Preserving Global and Local Features for Robust Face Recognition under Various Noisy Environments

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Abstract

Much research on face recognition considering the variations in visual stimulus due to illumination conditions, viewing directions or poses, and facial expressions has been done earlier. However, in reality the noises that may embed into an image document will affect the performance of face recognition algorithms. Though different filtering algorithms are available for noise reduction, applying a filtering algorithm that is sensitive to one type of noise to an image which has been degraded by another type of noise lead to unfavorable results. These conditions stress the importance of designing a robust face recognition algorithm that retains recognition rates even under noisy conditions. In this work, numerous experiments have been conducted to analyze the robustness of our proposed Combined Global and Local Preserving Features (CGLPF) algorithm along with other existing conventional algorithms under different types of noises such as Gaussian noise, speckle noise, salt and pepper noise and quantization noise.

Keywords: Biometric Technology, Face Recognition, Noise Reduction, Global Feature and Local Feature

1. INTRODUCTION

Biometric technologies are becoming the foundation of an extensive array of highly secure identification and personal verification solutions. As the level of security breaches and transaction fraud increases, the need for highly secure identification and personal verification technologies is becoming apparent. Biometric authentication has been widely regarded as the most foolproof - or at least the hardest to forge or spoof. The increasing use of biometric technologies in high-security applications and beyond has stressed the requirement for highly dependable face recognition systems. The biometric technology of a face recognition system is used to verify an identity of a person by matching a given face against a database of known faces. It has become a viable and an important alternative to traditional identification and authentication methods such as the use of keys, ID cards and passwords.

Face recognition involves computer recognition of personal identity based on geometric or statistical features derived from face images [1-6]. Even though human can detect and identify faces in a scene with little or no effort, building an automated system that accomplishes such objectives is very challenging. The challenges are even more profound when one considers the large variations in the visual stimulus due to illumination conditions, viewing directions or poses, facial expressions, aging, and disguises such as facial hair, glasses, or cosmetics [7, 8]. Face recognition technology provides the cutting edge technologies that can be applied to a wide variety of application areas including access control for PCs, airport surveillance, private surveillance, criminal identification and as an added security for ATM transaction. In addition, face recognition system is also currently being used in growing numbers of applications as an initial step towards the next-generation smart environment where computers are designed to interact more like humans.

In recent years, considerable progress has been made in the area of face recognition with the development of many techniques. Whilst these techniques perform extremely well under constrained conditions, the problem of face recognition in uncontrolled noisy environment remains unsolved. During the transmission of images over the network, some random usually unwanted variation in brightness or colour information may be added as noise. Image noise can originate in film grain, or in electronic noise in the input device such as scanner [9], digital camera, sensor and circuitry, or in the unavoidable shot noise of an ideal photon detector. Slow shutter speed and in low light having high exposure of the camera lens are also some of the reasons that noise gets added to the image. Noise causes a wrong conclusion in the identification of images in authentication and also in pattern recognition process. The noise should be removed prior to performing image analysis processes. The identification of the nature of the noise [10] is an important part in determining the type of filtering that is needed for rectifying the noisy image. Noise in imaging systems is usually either additive or multiplicative [11]. In practice these basic types can be further classified into various forms [12] such as amplifier noise or Gaussian noise, Impulsive noise or salt and pepper noise, quantization noise, shot noise, film grain noise and non-isotropic noise. However, in our experiments, we have considered the common noises such as, Gaussian additive noise, speckle multiplicative noise, quantization and salt and pepper impulsive noise.

