

# A Novel Approach for Blurred Face Recognition System Using GLDA Features with LCDR Classification

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## Abstract

**Objective:** To design an effective face recognition system invariant to all image degradation parameters. **Methods:** The proposed system designed an efficient image restoration based on Iterative Graph based Image Restoration technique. It provides high reconstruction rate. Gabor Linear Discriminant Analysis (GLDA) feature extraction method is used to extract features for the restored faces images and Linear Collaborative Discriminant Regression Classifier (LCDRC) is adopted. GLDA based feature extraction is the combination of both the features like Gabor and LDA which are used to obtain the maximum recognition rate. **Findings:** The LCDRC gives a discriminant subspace with maximum collaborative between-class reconstruction error and minimum within-class reconstruction error. **Applications/Improvements:** It is an improvement over the linear discriminant regression classifier (LDRC). From the experimentation results, it has been achieved a recognition rate of 99.2% even in the case of blurred face images.

**Keywords:** Collaborative, Face Recognition, Feature Extraction, Gabor Linear Discriminant Analysis (GLDA) and Image Restoration

## 1. Introduction

With the advent of digital technology, face recognition is the most widely used feature in many applications especially as the biometric authentication. This feature makes easier and unique type of authentication. This kind of biometric authentication is contactless when compared to fingerprint biometric authentication. Face recognition based biometric authentication provides good reliability over the fingerprint biometric authentication and is more secure.

This algorithm of face recognition is also widely used in the robotics and artificial intelligence-based applications. In early years of 2000, face recognition was the complex problem, but now with the advent of high-speed computing machines, it has become easier. In future with the rapid growth of robotics, automation and artificial intelligence, the face recognition module will

be used as a basic part of every system. Face recognition finds applications in many systems like authentication process, security, surveillance, teleconferencing, defence and computer/mobile applications. Also, it is necessary to provide the reliability, high speed and accuracy of the systems.

## 2. Literature Survey

In<sup>1</sup> have implemented blur and illumination robust face recognition system. Here in this system, the problem statement is based on the face recognition of distant captured images. Also, here the captured image is the degraded image due to blur and poor illumination. The algorithm was implemented using the set theoretic characterization. Nearest-neighbour classification has been adopted in this implementation.

In<sup>2</sup> it has been developed based on Iterative Graph based Image restoration approach. The normalizing coefficients are calculated with the help of fast symmetry preserving matrix balancing. Then the desired spectral properties of the normalized Laplacian are obtained. The algorithm consists of outer and inner iterations. The outer iteration is used to re-compute the similarity weights using the previous estimate. And the inner iterations are used to update the minimized objective. These improve the performance of algorithm.

A face recognition system is implemented using the Discrete Cosine Transform (DCT)<sup>3</sup>. Here DCT is applied to obtain the local & global features. Both features are used for the comparison with the face database features. Here the best matched image is considered as the recognized image.

In<sup>4</sup> implemented the system for recognition of images degraded. It is based on the theory of invariants to Gaussian blur. In this approach, a primordial image is used which is a canonical form of all Gaussian blur-equivalent images. This method uses the concept of primordial image. It is defined in spectral domain with the help of projection operators. It has been proved that its moments are Gaussian blur-invariant. Recursive formulas are used for the direct computation without constructing the primordial image itself. Its application is found in blur-invariant image comparison and recognition.

Linear Collaborative Discriminant Regression Classifier (LCDRC)<sup>5</sup> is used for the classification of face images. LCDRC gives a discriminant subspace with maximum collaborative between-class reconstruction error and minimum within-class reconstruction error. Also, it gives the higher recognition rate than the LDRC, PCA, LDA and LRC methods<sup>6-9</sup>.

A face recognition algorithm was implemented using the fusion of Linear Discriminant Analysis (LDA) and Artificial Neural Network (ANN)<sup>10</sup>. It has been achieved a recognition rate of 92%. The process consists of two steps. In the first step, face is detected using Viola-Jones algorithm. In the second step, the face is identified using LDA and ANN.

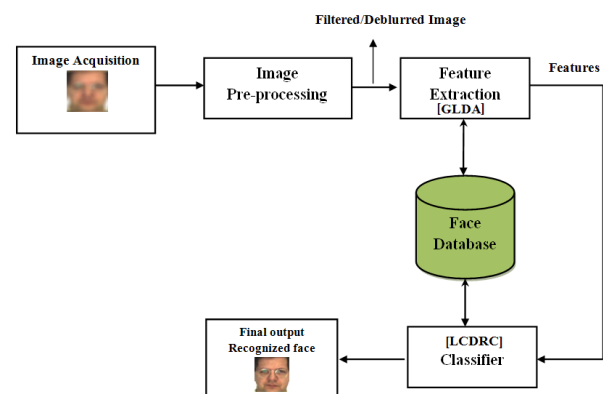
Blurred face recognition methods are categorized into three forms.

