environments. There is no exact definition of unconstrained environment, but the randomness in overall process is the key factor. Real time situations are elusive i.e. to capture face image under movement of a person, in race, at distance [1], low resolutions, and different internal or external human activities. Surveillance and vigilance applications are the best example for the same. Various physical constraints such as illumination [2], occlusion, pose, expression and disguise have vital influence on performance of recognition system. Representing digital face images through imaging against to these constraints in Visible Spectrum (VS) limits the usage of samples. Remedy is to capture images in Infrared Spectrum (IS) [3] which is robust to VS influencing parameters. Additionally the imaging is based on the pattern of blood vessels of face, which does not vary with age. The recognition accuracy is greatly influenced by physiological and eyeglass problem in IS, which limits its applications.

Another factor of interest is Dimension Reduction (DR), where the input image data is transformed into less quantity by retaining vital information. DR is to reduce memory requirement and computations. Linear and nonlinear methods [4] are used for the same. Independent Component Analysis (ICA), Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) are the three approaches in linear DR category. Original image structure is preserved using Random Projections (RP) by nonlinear methods. RP has the advantage of data independence and low computational complexity [5]. Various feature descriptors [6] are proposed to represent data appropriately towards variation in rotation, such as Short Term Fourier Transform (STFT), Scale Invariant Feature Transform (SIFT) [7]. The advantage of SIFT made it to use widely, but suffers partially from illumination changes. No algorithm has declared that it is ideal for all the challenges involved by using complete repertoire for face recognition problem. Different methods proposed by various researchers considered either one or fewer number of challenges. The issues such as rotation of images for testing purpose and fewer samples of images are considered in the proposed method.

II. Literature Review

Xiaoyang Tan, et al., [8] made a detailed survey on one sample size problem. The challenges, significance, and different methods used to recognize human faces with single image are discussed. Obtaining accuracy with less number of images and difficulty in acquiring many samples are key challenges. Even with DR techniques, storing and processing time improvements are significant factors. Conventional methods such as PCA, LDA and extensions either individually or in hybrid manner are used as feature extraction techniques. The accuracy of various approaches on different face databases is compared. Kin-Man Lam, and Hong Yan [9] proposed an approach for identifying faces using analytic to holistic concept. Forty frontal view faces are considered for test database. Using fifteen feature points of each face with

Author α: Research scholar, ECE Department, Rayalaseema university.
e-mail: jagadeesh.11@gmail.com
Authorσ ρ: Department of Electronics and Communication Engineering, UVCE, Bengaluru, 560001, India.

head model, rotation of the face is estimated. Face feature points of database and feature points of front view image are compared using similarity transform. Comparison is repeated using correlation by setting up windows for mouth, nose, and eyes. Results obtained are similar on Olivetti Research Laboratory (ORL) face database as with different face viewing directions.

Yu Zhao, et al., [10] investigated a framework for face recognition, which is useful in conference socialization scenarios. Using an arbitrary view of a subject as query image with only frontal images used for training images the framework is proposed. It consists of a feature point detection scheme, feature area smoothing and feature mapping. The registration process of conference participants is completed using a frontal photo. A mobile phone camera is used to acquire probe image with an arbitrary angle at the conference for identifying a person. Experimental results are robust to pose variations on FERET dataset and two self-collected conference socializing datasets. Kuo-Chin Fan and Tsung-Yung Hung [11] proposed a local pattern descriptor named Local Vector Pattern (LVP) for face recognition. The micro patterns are generated using high-order derivative space with pixel level computations. Performance of LPV is better compared with Local Binary Pattern (LBP), local tetra pattern, and local derivative pattern descriptors on FERET, CAS-PEAL, CMU-PIE, Extended Yale B, and LFW face databases.

Zhen Lei et al., [12] introduced a data-driven Discriminant Face Descriptor (DFD) using image filters, optimal neighborhood sampling and dominant patterns. It is able to extract discriminant features for the images of different persons compared to different images of same person. DFD is applied to heterogeneous face recognition problem also. Experiments on FERET, CAS-PEAL-R1, LFW, and HFB face databases validate the ability of DFD. Zhenhua Guo et. al., [13] proposed a hybrid LBP scheme for texture classification using locally variant LBP features and globally rotation invariant matching. Principal orientations are estimated and aligned for texture image based on LBP distribution. Dissimilarity measure between images is performed based on LBP histograms. LBP variance (LBPV) texture descriptor is also developed for exploiting the local contrast information. In addition to this, the time required for matching is reduced by a feature size reduction method. Higher classification accuracy is obtained on Outex and Columbia-Utrecht (CUReT) texture database compared with traditional rotation invariant LBP methods. Jiansheng Chen, et al., [14] introduced a face image quality assessing framework. Rank based quality score is used in registration for face quality control and recognition is performed by selecting the high quality face images. The results on Chinese ID card photo database, FRGC, FERET, LFW and AFLW face databases has superior performance compared to conventional methods.