The previous study [13] proposed several noise removal filtering algorithms. Most of them assume certain statistical parameters and know the noise type a priori, which is not true in practical cases. Applying a filtering algorithm that is sensitive to additive noise to an image that has been degraded by a multiplicative noise doesn’t give an optimal solution. Also the difficulty in removing salt/pepper noise from binary image is due to the fact that image data as well as the noise share the same small set of values (either 0 or 1) which complicates the process of detecting and removing the noise. This is different from grey images where salt/pepper noise could be distinguished as pixels having big difference in grey level values compared with their neighbourhood. Many algorithms have been developed to remove salt/pepper noise in document images with different performance in removing noise and retaining fine details of the image. Most methods can easily remove isolated pixels while leaving some noise attached to graphical elements. Other methods may remove attached noise with less ability in retaining thin graphical elements. These conditions in turn stress the importance of the design of robust face recognition algorithms that retain recognition rates even under noisy environments.

In general all the face recognition algorithms uses any one or the combinations of the features namely shape, texture, colour, or intensity to represent the facial image structure. It has been seen from previous works that the appearance based representations that uses the intensity or pixel values produces the better result compared with other techniques. But the intensity features are very vulnerable to image noises that may add with the original image during transmission or during the capturing processes itself. In reality, most of the face recognition algorithms that uses appearance based representations are considered only for the noiseless environments and are not dealing with different type of noises occurred in the image.

From an appearance representation standpoint, Principal Component Analysis (PCA) [14], Multidimensional Scaling (MDS), Linear Discriminant Analysis (LDA) [3], and Locality Preserving Projections (LPP) [4] based techniques are more relevant. In those appearance based face recognition, the global features preserving techniques namely PCA, MDS, and LDA effectively preserves the Euclidean structure of face space or the global features. On the other hand, the local feature preservation technique namely Locality Preserving Projections (LPP) preserves local information and obtains a face subspace that best detects the essential face manifold structure. Global features preserving techniques suffer when the noises affect the global features like the

structure of the facial images, while local features preserving techniques suffer when the image noises affect the local intensity pixels. Hence in our proposed work, for the first time up to our knowledge, we employ the combination of global feature extraction technique LDA and local feature extraction technique LPP, to achieve a high quality feature set called Combined Global and Local Preserving Features (CGLPF) that captures the discriminate features among the samples considering the different classes in the subjects [15]. This increases the robustness of face recognition against noises affecting global features and / or local features. In this work, experiments have been conducted to reveal the robustness of our proposed Combined Global and Local Preserving Features algorithm under different types of noises and the results are compared with that of other traditionally employed algorithms.
The rest of the paper is organized as follows: Section 2 describes various types of common noises that affect the biometric identification of facial images. The basic concepts of proposed CGLPF algorithm is given in section 3. In section 4, the experimental results have been discussed with respect to percentage of correct recognition considering ORL facial image database under various noisy environments for CGLPF in comparison with other traditional PCA, LDA and LPP algorithms. The paper is concluded with some closing remarks in section 5.

2. DIFFERENT CATEGORIES OF NOISES AFFECTING IMAGES

Image Noise [12] is usually an unwanted random variation observed in the brightness or the color information of an image. Image noise can be originated due to an electronic noise in the sensors of the digital cameras or scanners circuitry. Slow shutter speed and in low light having high exposure of the camera lens are some of the reasons that noise gets added to the image. There are different types of noises such as additive noise, multiplicative noise, quantization noise and impulse noise. The identification of the nature of the noise [10] is an important part in determining the type of filtering that is needed for rectifying the noisy image. Most of the filtering algorithms for noise rectification assume certain statistical parameters and the type of noise, which is not true in the practical cases. Applying a filtering algorithm that is sensitive to additive noise to an image degraded by a multiplicative noise doesn't yield an optimal solution. The different types of noises and their properties are discussed here.