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

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. In, 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<sup>11-14</sup>.

### 3. Block Diagram

The implemented system for face recognition consists of following major stages, as shown in Figure 1.



**Figure 1.** Block diagram of Blur invariant face recognition system.

- i. Image Acquisition
- ii. Image Pre-processing
- iii. Feature Extraction
- iv. LCDRC Classifier
- v. Final Output stage

#### 3.1 Image Acquisition

The method for acquiring face images depends on its application. In surveillance applications, face images are captured by video cameras while image database investigations require static images captured by standard cameras. In many cases, the captured image can be a blurred/noisy/out-of-focus image. Here, it is corrected in the image pre-processing stage.

The captured image is blurred due to effect of atmospheric turbulence that causes Gaussian blur or change in the motion of the camera (Motion blur) or due to out of focal length (out-of-focus blur).

### 3.2 Image Pre-processing

The captured image is fed as the input to the system, which is undergone for the pre-processing initially. In this stage mainly, the following operations are performed.

- i. In this stage the image is resized to the predefined limits.
- ii. The image is filtered to remove the noise.
- iii. In case of blurred images, it will be deblurred with Iterative Graph based image restoration method based on BM3D.

#### 3.2.1 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<sup>15</sup>.

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

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  $\sigma$ ,  $A$ - Blurring matrix of size  $N^2 \times N^2$  is constructed from PSF based on the assumptions. Many of the deblurring methods depend on optimizing the cost function of the form<sup>16</sup>.

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

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<sup>17</sup>. 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)<sup>18</sup>. 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<sup>19</sup>.

### 3.3 Feature Extraction

The face representation plays a very important role in recognition. A good face representation must be insensitive to different image transformations. So, designing robust and distinctive descriptors is dynamic research area in Face Recognition. Many global and local descriptors are proposed in literature. Global descriptors include shape, texture and contour features to define an image as a complete set. Examples of global descriptors are shape matrices, invariant moments, etc. Local descriptors represent significant points in the image as patches. Examples of local descriptors are LBP, Gabor filters, LGXP, SURF, SIFT HOG, LGGP<sup>20</sup>, etc. For low level applications like detection and classification, global descriptors are used and for high level application like recognition, local features are used to attain efficient/best results. The basic idea used in local matching method is to locate numerous facial features so that faces can be classified by combining and comparing local statistics. The local methods are categorized into a) Local appearance-based methods and b) Local feature-based methods. The local appearance-based methods detect feature points by segmenting the image into sub regions and later proper image representation must be done for the extracted local features. This is most critical step in the presence of geometric structures and illumination variations. But in local feature-based methods the feature points are detected in which they are highly invariant to different imaging conditions. These features points are further described by local statistics<sup>21</sup>.

The method used here is to combine local and global features (Gabor + LDA) to attain informative feature descriptor which further improves classification efficiency.

In this stage, the large set of image data will be reduced into a small set of data. Here, Gabor Linear Discriminant Analysis (GLDA) algorithm is applied for feature extraction. In this algorithm, both the Gabor and Linear Discriminant Analysis (LDA) features are used. Gabor filter is used to analyze the frequency components of the image in different directions. Also, image texture can be analyzed effectively by using the Gabor filter.

Feature extraction using Gabor filter is represented as Gabor filter function in 2D<sup>22</sup>

$$\psi(x, y) = \frac{f^2}{\pi\gamma\eta} e^{-\left(\frac{f^2}{\gamma^2}x'^2 + \frac{f^2}{\eta^2}y'^2\right)} e^{j2\pi x'} \quad (3)$$

