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ROBUST FACE RECOGNITION FOR BLURRED IMAGES WITH ITERATIVE GRAPH BASED RESTORATION USING LINEAR COLLABORATIVE DISCRIMINANT REGRESSION CLASSIFICATION

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ABSTRACT

Face Recognition using images obtained from the unconstrained environment is the challenge, yet to be resolved. This situation is due to cluttered background and poor lighting conditions or illumination. Capturing images from a long distance, atmospheric turbulence, out of focal length and camera in motion are also the reasons behind the drastic decline in the performance of face recognition. A novel three-step formula has been proposed in this paper to address the issues from existing methodologies and provide the consistent accuracy in final face recognition. First and foremost, the query image of a face is thoroughly analysed to know the blur presence and its type. Later, the model images are also blurred to the same extent as of query image and face recognition is done using deblurring both model and query images by iterative graph based image restoration technique. The accuracy of the face recognition using the proposed algorithm is consistent under different levels and types of blurring. The performance of the proposed method (for blurring and deblurring the models) is validated for different classification algorithms namely collaborative representation classification (CRC), relaxed collaborative representation (RCR) and linear collaborative discriminant regression classification (LCDRC). LCDRC outperformed the existing peers in accuracy and robustness. The best recognition rate of 96.25 % is obtained for blur face images using this proposed method.

Keywords: blur metric, collaborative, deblurring, Haar wavelet transform.

INTRODUCTION

Face recognition is a challenging topic in biometrics research. Face recognition can be divided into two types. Images acquired under constrained conditions like proper lighting (illumination), focal length, fixed view position, etc. example: Passport photo. These types of images can be used in the applications like access control using face recognition. The performance of the Face Recognition rate is satisfactory with images acquired and processed by the system with full-face images of good quality [1].

However, for some of the applications like security and video surveillance systems, it is not possible to constrain the environment like lighting, distance, movement of objects or people (causes blurring) and pose. To ensure public safety at industries, institutions and in common places, face recognition with the images acquired under uncontrolled conditions is an important and challenging task [2]. Variation in lighting conditions, blur effects, blocking effects, large changes in facial pose, etc. are making the performance of the face recognition unsatisfactory. The big challenging problem in Face recognition is due to degradations of an image because of different blur types, noise and changes in appearance due to light variation [3]. Images will be degraded or blurred when they are acquired from distant cameras, improper focused lens of the camera, the relative motion between the camera and the scenes or atmospheric turbulence.

In this paper, the gallery data-set consisting of face images are increased by blurring and deblurring with known degradation function. The Original face images in the gallery are blurred with Gaussian, motion and out-of-focus blur. Haar Wavelet transform based method is used to identify whether the given image is blurred or not and if blurred, it also finds the type of blur. Based on the type of blur, an Iterative Graph(IG)-based Image Restoration Scheme is used to deblur the face images. It is assumed that deblurred query image which is naturally blurred during acquisition will be close to the model image with the same type of blurring and deblurring as compared to original clean model image. Later, face recognition is done using different algorithms such as principal component analysis (PCA), linear discriminant analysis (LDA), linear regression classification (LRC), collaborative regression classification (CRC), relaxed collaborative representation (RCR) and linear collaborative discriminant regression classification (LCDRC) algorithms. The performance of LCDRC is found to be more efficient than other classification methods. This procedure makes an accurate and robust face recognition process for blurred images.

The rest of the paper is organized as follows. Section 2 discusses on the related work done. Section 3 describes the proposed method in detail. Section 4 gives the details of how to determine the type of blur and its extent using Haar wavelet transform. Section 5 discusses on deblurring the images with Iterative Graph-based Image Restoration Technique. Section 6 discusses on emerging face recognition algorithms and about efficient LCDRC algorithm. Section 7 presents the results for AR and ORL database and section 8 concludes the paper.

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RELATED WORK

Blurred face recognition methods are categorized into three forms.

i Extraction of blur invariant descriptors [4]
ii Deblurring the test images to restore the sharp image [5] and
iii To blur the gallery with the estimated kernel to construct a specific classifier for a query face [6].

In video surveillance applications, various problems such as blur and pose changes can be encountered on the same image. Also, it is not possible to capture the whole space of blur kernels. Identification becomes very difficult when blur kernels are complex [7]. In [8], an exemplar face is developed to detect initial blur kernel. It works well for deblurring faces that contain lots of background but lose its efficiency in identifying face images produced from a face detector.