Additive Noise

This kind of noise gives a linear impairment to the image. It involves a linear addition of white noise with constant spectral density to the original image. The noise added is constant i.e., additive noises are independent at each pixel and independent of the signal intensity. When noise is additive, an observed image can be described as

$$I_v(x, y) = I(x, y) + V(x, y) \tag{1}$$

where I_v is the observed image with noise, I is the true signal (image), and V is the noise component. Many additive noise models exist and the following are some common additive noise models with their Probability Density Function (PDF) [11].
Gaussian noise provides a good model of noise in many imaging systems. Generally, we consider the normal distribution with arbitrary center μ, and variance σ^2. The PDF for such distribution is given by the formula

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{2}$$

where the parameter μ is called the mean, and it determines the location of the peak of the density function, parameter σ is called standard deviation, and σ^2 is variance of the distribution.
Laplacian noise are also called as biexponential noise and its PDF is represented by,

$$f(x) = \frac{1}{\sqrt{2\sigma}}\, e^{-\frac{\sqrt{2}\,|x|}{\sigma}} \tag{3}$$

Uniform noise is not often encountered in real-world imaging systems, but provides a useful comparison with Gaussian noise. The PDF of uniform distribution is given by

$$f(x) = \begin{cases} \frac{1}{\sigma^2 \sqrt{3}} & for\ |x| \le \sigma\sqrt{3} \\ 0 & else \end{cases} \tag{4}$$

Multiplicative Noise

When noise introduces is multiplicative effect, an observed image can be described as

$$I_{xv}(x, y) = I(x, y)H(x, y) \tag{5}$$

where I_{xv} is the observed image with noise, I is the true signal (image), and H is the multiplicative noise component.

When this noise is applied to a brighter area of an image, it presents a magnified view and a higher random variation in pixel intensity is observed. On the other hand, when this noise is applied to a darker region in the image, the random variation observed is not that much as compared to that observed in the brighter areas. Thus, this type of noise is signal dependent and distorts the image in large magnitude and is often called as the speckle noise [16].

Normally data-dependent noises arise when monochromatic radiation is scattered from a surface whose roughness is of the order of a wavelength, causing wave interference which results in image speckle. It is possible to analyze this noise with multiplicative or non-linear models. These models are mathematically more complicated and hence if possible, the speckle noise is mostly assumed to be data independent. The following is the PDF of the multiplicative (speckle) noise with Rayleigh distributions [17]:

$$f(x) = \begin{cases} \frac{2}{b}(x-a)\, e^{-\frac{(x-a)^2}{b}} & for\ x \ge a \\ 0 & for\ x < a \end{cases} \tag{6}$$

where the parameters are such that $a > 0$, b is a positive integer. The mean and variance of this PDF are given by equation 7 and 8.

$$\mu = a + \sqrt{\frac{\pi b}{4}} \tag{7}$$

$$\sigma^2 = \frac{b\,(4-\pi)}{4} \tag{8}$$

Quantization Noise

Quantization noise [18] is the quantization error introduced by the process of quantization in the analog-to-digital conversion (ADC) in telecommunication systems and signal processing applications. It is a rounding error between the analog input voltage to the ADC and the output digitized value. The noise is non-linear and signal-dependent in nature. It can be modeled in several different ways.

In image processing, the noise caused by quantizing the pixels of a sensed image to a number of discrete levels is known as quantization noise. It has an approximately uniform distribution, and can be signal dependent, though it will be signal independent if other noise sources are big enough to cause dithering, or if dithering is explicitly applied. Quantization of number of discrete levels is important for displaying images on devices that support a limited number of colors and for efficiently compressing certain kinds of images. The human eye is fairly good at seeing small differences in brightness over a relatively large area, but not so good at distinguishing the exact strength of a high frequency brightness variation. This fact allows one to get away with a greatly reduced amount of information in the high frequency components. This is done by simply dividing each component in the frequency domain by a constant for that component, and then rounding to the nearest integer. As a result of this, it is typically the case that many of the higher frequency components are rounded to zero, and many of the rest become small positive or negative numbers. Losses occur due to this process is termed as quantization noise.