III. Block Diagram of the Proposed Model

The details of input data, preprocessing, features extraction and matching are discussed in this section. Figure 1 shows the block diagram of proposed Face Recognition using Diagonal and Matrix Features (FR DMF) model.

a) *Databases*

i. Yale database [15] consists of 15 subjects, each subject with 11 different images with a total of 165 images in Graphics Interchange Format (GIF). The either variation in facial expressions such as neutral, happy, sleepy, surprised, sad, and wink or different configurations such as left-light, center-light, right-light, wearing glasses, without wearing glasses are considered. Dimension of each image captured has 243*320 size and 24 bit pixel depth. All images have 96 dpi horizontal and vertical resolutions. The GIF is converted to JPEG in the proposed work.

ii. Kinect face database [16] has 468 images with nine types of expressions under different occlusion and lighting variations. Nine images of 52 subjects are captured in two sessions, with in a fortnight consisting of 38 male and 14 female persons. Expressions such as neutral, smile, opening mouth, left profile, right profile and occlusion in eyes, mouth, paper, wearing glasses are considered. The images are acquired at one meter distance in EURECOM Institute laboratory. Each pixel is represented by 24 bit with 256*256 image size in Bitmap format.

iii. Indian face database [17] contains images of 39 male and 22 female subjects for eleven different pose variations per person. Totally it has 671 images are in frontal position with bright homogeneous background. Different poses include; looking front, looking left, looking right, looking up, looking up towards left, looking up towards right, and looking down. Neutral, smile, laughter, sad / disgust expressions are incorporated during image capturing. Each image has the spatial resolution of 640x480 pixels, with 24 bits per pixel in JPEG format and 96 dots per inch.

Figure 2 shows one image sample each of Yale, Kinect and Indian face database respectively.

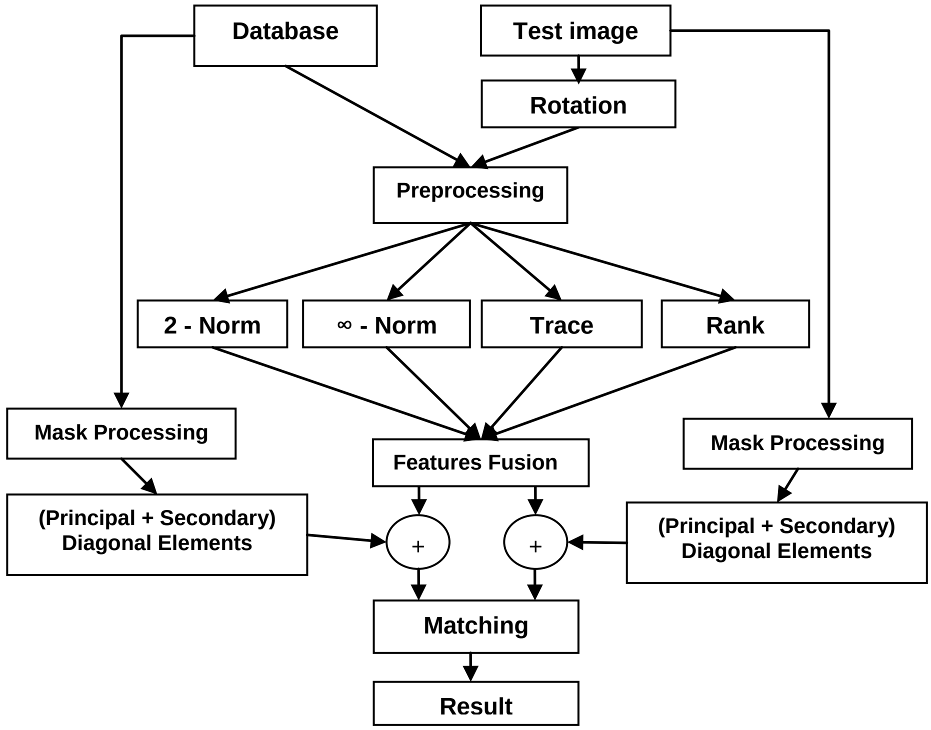
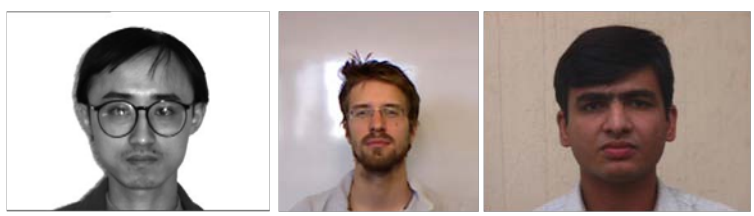


Fig. 1: Block diagram of the Proposed FR DMF model



(a) (b) (c)

Fig. 2: Sample images of three databases (a) Yale, (b) Kinect, and (c) Indian database

b) Pre-processing

Figure 3 shows the result of preprocessing for input image 3 (a) The significance of preprocessing is to refine the input image for any noise associated and to remove any unwanted trivial information content, which do not contribute vital part of face image e.g. background. The preprocessing involves; (i) RGB to gray conversion (optional), (ii) Boundary detection using Roberts edge operator, (iii) Scanning; (iv) Cropping, and (v) resizing. The conversion of any type of image to gray form reduces the dimension of each image to one dimension with appreciable quality. Further it reduces the burden in number of computations. Using Roberts's operator or mask the edges are emphasized and the two different forms of Roberts's operators are given in Table 1. Edges are identified based on the maximum value of gradient between input image and the mask at any point. It is non symmetric and fails to detect edges at 45^0 multiples [18]. The output image after applying Roberts's edge operator is shown in Figure 3 (b).