PROPOSED METHOD

Face recognition from blurred faces is proposed in this paper in three stages. In the first stage, the extent and type of blur for the query is identified using Haar Wavelet Transform method. In the second stage the blurred face is deblurred using IG-based image restoration method and in the last stage LCDRC method is used to recognize the blurred faces. The block diagram of the proposed method is shown in Figure-1. Initially the gallery dataset (models) is expanded with blurred and deblurred images. Three types of blurring methods are considered for expanding the gallery, for which the degradation transformation is known i.e. with Gaussian blur, Motion blur and Out-of-Focus blur. Based on the type of blur, an Iterative Graph (IG)-based Image Restoration method is used to obtain deblurred face images of gallery [10]. An appropriate objective function is chosen which enhances face image by coupling the data and prior terms through structurally encoded filtering and Laplacian matrices. Now the gallery consists of gaussian deblurred represented by G(g,h), motion deblurred represented by G(m,h) and out-of-focus deblurred represented by G(of,h) datasets along with original dataset G(o,h). The blur metric values for Gaussian, Motion and Out-of-focus blur are represented as b_g b_m, b_{of}. The complete gallery G(s,h) represents the gallery with all types of blur and the original dataset[g,m,of,o].

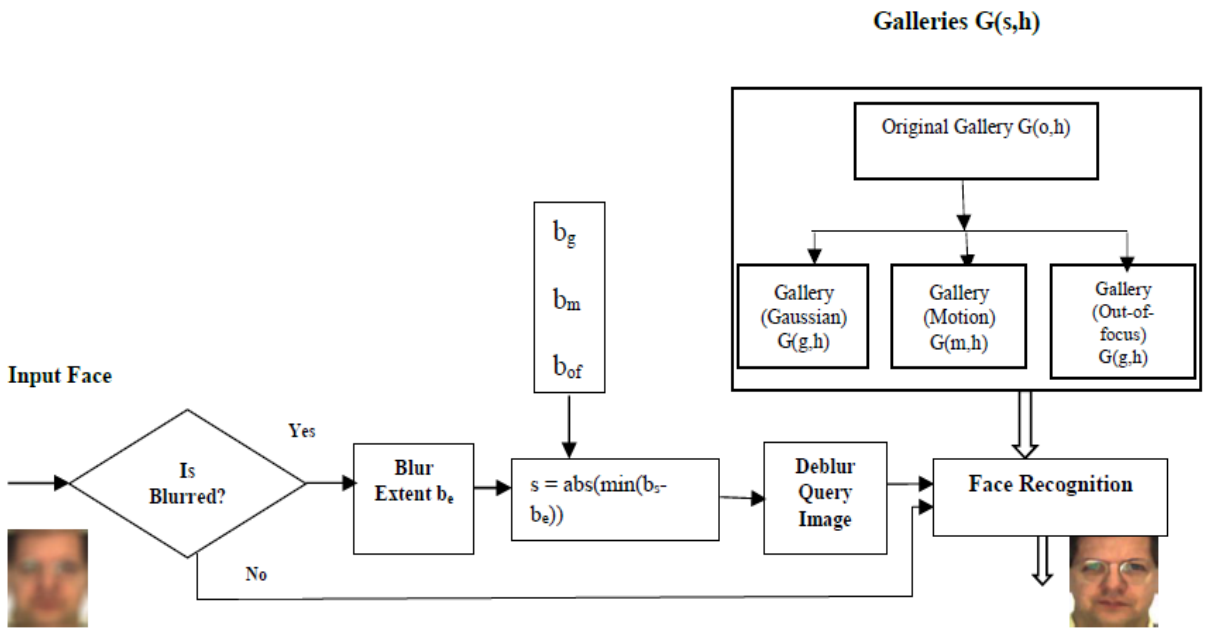


Figure-1. Block diagram of the proposed method.

When a test/query face is given, the presence of blur is determined by a blur detection algorithm using Haar Wavelet Transform. This method firstly decides whether the face image is blurred or not and if blurred it gives the blur level or metric 'b_s'. This value determines whether the given face image is blurred with Gaussian or Motion or Out-of-focus blur (bg bm, bof). Once the test face is identified as blurred face, it is deblurred with IG-based image restoration method based on the type of blur. Suppose the test face is affected with gaussian blur, then gaussian deblurred test face is compared with the Gaussian deblurred gallery G (g,h) dataset using classification algorithms. Similar process is done for Motion and Out-of-focus blurred face images. The performance of different classification methods like principal component analysis (PCA), linear discriminant analysis (LDA), linear regression classification (LRC), collaborative representation classification (CRC) and relaxed collaborative representation (RCR) is computed and compared using extended gallery or models.

BLUR DETECTION USING HAAR WAVELET TRANSFORM

The presence of Blur in an image leads to quality degradation. Automatic blur detection method is used to judge whether the given image is blurred or not. If it is blurred it determines the extent of blur. Based on this, the nature of blur will be identified. Most images contain many types of edges. The sharpness of the edge depends on the level of blur. The sharpness of the sharpest edges in the blurred image will give information about the type of blurring.