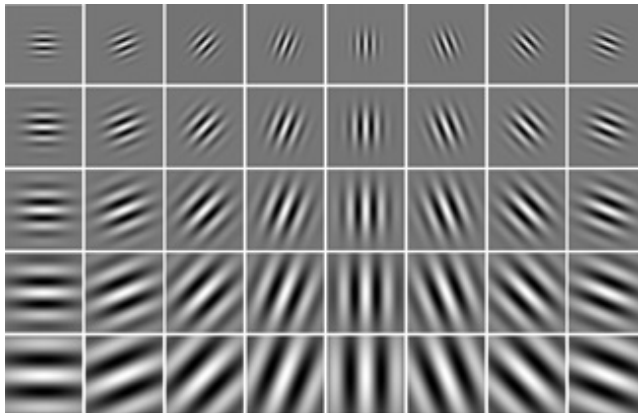
where  $x' = x\cos\theta + y\sin\theta$  and  $y' = -x\sin\theta + y\cos\theta$

Where  $\theta$  is the rotation angle (orientation),  $f$  the central frequency,  $\gamma$  and  $\eta$  represents the sharpness along Gaussian major and minor axis. In frequency domain Gabor filter in 2D is represented as

$$\psi(u, v) = e^{-\frac{\pi^2}{\gamma^2}(u'-f)^2 + \eta^2v'^2} \quad (4)$$

where  $u' = u\cos\theta + v\sin\theta$  and  $v' = -u\sin\theta + v\cos\theta$

By using the Gabor wavelet, the 2-D image is represented as the linear combination of set of wavelets. The image plane is subdivided into a grid of non-overlapping regions. Figure 2 shows the Gabor features which represent a range of frequencies, directions. These wavelets are used as features to describe the given image.



**Figure 2.** Gabor features.

LDA is used to reduce the number of features to a more manageable number before classification. Gabor LDA is an improvement over the LBPH, HOG, LGRP, GPCA and PCA. LDA tries to find projection axis, such as classes are best separated. Whereas the projection axis of PCA does not provide good discrimination. By combining the both the features like Gabor and LDA, it obtains the maximum recognition rate. The obtained feature vectors in this stage are given as the input to the classifier.

### 3.4 LCDRC Classifier

In this stage, the Linear Collaborative Discriminant Regression Classifier (LCDRC) is used for the classification of face images. LCDRC gives a discriminant subspace with maximum collaborative between-class reconstruction error and minimum within-class reconstruction error. This method shows the improvement over the linear discriminant regression classification (LDRC) algorithm.

The complete algorithm of LCDRC is as follows:

1. All the training and test face images are normalized to predefined limit.
2. Projection matrix  $U$  is obtained from the train image set  $X$ . Project  $X$  into the discriminant subspace to obtain  $Y = U^T X$ .
3. Calculate the hat matrix  $H_i$  for each class,  $i = 1, 2, \dots, c$ .
4. The test face image  $x$  will be transformed into the learned subspace with the help of  $y = U^T x$  transformation equation. The reconstruction will be calculated using,  $\hat{y}_i = H_i y$ , for each class  $i$ .
5. The reconstruction error will be calculated using the equation,  $e_i = \|y - \hat{y}_i\|_2$ , for each class  $i$ . The classification of test face image depends on the minimum reconstruction error.

### 3.5 Final output stage

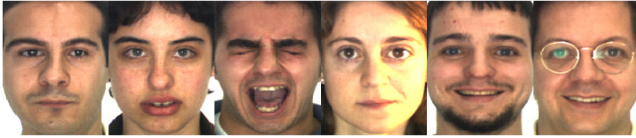
In this stage, the final output i.e. the recognized face image will be displayed on the display device. Here the recognized image is obtained using the LCDRC classifier from the face database. The best matching face image from the database will be the selected as the recognized face.

## 4. Results

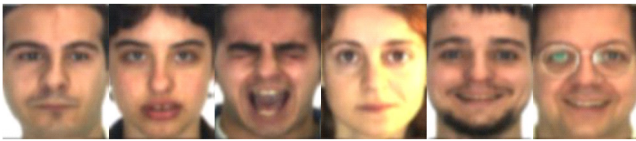
Simulation results are obtained using the MATLAB/SIMULINK tool. AR database is used in this experiment. The algorithm has been tested for different test faces (Gaussian Blur/Motion Blur/Out-of-focus Blur) at different levels, expressions with illumination variations and the face recognition has been obtained with the highest accuracy of 99.2%.

Basically, the Original gallery is blurred with different kernels obtaining Gaussian, Motion and out-of-focus blurred faces. Later these are deblurred using Iterative Graph based Image restoration method.