Table1: Roberts Operator

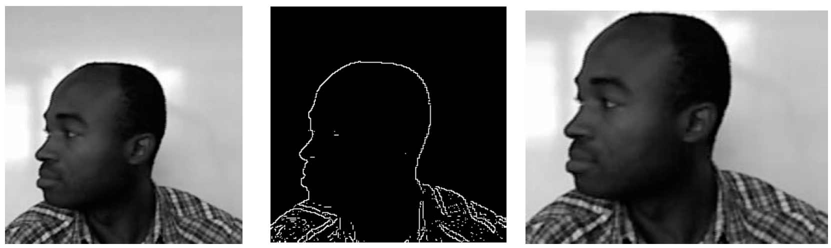
-1	0
0	1

0	-1
1	0

In the next step the whole image is divided into two parts in column wise. First 25 columns are searched in each row for the edges, as soon as it finds an edge, it stops searching and the corresponding coordinates are noted both in X and Y direction. Similar steps are carried out for the remaining columns but in opposite direction. As the Roberts operator produces high at edges which is useful to refine the facial part in the input image through scanning. Based on the scanned information the all images are cropped to different sizes. Finally all images are resized to 50*50 uniformly to complete the preprocessing step as shown in Figure 3(c). Only preprocessed test images are rotated with any one of different angles such as $+/-1^0$, $+/-2^0$, $+/-3^0$, $+/-4^0$ and $+/-5^0$ to observe the robustness of proposed method.

c) Feature extraction

The aim of extracting features is to compress the preprocessed image such that it should retain original information. Features derived should have the distinct quality and uniquely represent the original image. In the proposed work, four simple matrix features are elicited and fused. The preprocessed image of Size 50*50 is divided into ten equal non overlapping parts with 5*5 sizes each and is shown in Figure 4. On each part of the segmented image matrix 2-norm, infinite norm, trace and rank of the matrix are separately calculated. For each 5*5 segment of image four different matrix features are obtained, totally one hundred matrix 2-norm, infinite norm, trace and rank of the matrix features generated respectively. Finally these features are normalized and algebraically averaged to get final unique coefficients. Figure 4 is the segmented input image.



(a) (b) (c)

Fig. 3: Pre-processing result on a Kinect database image (a) Gray scale image, (b) Output of Edge detection, (c) Cropped image

Fig. 4: Segmented image with each fragment size of 5*5

In a vector space containing real and complex numbers denoted by K^{m*n}, where K is the field of numbers with m rows and n columns. Vector norm of a matrix A in K space is also named as induced norm and denoted as $||A||$. The general definition of matrix norm is the maximum value of absolute sum of elements in specific dimension [19]. Consider an input matrix A

$$= \begin{pmatrix} 1 & 2 & -3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix}$$

The 1- norm is the maximum value in each column sum, obtained for absolute value of elements column wise and 1-norm for matrix is given by $||A||_1$ = Maximum [(1+4+7),(2+5+8), (|-3|+6+9)] = Max[12,15,18] = 18. Similarly ∞ -norm is the maximum value in each row sum, obtained for absolute value of elements row wise and ∞ -norm [20] for matrix is given by $||A||_\infty$ = Maximum [(1+2+|-3|), (4+5+6), (7+8+9)] = Max[6,15,24] = 24. $||A||_2$ is the 2- norm which is the largest singular value of matrix A, where singular values are the square root of Eigen values of A^TA. The value of $||A||_2$ obtained for matrix A is 16.84 and it is also named as Euclidean and spectral norm.

Trace of a matrix is defined as the sum of diagonal elements in the matrix and which is similar to the sum of singular values of a matrix [21]. Finally, rank of a matrix is the number linearly independent columns or rows of a matrix. In our work, the rank [22] of segmented part of the image is considered. For the matrix A, trace is given by (1+5+9) = 15 and rank is 3. Table 2 infers the result of rotation with +/- 1^0 in these matrix parameters. Additionally it contains matrix 2-norm, Infinite norm, Trace, Rank of the matrix and averaged value of all these features.

On the other side, each original image pixel is computed by taking the difference between the maximum and minimum of pixel intensities within 3*3 overlapping mask. Then the principal and secondary diagonal elements are averaged to get another one hundred diagonal features. Table 3 depicts the process of obtaining diagonal features. The final one hundred features are obtained by fusing these diagonal features with the one hundred averaged matrix features.

d) Matching

One hundred fused features of each image are stored as database; these features are to be compared with the corresponding features of probe images. Euclidean Distance (ED) measure is used for the comparison of database and probe image features. The ED between any two vectors *P* and *Q* is given in Equation (1), where *'i'* vary from one to total number of elements in each vector.