Edges are generally classified into three types: a) Dirac-Structure, b) Roof Structure and c) Step-Structure (A-step-Structure and G-step-Structure). When blur occurs i) Dirac-structure and A-step Structure will disappear, ii) G-step Structure and Roof-Structure tend to lose their sharpness. There are two ways to analyze the Blur function, a) Indirect methods and b) Direct methods. The computational cost is very high for indirect methods. In the direct methods, DCT is used widely. But the efficiency of detection is very low when the image is over-illuminated or with a uniform background [11]. Wavelet Transforms are well known for its multi-resolution analysis. Wavelet-based method is used to estimate the blur in an image using information contained in the image itself. The flowchart in Figure-2 shows the procedure to detect the blurred image using Haar wavelet transform [12].

DEBLURRING WITH ITERATIVE GRAPH-BASED IMAGE RESTORATION SCHEME

The purpose of the restoration algorithms is to undo the undesirable distortions like noise, blur from the degraded image. The blurring process for a linear shift invariant point spread function (PSFs) is represented by the following linear model [13]

$$y = Az + n \quad (1)$$

where y- an ordered vector representation of the input blurred and noisy image, z- Latent image in vector form, n- Noise vector which is independent and identically distributed zero mean noise with standard deviation σ, A- Blurring matrix of size N2 x N2 is constructed from PSF based on the assumptions. Many of the deblurring methods depend on optimizing the cost function [14] of the form.

$$E(z) = \|y - Az\|^2 + \eta R(z) \quad (2)$$

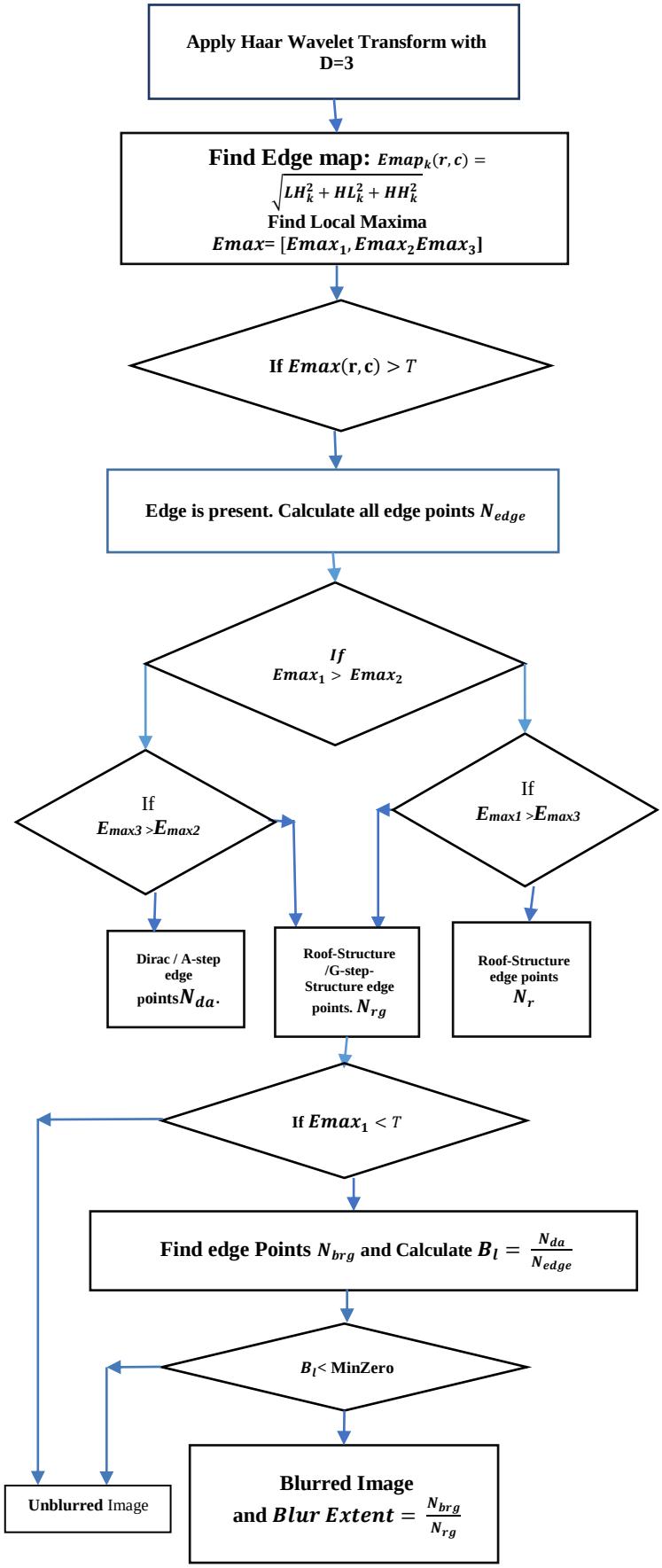


Figure-2. Flow chart to detect blur using HWT.

