Face Recognition using Fused Diagonal and Matrix Features

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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

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Index terms— cropping, edge detection, rotation variation, small sample size problem.

1 Introduction

revailing 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. [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 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.

2 II.

3 Literature Review

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 selfcollected 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.

4 III. Block Diagram of the Proposed Model

The details of input data, preprocessing, features extraction and matching are discussed in this section. Figure 1

5 Table1: Roberts Operator

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 **??**(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. b) Pre-processing Figure **??** 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 **??**. 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 **??** (b).

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 = ? 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 **??** infers the result of rotation with +/-1 0 in these matrix parameters. Additionally it contains matrix 2norm, 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 **??** 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.

6 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 (**??**), where 'i' vary from one to total number of elements in each vector.

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

8 Table 3 : Result of masking with diagonal features

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.

9 IV.

10 Algorithm

11 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 5 th 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 **??** 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 **??**. 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 9 th image. FAR is computed by using 5 th 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.

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.

12 Threshold

Single Trained Image Double Trained Images +/-1 0 , -2 0 , +/-3 0 , +/-4 0 Rotation 0 0 , 1 0 , 2 0 , 3 0 , 4 ALBP +BCD [23] 71.9 WM(2D)2PCA [24] 80.77 GABOR +DTW [25] 90 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 observed that the proposed algorithm achieve better results than the method compared.

proposed method with the other [27], [28] method. It is 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 **??**) contributes for improvement in performance. Fusion of matrix and diagonal features is also a key factor in boosting the recognition accuracy.

13 VI.

14 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. [1]

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Figure 1: Fig. 2 :Fig. 1 :Face

Figure 2: ?

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Figure 3: Fig. 4 :Fig. 3 :FThe 1 -

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Figure 4: (1)

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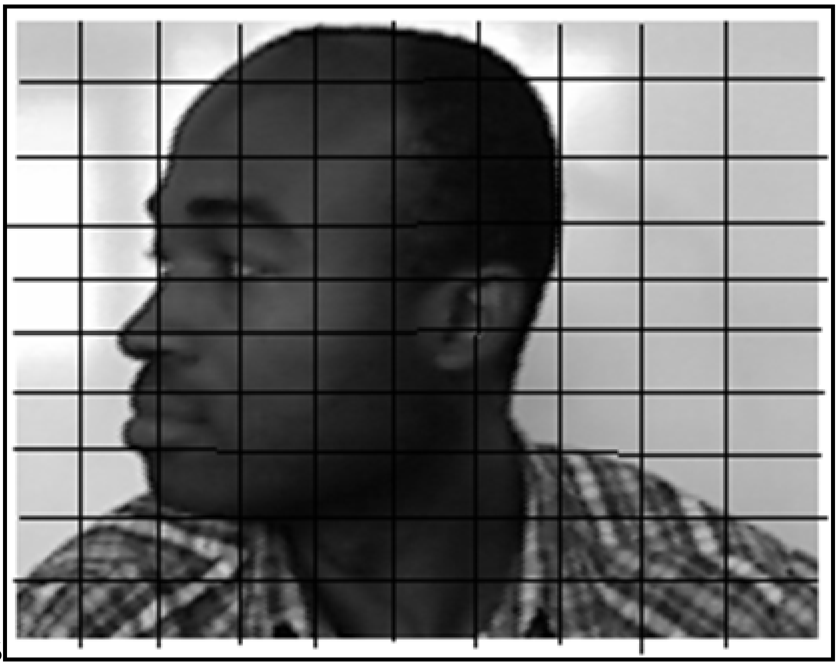

Figure 5: Fig. 5 :

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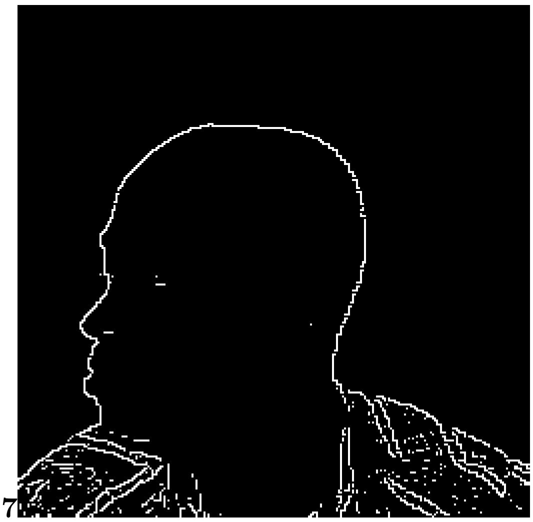

Figure 6: Fig. 7 :

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Figure 7: Fig. 8 :

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Figure 8: Fig. 9 :

shows the block diagram of proposed
Face Recognition using Diagonal and Matrix Features
(FR DMF) model.

Yeara) Databases i. Yale database [15] consists of 15 subjects, each subject with
201611 different images with a total of 165 images in Graphics Interchange Format
(GIF). The

18 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.

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*[Note: 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.]*

Figure 9:

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Figure 10: Table 4 :

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[Note: F]

Figure 11: Table 5 :

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Figure 12: Table 6 :

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Figure 13: Table 7 :

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Figure 14: Table 8 :

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Figure 15: Table 9 :

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(a) (b)

Figure 16: Table 10 :

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