Table 2 : Matrix features comparison for a resized 5*5 image

Rotation angle	Original Image					2-norm	∞-norm	Trace	Rank	Average
	168	101	36	155	153					
	193	73	26	133	186					
-1^0	167	64	35	151	172	585.7	613	468	5	417.9
	144	37	20	115	156					
	75	46	26	60	77					
	213	112	56	181	203					
	213	61	22	124	201					
0^0	190	60	35	147	193	660.1	765	517	5	486.7
	164	32	19	109	176					
	108	51	30	65	99					
	160	92	39	165	157					
	195	71	25	137	181					
1^0	170	65	35	152	172	586.1	613	444	5	412
	147	40	19	108	154					
	84	50	25	55	70					

Table 3 : Result of masking with diagonal features

Original Image					Mask Processed Image					Principal Diagonal Elements	Secondary Diagonal Elements	Average
188	196	197	195	190	91	139	124	129	22	91	22	56.5
212	121	73	180	202	151	188	173	178	72	188	178	183.0
209	61	24	130	199	168	188	156	178	72	156	156	156.0
175	44	26	133	188	165	185	109	175	129	175	185	180.0
119	45	26	70	113	131	149	107	162	118	118	131	124.5

$$\mathrm{D(Pi, Qi)} = \sqrt{((\mathrm{p1}-\mathrm{q1})^2 + (\mathrm{p2}-\mathrm{q2})^2 + ..} \quad (1)$$

A reference parameter named threshold is considered to compare and produce the results. Threshold is varied from 0 to 1 insteps of 0.1 and compared with the computed values of ED. Matching has two stages; (i) Probe images are within database; If the value of ED is lesser than threshold value and the image corresponding to right person is matched, Then matched person count is incremented by one, which accounts to the computation of Recognition Rate (RR) of the system. If ED value is less than the threshold, but not matching to right person, and then it leads to the calculation of mismatch count. Further, if ED value is greater than the threshold, it is considered as rejected the right person and is in the name of False Rejection Ratio (FRR). (ii) Probe images are out of database; As the name says the test images are taken out of the database and the procedure explained for FRR computation is repeated. If ED value is less than the threshold, match count is incremented which should be understood as unknown person is falsely accepting. The decision is made as unknown person is rejected correctly, when the ED value is higher than the threshold.

IV. Algorithm

Problem definition: The Face Recognition system with Diagonal and Matrix Features (FR DMF) model is used to identify a person. Proposed algorithm of the FR DMF model is described in Table 4 with the following objectives:

(i) To increase Recognition Rate (RR) or Total Success Rate (TSR)

(ii) To limit the value of FRR and FAR.

Table 4 : Algorithm of Proposed FR DMF model

Input: Face Images of Database and for query.
Output: Identifying / discarding of a person.

1. Preprocessing has following five steps
   (i) RGB to gray conversion (optional)
   (ii) Edge detection using Roberts operator
   (iii) Image Scanning
   (iv) Image Cropping
   (v) Image Resizing to 50*50
2. Only preprocessed test images are rotated in any one of +/-1^0, +/-2^0, +/-3^0, +/-4^0 and +/-5^0
3. All images of 50*50 size is partitioned into 100 pieces with each piece has 5*5 size
4. For each piece of 5*5, matrix 2-norm, infinite norm, trace and rank are computed.
5. For each 50*50 image, 100 coefficients are extracted using Matrix 2-norm, Infinite norm, Trace and Rank separately and averaged to yield one set of 100 features.
6. Using a 3*3 mask for each image pixel (without preprocessing), the difference between maximum and minimum is computed and resized to 100*100.
7. Principal and secondary diagonal elements, 100 each for the output of step 6 are added with 100 features of step 5 to get final features
8. Between the feature vectors of database and test images, Euclidean distance is computed.
9. For the image with minimum Euclidean distance, matching is decided.

V. Performance Evaluation

Performance of the proposed algorithm is tested on three publically available datasets such as Yale, Indian and Kinect face database. The objective is to test the algorithm for two parameter variations i.e. number of trained images and through image rotation. To make it clear the number of trained images used are limited to either one or two and only the test images are rotated in different angles viz. +/-1^0, +/-2^0, +/-3^0, +/-4^0 and +/-5^0. Anticlockwise rotation is considered as positive and clockwise is negative. Results are extracted by fixing the number of trained images either one or two for all the image rotation angles.

(i) *Yale database.* The images of 13 persons are used for database creation. Tenth image of 13 persons is used for FRR is computation and FAR is computed by using 5th image of remaining two persons. Performance is tested for single and double trained images case. The rotation invariance property is observed for +/-1^0, -2^0, +/-3^0, and +/-4^0 as in Table 5, where the maximum % RR is 53.8 for single trained image case. Similarly for two trained images it is exhibiting rotation invariance in 0^0, 1^0, 2^0, 3^0 and 4^0 rotation angles, the maximum % RR of 92.3 is obtained for the same. Figure 5 shows the plot of Threshold in X-axis with FAR and FRR in Y-axis for (a) Single and (b) Double trained images with 1^0 and 0^0 rotation respectively. Figure 6 consolidates the maximum % RR rotated in different angles on Yale database for single and double trained images. An average % RR of 52.2 and 90.7 is obtained respectively for single and double trained images for rotation angles mentioned in Figure 6. Table 6 compares the maximum % RR of the proposed method with other [23], [24], [25] techniques. It is observed that the proposed algorithm achieve better results than other methods.