The first term is called 'data fidelity term' and the second term is called 'prior term' which regularizes to keep final estimate free from exhibiting being too smooth and unpleasant noise amplification, ringing artifacts etc. This method consists of inner and outer iterations. An updated objective function in inner iteration is minimized using Conjugate Gradient (CG) that obtains the corresponding estimate [15]. The similarity weights are recomputed with the previous estimate in each outer iteration based on a new definition of the normalized graph Laplacian. Normalizing coefficients are extracted from a fast symmetry preserving matrix balancing algorithm (FSPMBA) [16]. This iterative method gives the best performance showing its effectiveness in different restoration problems that includes deblurring, denoising, and sharpening. It was reported that this algorithm performs more effectively in terms of objective criteria and visual quality [10].

Face recognition using linear collaborative discriminant regression classification

Automatic Face recognition system depends on two key factors: (a) How to represent a face image and (b) How to classify the face image. Many face recognition algorithms focus on face representation and design of the classifier. These algorithms are broadly classified into two categories: based on holistic features and based on local features. Holistic (Global) feature based methods include Geometric feature vector, face statistical model, elastic bunch graph matching, Gabor information on deformable graphs etc. Some of the local appearance-based methods are Locally Linear Embedding (LLE), Nearest Neighbor (NN), linear regression classifier (LRC), Locality Preserving Projection (LPP) and Local Binary Patterns [17]. The Classifier efficiency is improved by combining both global and local analysis of a face [18]. Some of them are combination of PCA and Gabor wavelets, Local directional pattern, HMM-SVM-SVD, SIFT-2DPCA, etc. [18].

The classification of test images with different levels of blur, was done with PCA [19], LDA [20], LRC [21], CRC [22], RCR [23] and LCDRC [24] methods. LCDRC algorithm is giving more accurate and robust recognition results. The LCDRC method is given below.

LCDRC method

The main idea is to find out similarities among the elements in the same class and dissimilarities between the elements belong to different classes. The test face can be reconstructed with the images of faces that belong to same class with small error compared to reconstruction with images of faces that belong to different classes. Therefore, each class can be represented by a common vector, obtained from within scatter matrix is used to represent all elements that belongs to same class. The LCDRC uses collaborative between class reconstruction error (CBCRE) instead of between class reconstruction error (BCRE). It uses cross-class training faces to represent a probe face so that CBCRE is smaller than each class-specific between class reconstruction error [25].

Algorithm

The complete face database is represented as Z= $[Z_1, Z_2, Z_3, Z_4 \ldots Z_i \ldots\ldots Z_c] \in R_{mxn}$. where Z_i is the set of images belong to i^{th} Face. Each image is represented by a column vector of length m (rows x columns of image), $n=n_1+n_2+\ldots n_i \ldots+n_c$ and n_i is the number of images for i^{th} face.

a. Normalize all the training and testing face images with unit l_2-norm.
b. Find the Projection Matrix U = $[u_1, u_2, \ldots\ldots u_k, \ldots\ldots u_d] \in R$ m x d. This is obtained by choosing Eigen vectors with highest Eigen values, of the covariance matrix of all images belonging to all classes (intra and Inter).
c. Project the training face images Z into the discriminant subspace to obtain Y =$\boldsymbol{U^T Z}$ .i.e. Each z_{ij} is mapped to the learned subspace by $y_{ij}= U^T z_{ij}$, where $1<j<n_i$ and the entire training face image matrix is mapped as Y = UT Z $\in$ Rd x n, and for each class Yi = UTZi $\in$ Rd x ni. The CBCRE and WCRE are defined as

$$CBCRE = \frac{1}{n}\sum_{i=1}^{c}\sum_{j=1}^{c}\left\|y_{ij} - \hat{y}_{ij}^{inter}\right\|_2^2 \quad (3)$$

$$WCRE = \frac{1}{n}\sum_{i=1}^{c}\sum_{j=1}^{c}\left\|y_{ij} - \hat{y}_{ij}^{intra}\right\|_2^2 \quad (4)$$

where $\boldsymbol{\hat{y}_{ij}^{inter}}= Y_{ij}^{inter}\alpha_{ij}^{inter}$where Y_{ij}^{inter} is Y with $Y_i$eliminated. $\boldsymbol{\hat{y}_{ij}^{intra}}=Y_{ij}^{intra}\alpha_{ij}^{intra}$, where $Y_{ij}^{intra}$is Y with y_{ij}eliminated. $\alpha_{ij}^{inter}$and α_{ij}^{intra} are obtained by$\hat{\alpha}_i = (Z_i^T Z_i)^{-1} Z_i^T y = H_i y$, where H_i is called Hat Matrix [17].

d. For each class, i = 1, 2. …. c, calculate the hat matrix Hi, where $H_i = (Z_i^T Z_i)^{-1} Z_i^T$.
e. Transform the given test face image z into the learned sub-image $y = \boldsymbol{U^T z}$ and find the reconstruction by i^{th} class as $\hat{y}_i = H_i y$
f. Reconstruction error from the i^{th}class is calculated as $e_i = \|y - \hat{y}\|_2$.The class which has minimum reconstruction error is identified for the given test face.