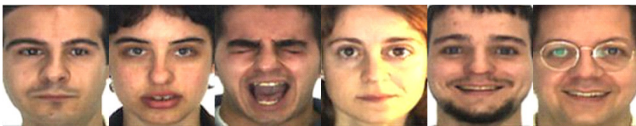
Figure 3 shows the normal faces without blur. A Gaussian kernel is used to blur all the faces in the given database. These faces are shown in Figure 4. The reconstruction was performed by using Iterative Graph based image restoration method which uses BM3D function is shown Figure 5. Similarly, Motion blur and Out-of-focus blur face images are obtained by appropriate kernels which are shown in Figures 6, 7. Degradation model was applied on the images and reconstructed faces as shown in Figures 8, 9.



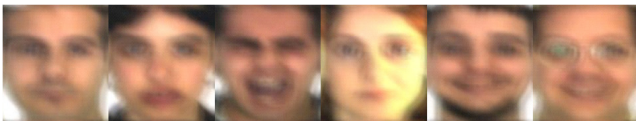
**Figure 3.** Normal faces without blur.



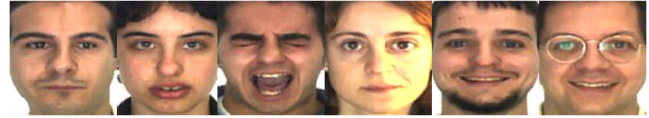
**Figure 4.** Gaussian blurred faces.



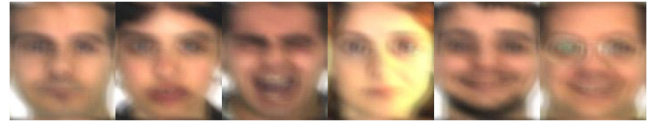
**Figure 5.** Gaussian deblurred faces.



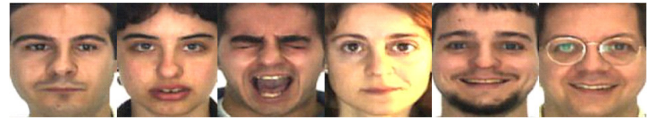
**Figure 6.** Motion blurred faces.



**Figure 7.** Motion deblurred faces.



**Figure 8.** Out-of-focus blurred faces.



**Figure 9.** Out-of-focus deblurred faces.

Classification is done using LCDRC method by considering different local feature descriptors such as LBPH, HOG, LGRP, and combination of Local and global feature descriptors like GPCA and GLDA for the training and test faces.

Four different experiments are carried out on the AR database of face images. In the first experiment, the different feature descriptors of face image inputs are applied without any blur. The process of recognition is carried out by considering 320 training faces and 80 test faces. Here, the training faces are taken from 40 different people, each with 8 random face images. And the 2 faces of each person are considered as the test face images. Later the experiment is performed by reducing the number of training faces and increasing the number of test faces. Table 1 shows the results of face recognition rate performed on original AR database.

**Table 1.** Face recognition rate results performed on original AR database

| S. No. | No. of training faces | No. of testing faces | AR Database |        |        |       |                |
|--------|-----------------------|----------------------|-------------|--------|--------|-------|----------------|
|        |                       |                      | LBPH        | HOG    | LGRP   | GPCA  | GLDA           |
| 1      | 320                   | 80                   | 98.75       | 95.833 | 99.167 | 99.16 | <b>99.1667</b> |
| 2      | 280                   | 120                  | 96.25       | 95     | 98.75  | 98.99 | <b>98.75</b>   |
| 3      | 240                   | 160                  | 95          | 91.25  | 92.08  | 96.5  | <b>98.75</b>   |
| 4      | 200                   | 200                  | 95          | 90.83  | 91.25  | 95    | <b>98.5</b>    |
| 5      | 160                   | 240                  | 92          | 90     | 90.5   | 92.5  | <b>96.25</b>   |
| 6      | 120                   | 280                  | 91.78       | 88.5   | 86.42  | 88.43 | <b>95</b>      |
| 7      | 80                    | 320                  | 91.78       | 83.75  | 75     | 83.75 | <b>92.11</b>   |

The second experiment is also carried out by considering different feature descriptors of 320 training faces and 80 test faces and slowly reducing the training faces and increasing test faces. In this experiment Gaussian deblurred input face images are applied for the system. Different feature descriptors are extracted and compared with corresponding feature descriptors of the deblurred gallery database. Table 2 shows the results of face recognition rate performed on Gaussian deblurred AR database images. The third experiment is carried out by considering the Motion deblurred face images as the input Table 3 shows the results of face recognition rate performed on Motion deblurred AR database images.