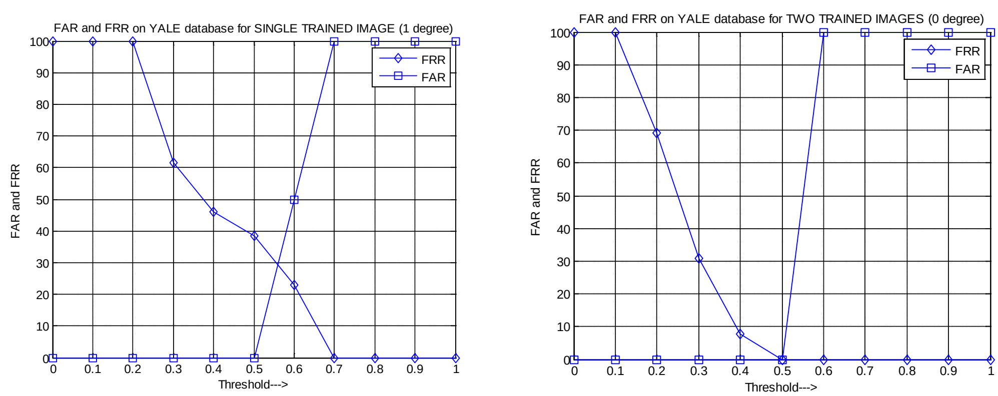
(ii) *Kinect database.* The images of 52 persons used to test the algorithm, images of 29 persons are used as database, and remaining 23 persons are used for testing purpose. For FRR computation, an image of a person which is not in database is used i.e. each person`s 9th image. FAR is computed by using 5th image of 23 out of database persons. Performance is tested for single and double trained images rotated in +/-1^0, +/-2^0, +/-3^0, +/-4^0 and +/-5^0. The rotation invariance property is observed for 0^0 and +/-1^0 angles for single trained image case as depicted in Table 7 and the maximum %RR for single and two trained images are 55.1 and 93.1 respectively. Figure 7 shows the plot of Threshold in X-axis with FAR and FRR in Y-axis for (a) Single and (b) Double trained images with 0^0 rotation. Figure 8 consolidates the maximum % RR rotated in different angles on Kinect database for single and double trained images. An average % RR of 50.3 and 79.7 is obtained respectively for single and double trained images for rotation angles mentioned in Figure 8. Table 8 compares the maximum % RR of the proposed method with the other [26], method. It is observed that the proposed algorithm achieve better results than the method compared.

Table 5 : Performance on Yale database for Single and Double Trained images

Threshold	Single Trained Image $+/-1^0$, -2^0 , $+/-3^0$, $+/-4^0$ Rotation			Double Trained Images 0^0, 1^0, 2^0 , 3^0, 4^0 Rotation		
	% FRR	% FAR	% RR	% FRR	% FAR	% RR
0.0	100	0	0	100	0	0
0.1	100	0	0	100	0	0
0.2	100	0	0	69.2	0	30.7
0.3	61.5	0	30.7	30.7	0	69.2
0.4	46.1	0	46.1	7.6	0	92.3
0.5	38.4	0	46.1	0	0	92.3
0.6	23	50	53.8	0	100	92.3
0.7	0	100	53.8	0	100	92.3
0.8	0	100	53.8	0	100	92.3
0.9	0	100	53.8	0	100	92.3
1.0	0	100	53.8	0	100	92.3

Table 6 : Comparison of Maximum % RR with other methods on Yale database

Method	Maximum % RR
ALBP +BCD [23]	71.9
WM(2D)2PCA [24]	80.77
GABOR +DTW [25]	90.67
Proposed FR DMF model	92.3



(a) (b)

Fig. 5 : Threshold versus FAR & FRR on Yale database for (a) One & (b) Two trained –images

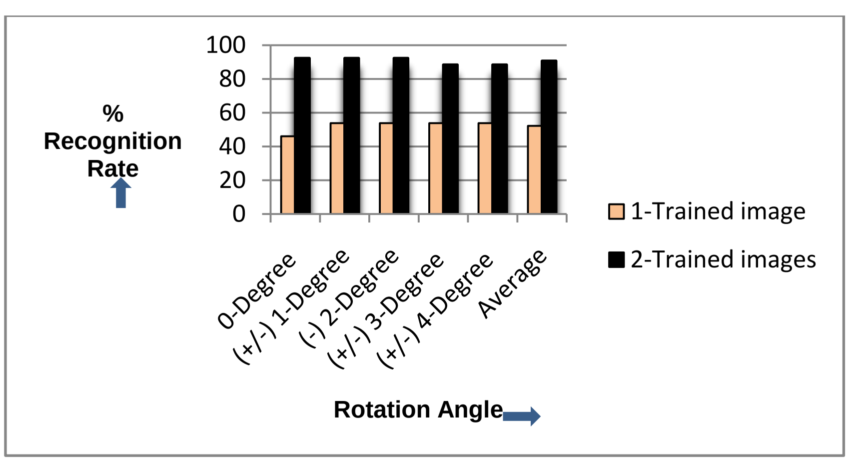


Fig. 6 : Comparison of Maximum % RR for Different Rotation Angles on Yale database