RESULTS AND DISCUSSIONS

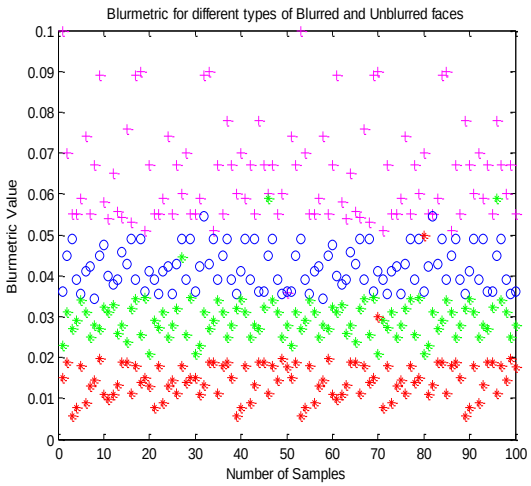
The query face, given for classification/recognition is blurred or not, is decided with Haar wavelet transform. Figure-3 shows the effect of gaussian, motion and out-of-focus blurs on sharp original images. The unblurred or sharp face image is shown in Figure-3(a). Gaussian blur is occurred when an image is acquired through turbulent medium (fog, underwater, fluorescence microscopy, etc.) and is shown in Figure-3(b). Motion blurred face image is shown in Figure-3(c), which is caused due to relative motion between original image and camera either when image is captured while the camera or the subject or both are moving. Out-of-focus blur occurs when the target face image is not in focus to the camera as shown in Figure-3(d). This leads to high frequency information loss in the image. By considering numerous observations as shown in Figure-4

(for different face images), Blur metric or Blur extent values for unblurred and blurred faces are computed. Blur metric is defined from flow chart in Figure-2 as the ratio of Dirac-Structure and A-step Structure edges (N_{da}) to all the edges (N_{edge}). Table-1 shows Blur Metric values for unblurred and different blur face images. Based on the blur Metric value, one can decide whether the face is blurred or not. If blurred, the type of blur i.e., Gaussian or Motion or Out-of-focus is also identified. As an example, if the blur metric value is between 0.02 and 0.035, it will be identified as Motion type of blur. Similarly, if the blur metric value is between 0.01 and 0.02, it will be identified as Out-of-focus blur. The last column shows the accuracy achieved in each type. In the second stage, the blurred face is deblurred.

(a)

(b) (c) (d)

Figure-3. Effect of gaussian, motion and out-of-focus blurs on original image.



* --- Unblurred,o ---Gaussian Blur,
+ --- Motion Blurand * --- Out-of-focus Blur, ,

Figure-4. Blur metric for different blurred and unblurred faces.

Table-1. Blur metric for different blurs.

S. No	Nature of face images	Number of faces	Blur metric value	Accuracy (%)
1	Un-blurred	1500	0.05	98.21
2	Gaussian Blur	500	[0.035,0.05]	98.33
3	Motion Blur	500	[0.02,0.035]	99.3
4	Out-of-focus Blur	500	[0.01,0.02]	99

AR face database developed by Ohio State University consisting of different facial expressions and illumination conditions is used to test the performance of the proposed method. In that database 400 face images with 40 subjects are considered. Each subject consists of 10 faces of all frontal views of: neutral expression, smile, anger, scream, left light on, right light on, eyes closed. This database is blurred with Gaussian, Motion and Out-of-focus blur separately and stored in the data base. Later these images are deblurred using Iterative Graph based Image Restoration method. The same procedure of deblurring process is also tested with FERET, ORL and CMUPIE databases.

Peak Signal to Noise Ratio (PSNR) is a measure of quality of the reconstructed image. High PSNR value means good quality and vice versa. Structural Similarity Index Measure(SSIM) is the similarity measure between any two images which is more consistent with human perception. Its range is between 0 and 1. SSIM closer to 1 are considered as more similar. Table-2 shows the PSNR and SSIM ratios for different database face images for variance equal to 0.2.

Figure-5.a shows some of the original AR database faces, Figure-5.b shows Gaussian blurred faces which are obtained by convolving original face image with 25 x 25 Gaussian blur with standard deviation of 1.6 added with additive white gaussian noise (variance =1). Figure-5.c shows gaussian deblurred faces with η=0.003, β=0.2 and h=5.5.

Figure-5.a. Normal faces without blur.

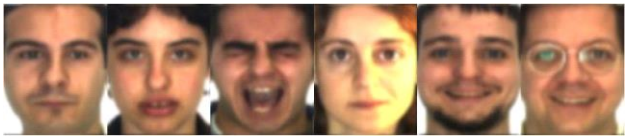


Figure-5.b. Gaussian blurred faces.

Figure-5.c. Gaussian deblurred faces.