The fourth experiment is carried out by considering the out-of-focus deblurred face images as the input. Table 4 shows the results of face recognition rate performed on out-of-focus deblurred AR database images. After performing all the different methods for the feature extraction and classification, the performance of

GLDA has been proved as the best among the all with a maximum recognition rate of 99.1667%.

## 5. Conclusion

The face recognition system has been implemented using the three efficient modules which are Iterative Graph based Image restoration method for image reconstruction, GLDA for feature extraction and LCDRC for classification. The algorithm has been tested on different input images like Gaussian blurred, Motion blurred and Out-of-Focus blurred face images. IG based image restoration provides the highest image reconstruction rate. Highest recognition rate is obtained using the Gabor Linear Discriminant Analysis (GLDA) feature extraction method with Linear Collaborative Discriminant Regression Classifier (LCDRC). From the experimentation results, it has been achieved a recognition rate of 99.1667% even in the case of blurred face images.

**Table 2.** Face recognition rate results performed Gaussian deblurred image database

| AR Database |                       |                      |       |       |       |       |                |
|-------------|-----------------------|----------------------|-------|-------|-------|-------|----------------|
| S. No.      | No. of training faces | No. of testing faces | LBPH  | HOG   | LGRP  | GPCA  | GLDA           |
| 1           | 320                   | 80                   | 97.5  | 98.75 | 96.25 | 99    | <b>99.1667</b> |
| 2           | 280                   | 120                  | 94.5  | 92.5  | 95.83 | 98.75 | <b>98.75</b>   |
| 3           | 240                   | 160                  | 94.16 | 91.25 | 91.25 | 98.75 | <b>98.75</b>   |
| 4           | 200                   | 200                  | 93.75 | 89.64 | 90    | 94.58 | <b>98</b>      |
| 5           | 160                   | 240                  | 92.5  | 86.87 | 88.12 | 93.92 | <b>96.25</b>   |
| 6           | 120                   | 280                  | 88.92 | 86.64 | 83.92 | 87.81 | <b>95</b>      |
| 7           | 80                    | 320                  | 86.56 | 85.31 | 72.5  | 83.75 | <b>90</b>      |

**Table 3.** Face recognition rate results performed motion deblurred image database

| AR Database |                       |                      |        |       |        |       |              |
|-------------|-----------------------|----------------------|--------|-------|--------|-------|--------------|
| S. No.      | No. of training faces | No. of testing faces | LBPH   | HOG   | LGRP   | GPCA  | GLDA         |
| 1           | 320                   | 80                   | 97.5   | 95    | 99.5   | 98.6  | <b>99.23</b> |
| 2           | 280                   | 120                  | 95.5   | 93.75 | 95.833 | 97.86 | <b>99</b>    |
| 3           | 240                   | 160                  | 94.975 | 89.28 | 90.41  | 97.5  | <b>98.75</b> |
| 4           | 200                   | 200                  | 93.33  | 89.16 | 88.75  | 96.25 | <b>98.7</b>  |
| 5           | 160                   | 240                  | 91.25  | 88.12 | 88.5   | 92.85 | <b>95.41</b> |
| 6           | 120                   | 280                  | 91.07  | 87    | 83.21  | 88.75 | <b>95</b>    |
| 7           | 80                    | 320                  | 84.68  | 83.12 | 72.5   | 87.5  | <b>89.35</b> |

**Table 4.** Face recognition rate results performed out-of-focus deblurred image database

| AR Database |                       |                      |       |       |       |       |              |
|-------------|-----------------------|----------------------|-------|-------|-------|-------|--------------|
| S. No.      | No. of training faces | No. of testing faces | LBPH  | HOG   | LGRP  | GPCA  | GLDA         |
| 1           | 320                   | 80                   | 93.5  | 95.83 | 98.23 | 97.83 | <b>98.75</b> |
| 2           | 280                   | 120                  | 93.33 | 91.25 | 95.33 | 97    | <b>97.5</b>  |
| 3           | 240                   | 160                  | 93.12 | 89    | 90.41 | 97.12 | <b>97.5</b>  |
| 4           | 200                   | 200                  | 92.5  | 88.57 | 89.5  | 96.56 | <b>97.23</b> |
| 5           | 160                   | 240                  | 90.83 | 87    | 86.25 | 95.83 | <b>96.66</b> |
| 6           | 120                   | 280                  | 89.28 | 85.62 | 83.21 | 92.5  | <b>92.85</b> |
| 7           | 80                    | 320                  | 82.5  | 81.87 | 69.68 | 87.81 | <b>91.87</b> |

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