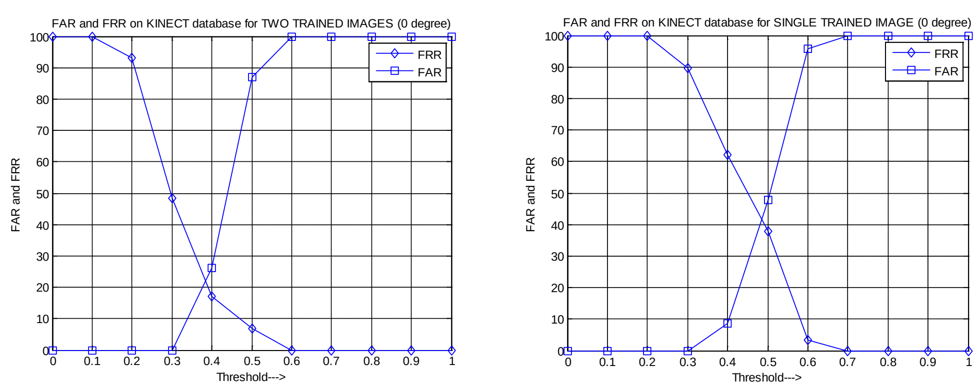
(iii) *Indian database* of 50 persons are considered to test the algorithm, images of 23 persons are used as database, and remaining 27 persons are used for testing purpose. Other than the image of a person in database is used for FRR computation i.e. Each person`s 11th image and FAR is computed by using 5th image of 27 persons. Performance is tested for single and double trained images rotated in +/-1^{0}, +/-2^{0}, +/-3^{0}, +/-4^{0} and +/-5^{0} on Indian database. From Table 9 the maximum % RR for single and two trained images are 55.1 and 93.1 respectively with no rotation. Figure 9 shows the plot of Threshold in X-axis with FAR and FRR in Y-axis for (a) Single and (b) Double trained images with 0^{0} rotation. Figure 10 consolidates the maximum % RR rotated in different angles on Indian database for single and double trained images. An average % RR of 76.5 and 78.2 is obtained respectively for single and double trained images for rotation angles depicted in Figure 10. Table 10 compares the maximum % RR of the proposed method with the other [27], [28] method. It is observed that the proposed algorithm achieve better results than the method compared.

Table 7: Performance on Kinect database for Single and Double Trained images

Threshold	Single Trained Image 0^{0} , +/- 1^{0} Rotation			Double Trained Images 0^{0} Rotation		
	% FRR	% FAR	% RR	% FRR	% FAR	% RR
0.0	100	0	0	100	0	0
0.1	100	0	0	100	0	0
0.2	100	0	0	93.1	0	6.8
0.3	89.6	0	10.3	48.2	0	51.7
0.4	62	8.6	31	17.2	26	82.7
0.5	37.9	47.8	37.9	6.8	86.9	89.6
0.6	3.4	95.6	55.1	0	100	93.1
0.7	0	100	55.1	0	100	93.1
0.8	0	100	55.1	0	100	93.1
0.9	0	100	55.1	0	100	93.1
1.0	0	100	55.1	0	100	93.1

Table 8 : Comparison of Maximum % RR with other method on Kinect database

Method	**Maximum % RR**
HOG – 100 Samples Case [26]	86
Proposed FR DMF model	93.1



(a) (b)

Fig. 7 : Threshold versus FAR & FRR on Kinect database for (a) One & (b) Two trained images

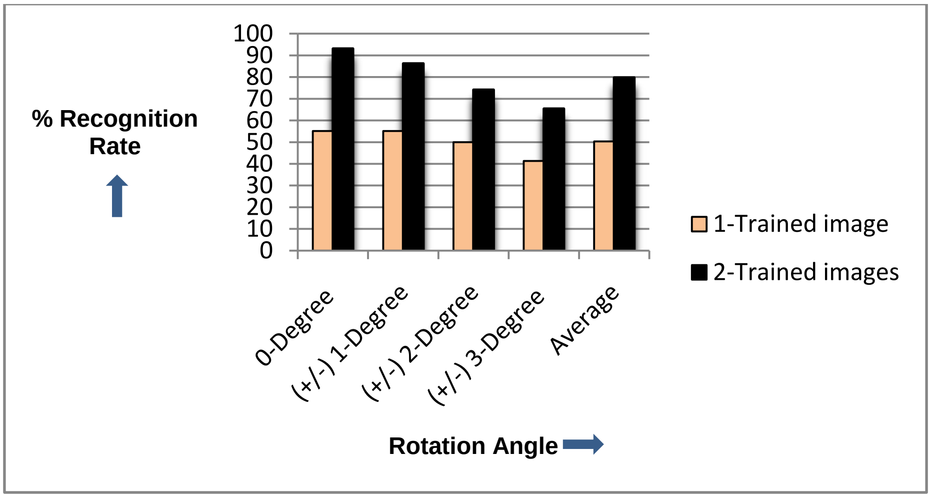


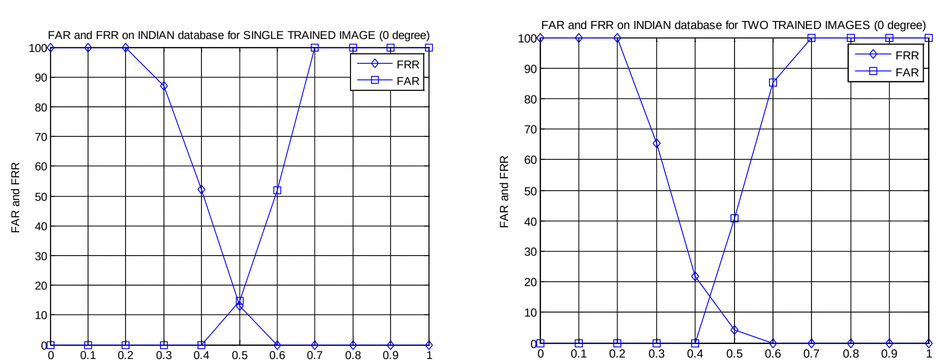
Fig. 8: Comparison of Maximum % RR for Different Rotation Angles on Kinect database