Figure-5.d shows Motion blurred faces obtained by complex Motion blur kernel in [23] added with additive white gaussian noise (variance =1) and Figure 4.e shows motion deblurred faces with η=0.006, β=0.4 and *h*=6.

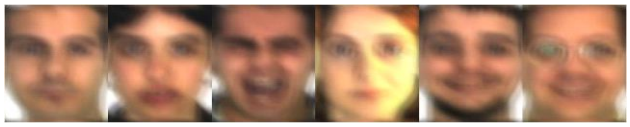


Figure-5.d. Motion blurred faces.

Figure-5.e. Motion deblurred faces.

Finally, Figure-5.f shows Out-of-focus blurred faces obtained using disk function with radius 7 added with additive white gaussian noise (variance =1). Figure-5.g shows Out-of-focus deblurred faces with η=0.008, β=0.001 and *h*=7.5.

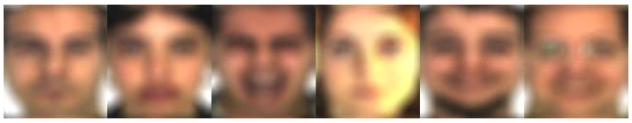


Figure-5.f. Out-of-focus blurred faces.

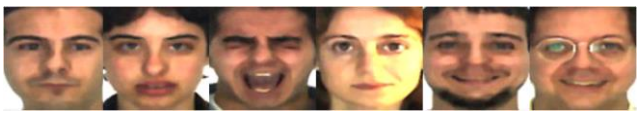


Figure-5.g. Out-of-focus deblurred faces.

Table-2. PSNR and SSIM performance on different database face images.

Blur/ DB	Gaussian(σ^2 = 1)		Motion(σ^2 =1)		Out-of-focus(σ^2 = 1)	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
AR Database	33.18	0.9693	32.28	0.9522	32.28	0.9378
FERET Database	33.84	0.9732	32.97	0.9630	33.00	0.9489
ORL Database	32.89	0.9827	29.33	0.9677	31.35	0.9614
CMU PIE Database	30.45	0.9841	26.27	0.9717	27.25	0.9711

Now the gallery database is expanded by considering Original, Gaussian deblurred, Motion deblurred and Out-of-focus deblurred AR database. Randomly 200 (five images from each class) faces are selected for training and any one face image from remaining faces as test face, is considered for classification. Basically, (LCDRC) is used for classification. Later its performance is checked by decreasing the training set to 160,120 and 80 (four, three and two face images from each class) faces and increasing the training set to 240, 280 and 320 (six, seven and eight images from each class) faces respectively. Figure-6.a shows the classification results for Original AR database. The recognition rate is 98.75% (AR Database) and 94.45% (ORL Database) for 320 training and 80 test faces and the recognition rate decreases to 85.94% (AR Database) and 83.24% (ORL Database) for 80 training and 320 testing faces.

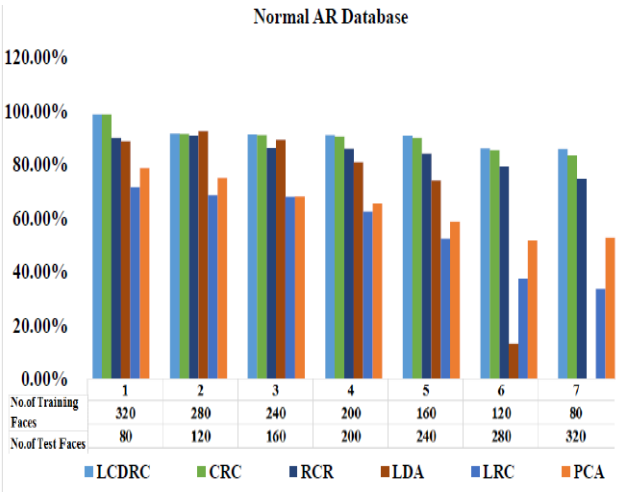


Figure-6.a Recognition rate for AR database.

Figure-6.b shows classification results for Gaussian deblurred AR database. It is observed that the recognition rate is 96.25%(AR Database) and 93.45%

(ORL Database) for 320 training and 80 test faces and 87.14% (AR Database) and 82.45% (ORL Database) for 80 training and 320 testing faces.

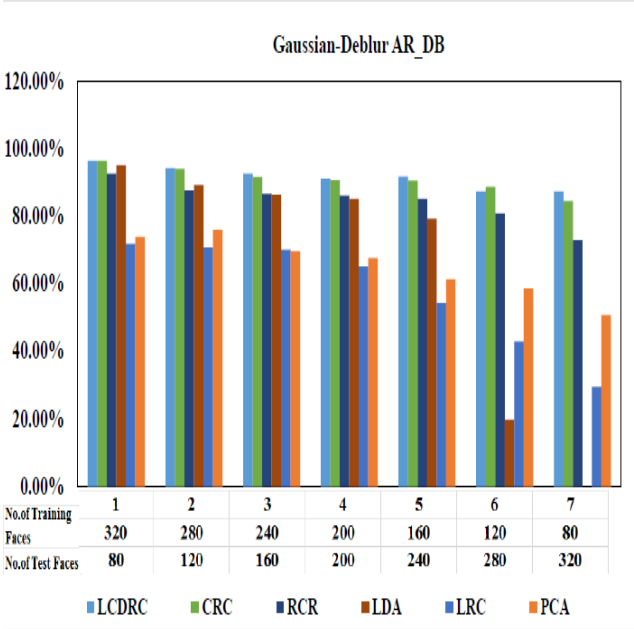


Figure-6.b. Recognition rate for Gaussian deblurred AR database.

Figure-6.c shows classification results for Motion deblurred AR database. It is observed that the recognition rate is 96.2%(AR Database) and 93.64% (ORL Database) for 320 training and 80 test faces and 86.88% (AR Database) and 83.29% (ORL Database) for 80 training and 320 testing faces.

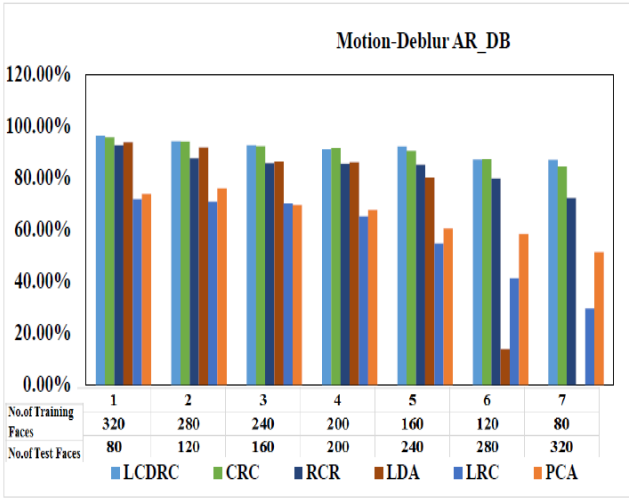


Figure-6.c. Recognition rate for motion deblurred AR database.

Figure-6.d shows classification results for Out-of-focus deblurred AR database. It is observed that the recognition rate is 96.15% (AR Database) and 94.12% (ORL Database) for 320 training and 80 test faces and 86.56% (AR Database) and 83.5% (ORL Database) for 80 training and 320 testing faces.

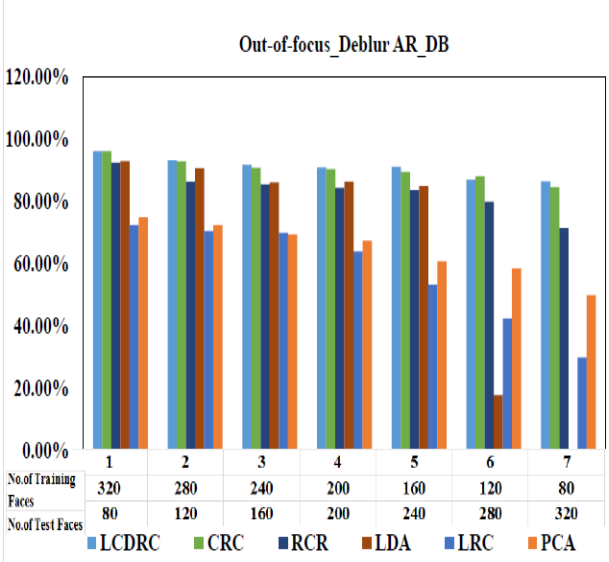


Figure-6.d. Recognition rate for out-of-focus deblurred AR database.

CONCLUSIONS

In this paper, robust face recognition method for blurred images is proposed. Firstly, the presence of blur and its extent are determined using Haar Wavelet Transform. Based on the value of the blur extent, it determines whether the query face image is blurred or not. If blurred, the type of blur is known. Blurred faces are deblurred using Iterative Graph(IG) based image restoration technique. The gallery set is also blurred and deblurred with the above process. Based on blur type of the query face, Linear Collaborative Discriminant Regression Classification is used for recognition. Training with less number of samples (80 faces with two faces in each subject) and testing with more number of samples (320 faces with 8 other faces in each subject), 87.14% recognition rate is achieved. The recognition rate is 89.12% for unblurred faces for AR database. Further, the recognition rate is 96.25% for Blurred faces and 98.75 for unblurred faces with 320 training and 80 test faces.

REFERENCES

[1] M. Hassaballah1, Saleh Aly. 2015. Face recognition: challenges, achievements and future directions, IET Computer Vision, 9(4): 614-626, The Institution of Engineering and Technology.

[2] T. Kanade. 1973. Picture Processing by Computer Complex and Recognition of Human Faces, Ph.D. thesis, Kyoto University.