Table 9 : Performance on Indian database for Single and Double Trained images

Threshold	Single Trained Image 0^0 Rotation			Double Trained Images 0^0 Rotation		
	% FRR	% FAR	% RR	% FRR	% FAR	% RR
0.0	100	0	0	100	0	0
0.1	100	0	0	100	0	0
0.2	100	0	0	100	0	0
0.3	86.9	0	13	65.2	0	34.7
0.4	52.1	0	43.4	21.7	0	78.2
0.5	13	14.8	82.6	4.3	40.7	91.3
0.6	0	51.8	95.6	0	85.1	95.6
0.7	0	100	95.6	0	100	95.6
0.8	0	100	95.6	0	100	95.6
0.9	0	100	95.6	0	100	95.6
1.0	0	100	95.6	0	100	95.6

Table 10 : Comparison of Maximum % RR with other method on Indian database

Method	Maximum % RR
MB-LBP [27]	79.2
Six- Morphological Operations case [28]	94.2
Proposed FR DMF model	95.6



(a) (b)

Fig. 9: Threshold versus FAR & FRR on Indian database for (a) One & (b) Two trained images

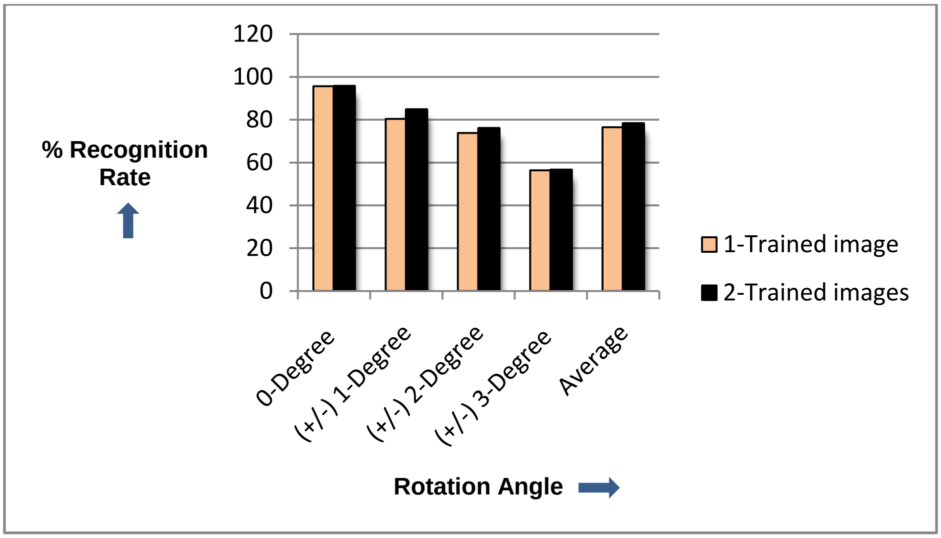


Fig. 10 : Comparison of Maximum % RR for Different Rotation Angles on Indian database

The results are improved based on following Reasons; Robert's operator used in preprocessing to detect edges is simple and efficient in extracting high frequency unique details of the image. The robustness of matrix 2-norm, infinite norm, trace and rank features for different rotations (from Table 2) contributes for improvement in performance. Fusion of matrix and diagonal features is also a key factor in boosting the recognition accuracy.

VI. Conclusion

Recognizing a person using fewer acquired images is a thrust area for research and rotation parameter attracts considerably in realtime applications. In this paper, the face recognition method proposed is simple and efficient using fewer database images. Image rotation is performed only on test images. Preprocessing uses an edge detection method for cropping facial part. All preprocessed images are divided into one hundred matrices of 5*5 size each. For each 5*5 part of image, matrix 2-norm, infinite norm, trace and rank are computed. These four matrix coefficients are respectively averaged to yield one hundred matrix features. In addition to this, all preprocessed images are transformed in spatial domain using a 3*3 mask. Another one hundred diagonal features are obtained by adding both principal and secondary diagonal elements of transformed matrix. Final features are computed by fusing matrix and diagonal features. Comparision of database and query image features is made using Euclidian distance measure. The results on Yale, Kinect, and Indian face databses are considerably improved over other existing methods.

References Références Referencias

1. Amrit Kumar, A., Yogendra N.S., 2015, Evaluation of Face Recognition Methods in Unconstrained Environments, ELSEVIER - Procedia Computer Science International Conference on Intelligent Computing, Communication & Convergence, 48, 644 – 651.
2. Ashwini, G.P., Steven L.F., Keerthan, N., Nagesha, Accamma, K.K., Sushmitha, K., Kushalakumari, 2015, Recognizing Human Faces under Varying Degree of Illumination: A Comprehensive Survey, 2nd IEEE International Conference on Electronics and Communication System, 577- 582.
3. Shwetank, A., Neeraj, P. Karamjit, B., 2015, Future of Face Recognition: A Review, *2nd* ELSEVIER International Symposium on Computer Vision and the Internet, Procedia Computer Science, 58, 578 – 585.
4. Bouzalmat, A., Belghini, N., Zarghili, A., Kharroubi, J., 2015, Face Recognition: Comparative Study between Linear and non Linear Dimensionality Reduction Methods, 1st IEEE International Conference on Electrical and Information Technologies, 224-228.
5. Jing, W., 2015, Efficient Face Recognition Research Based on Random Projection Dimension Reduction, 7th IEEE International Conference on Measuring Technology and Mechatronics Automation, 415-518.
6. Ville, O., Esa, R., Janne, H., 2008, Rotation Invariant Local Phase Quantization for Blur Insensitive Texture Analysis, 19th IEEE International Conference on Pattern Recognition, 1-4.
7. Nerella, A.M.K., Sathidevi, P.S., 2013, Wavelet SIFT Feature Descriptors for Robust Face Recognition, Springer-Verlag Berlin Heidelberg: Advances in Computing & Information Technology, 177, 851–859.
8. Xiaoyang, T., Songcan, C., Zhi-Hua Z., Fuyan, Z., 2006, Face Recognition from a Single Image per Person- A Survey, ACM Journal on Pattern Recognition, 39, 9, 1725-1745.