[3] Cecile Fiche. 2010. Patrica Ladret and Ngoc-son Vu, Blurred Face Recognition Algorithm guided by No-Reference Blur Metric, Image Processing: Machine Vision Application III, France.

[4] Ojansivu V. and Heikkila J.Blur insensitve texture classification using local phase quantization, in ICISP'08: Proceedings of the 3rd International Conference on Image and Signal Processing, 236-243, Springer-Verlag, Berlin.

[5] H. Hu and G. De Haan. 2007. Adaptive image restoration based on local robust blur estimation, In Proc. Int. Conf. Adv. Concep. Intell. Vis.Syst.

[6] Priyanka Vageeswaran, Kaushik Mitra, and Rama Chellappa. 2013. Blur and Illumination Robust Face Recognition via Set-Theoretic Characterization, IEEE Transactions on Image Processing. 22(4).

[7] PurvaD.Kandelkar, P.A.Tijare, S.N.Sawaljar. 2015. SET-Theoritic Charaterization for Blur Face Recognition, International Journal of Innovative Research in Computer and Communication Engineering. 3(7).

[8] Dayong Tian and Dacheng Tao. 2016. Coupled Learning for Facial Deblur, IEEE transactions on Image Processing. 25(2).

[9] Jun Li, Shasha Li, Jiani Hu and Weihong Deng. 2015. Simultaneous Blurred Face Restoration and Recognition, 3rd IAPR Asian Conference on Pattern Recognition.

[10] Amin Kheradmand, PeymanMilanfar. 2014. A General framework for regularized, similarity-based Image Restoration, IEEE transactions on Image Processing. 23(12).

[11] Rupali Yashwant Landge and Rakesh Sharma. 2013. Blur Detection Methods for Digital Images- A Survey. International Journal of Computers Applications Technology and Research. 2(4): 495-498, 2013, ISSN: 2319-8656.

[12] Hanghang Tong, Mingjing Li, Hongjiang Zhang, Changshui Zhang. 2004. Blur Detection for Digital Images Using Wavelet Transform. The 2004 IEEE International Conference on Multimedia and Expo (ICME' 2004), Taipei, Taiwan.

[13] P. C. Hansen, J. G. Nagy and D. P. O'Leary. 2006. Deblurring Images: Matrices, Spectra, and Filtering, 1st ed. Philadelphia, PA, USA: SIAM.

[14] K. Dabov, A. Foi, V. Katkovnik and K. Egiazarian. 2007. Image denoising by sparse 3-D transform-domain collaborative filtering, IEEE Trans. Image Process. 16(8): 2080–2095.

[15] T. S. Cho, C. L. Zitnick, N. Joshi, S. B. Kang, R. Szeliski, and W. T. Freeman. 2012. Image restoration by matching gradient distributions. IEEE Trans. Pattern Anal. Mach. Intell. 34(4): 683–694.

[16] P. A. Knight and D. Ruiz. 2015. A fast algorithm for matrix balancing. IMAJ. Numer. Anal. 33: 1029-1047.

[17] M. Hassaballah, Saleh Aly. 2015. Face recognition: challenges, achievements and future directions. The Institution of Engineering and Technology 2015, IET Comput. Vis.9(4): 614–626.

[18] MejdaChihaoui, AkramElkefi, WajdiBellil and Chokri Ben Amar. 2016. A Survey of 2D Face Recognition Techniques. Computers. 5(4),MDPI;doi:10.3390/computers5040021

[19] M.A. Turk, A.P. Pentland. Face recognition using eigenfaces, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 586–591.

[20] P.N. Belhumeur, J.P. Hespanha, D. Kriegman. 1997. Eigenfaces vs. Fisherfaces: Recognition using Class Specific Linear Projection, IEEE Trans. Pattern Anal. Mach. Intell. 19: 711-720.

[21] Naseem, R. Togneri, M. Bennamoun. 2010. Linear regression for face recognition, IEEE Trans. Pattern Anal. Mach. Intell. 32: 2106–-112.

[22] D.Zhang, M.Yanf, X.Fng. 2011. Sparse representation or collaborative representation: which helps face recognition?, IEEE International Conference on Computer vision(ICCV), IEEE..pp. 471-478.

[23] Meng Yang, Lei Zhang, David Zhang, Shenlong Wang. 2012. Relaxed Collaborative Representation for Pattern Classification. IEEE, Computer Vision and Pattern Recognition (CVPR).

[24] Xiaochao Qu, Suah Kim, Run Cui, Hyoung Joong Kim. 2015. Linear Collaborative Discriminant Regression Classification for Face Recognition, Journal of Visual Communication and Image Representation, Elsevier.pp. 312–319.

[25] S. M. Huang, J. F. Yang. 2003. Linear discriminate regression classification for face recognition, Signal Process .Lett, IEEE. 20: 91-95.