9. Kin-Man, L., Hong, Y., 1998, An Analytic-to-Holistic Approach for Face Recognition Based on a Single Frontal View, IEEE Transactions on Pattern Analysis and Machine Intelligence, 20, 7, 673-686.
10. Zhao, Y., Yan, L., Yang, L., Shenghua, Z., Kien A. H., 2015, Face Recognition from a Single Registered Image for Conference Socializing, ELSEVIER International Journal on Expert Systems with Applications, 42, 973-979.
11. Kuo-Chin, F., Tsung-Yung, H., 2014, A Novel Local Pattern Descriptor-Local Vector Pattern in High-Order Derivative Space for Face Recognition, IEEE Transactions on Image Processing, 23, 7, 2877-2891.
12. Zhen, L., Pietikainen, M., Stan, Z.L., 2014, Learning Discriminant Face Descriptor, IEEE Transactions on Pattern Analysis and Machine Intelligence, 36, 2, 289-302.
13. Zhenhua, G., Zhang, L., David Z., 2010, Rotation Invariant Texture Classification using LBP Variance with Global Matching, An International Journal on Pattern Recognition, 43, 706-719.
14. Jiansheng, C., Deng, Yu., Gaocheng, B., Guangda, S., 2015, Face Image Quality Assessment Based on Learning to Rank, IEEE Signal Processing Letters, 22, 1, 90-94.
15. http://vision.ucsd.edu/datasets/yale_face_dataset_original/yalefaces.zip.
16. Min, R., Kose, N., Dugelay, J., 2014, KinectFaceDB - A Kinect Database for Face Recognition, IEEE Transactions on Systems, Man, and Cybernetics, 44, 11, 1534--1548.
17. Vidit, J., Amitabha, M., 2002, The Indian Face Database, http://vis-www.cs.umass.edu/~ vidit/IndianFaceDatabase/.
18. Gonzalez, R.C., Woods, R.E., Eddins, S.L., 2004, Digital Image Processing using MATLAB, Pearson Education India.
19. Chris, D., Ding, Z., Xiaofeng, H., Hongyuan, Z., 2006, R1-PCA-Rotational Invariant L1-norm Principal Component Analysis for Robust Subspace Factorization, 23rd International Conference on Machine Learning, Pittsburgh, 1--8.
20. Guangcan, L., Zhouchen, L., Shuicheng, Y., Sun, J., Yong, Y., Yi, M., 2013, Robust Recovery of Subspace Structures by Low-Rank Representation, IEEE Transactions on Pattern Analysis and Machine Intelligence, 35, 1, 171--184.
21. Martin, J., Sulovsky, M., 2010, A Simple Algorithm for Nuclear Norm Regularized Problems, 27th International Conference on Machine Learning, Israel, 1--8.
22. Zhengming, D., Sungjoo, S., Jae-Joon, H., Changkyu, C., Yun, F., 2015, Discriminative Low-Rank Metric Learning for Face Recognition, 11th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition, 1, 1--6.
23. Shyam, R., Yogendra, N. S., 2015, Face Recognition using Augmented Local Binary Pattern and Bray Curtis Dissimilarity Metric, 2nd IEEE International Conference on Signal Processing and Integrated Networks, 779 --784.
24. Zhang, E., Yongchao, L., Faming, Z., 2013, A Single Training Sample Face Recognition Algorithm Based on Sample Extension, 6th IEEE International Conference on Advanced Computational Intelligence, pp. 324—327.
25. Venkatramaphanikumar, S., Kamakshiprasad, V., 2013, Gabor Based Face Recognition with Dynamic Time Warping, 6th IEEE International Conference on Contemporary Computing, 349 - 353.
26. Poornima, K., Naveen, S., 2015, RGB-D Face Recognition System Verification using Kinect and FRAV3D Databases, ELSEVIER - Procedia Computer Science International Conference on Information and Communication Technologies, 46, 1653--1660.
27. Girish, G.N., Shrinivasa, N., Pradip, C.L., Das, K., 2014, Face Recognition using MB-LBP and PCA- A Comparative Study, IEEE International Conference on Computer Communication and Informatics, India, pp. 1--6.
28. Harendra, U., Arya, K.V., 2014, Efficient Face Recognition using Morphological Operations, 9th IEEE International Conference on Industrial and Information Systems, 1-6.

Global Journals Inc. (US) Guidelines Handbook 2016

www.GlobalJournals.org