Impulsive Noise

Impulsive noise is sometimes as called salt-and-pepper noise or spike noise [17]. An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. This type of noise can be caused by dead pixels, analog-to-digital converter errors, and bit errors in transmission. It represents itself as randomly occurring white and black pixels.
Bipolar impulse noise follows the following distribution

$$f(x) = \begin{cases} f_a & for\, x = a \\ f_b & for\, x = b \\ 0 & otherwise \end{cases} \qquad (9)$$

In this equation, if f_a or f_b is zero, we have unipolar impulse noise. If both are nonzero and almost equal, it is called salt-and-pepper noise. Impulsive noises can be positive and / or negative. It is often very large and can go out of the range of the image. It appears as black and white dots, or saturated peaks.

3. FORMATION OF COMBINED GLOBAL AND LOCAL PRESERVING FEATURES (CGLPF)

Earlier works based on PCA [14] or LDA [19] suffer from not preserving the local manifold of the face structure whereas the research works on LPP [4] lacks to preserve global features of face images. Some papers [1, 20] uses the combination of both PCA and LPP, captures only the most expressive features whereas our proposed work uses the combination LDA and the distance preserving spectral method LPP, that captures the most discriminative features which plays a major role in face recognition. Also those works that uses PCA captures the variation in the samples without considering the variance among the subjects. Hence in our proposed work, for the first time up to our knowledge, we employ the combination of global feature extraction technique LDA and local feature extraction technique LPP to achieve a high quality feature set called Combined Global and Local Preserving Features (CGLPF) that captures the discriminate features among the samples considering the different classes in the subjects which produces the considerable improved results in facial image representation and recognition.
The proposed combined approach that combines global feature preservation technique LDA and local feature preservation technique LPP to form the high quality feature set CGLPF is described in this section. Actually, the CGLPF method is to project face data to an LDA space for preserving the global information and then projecting to Locality Preserving Projection (LPP) space by using the distance preserving spectral methods, to add the local neighbourhood manifold information which may not be interested by LDA.

Preserving the Global Features

The mathematical operations involved in LDA, the global feature preservation technique is analyzed here. The fundamental operations are:

1. The data sets and the test sets are formulated from the patterns which are to be classified in the original space.
2. The mean of each data set μ_i and the mean of entire data set μ are computed.

   $$\mu = \sum_i p_i \mu_i \qquad (10)$$

   where p_i is priori probabilities of the classes.

3. Within-class scatter S_w and the between-class scatter S_b are computed using:

$$S_w = \sum_j p_j * \left(cov_j\right) \tag{11}$$

$$S_b = \sum_j \left(x_j - \mu\right)\left(x_j - \mu\right) \tag{12}$$

where cov_j the expected covariance of each class is computed as:

$$cov_j = \prod_i \left(x_j - \mu_i\right) \tag{13}$$

Note that S_b can be thought of as the covariance of data set whose members are the mean vectors of each class. The optimizing criterion in LDA is calculated as the ratio of between-class scatter to the within-class scatter. The solution obtained by maximizing this criterion defines the axes of the transformed space.

The LDA can be a class dependent or class independent type. The class dependent LDA requires L-class L separate optimizing criterion for each class denoted by C_1, C_2, …, C_L and that are computed using:

$$C_j = \left(cov_j\right)^{-1} S_b \tag{14}$$

4. The transformation space for LDA, W_{LDA} is found as the Eigen vector matrix of the different criteria defined in the equation 14.

Adding Local Features

The local features are added to the preserved global features in order to increase the robustness of our technique against various noises. Actually the local features preserving technique seeks to preserve the intrinsic geometry of the data and local structure. The following are the steps to be carried out to obtain the Laplacian transformation matrix W_{LPP}, which we use to preserve the local features.

1. **Constructing the nearest-neighbor graph:** Let G denote a graph with k nodes. The i^{th} node corresponds to the face image x_i. We put an edge between nodes i and j if x_i and x_j are "close," i.e., x_j is among k nearest neighbors of x_i, or x_i is among k nearest neighbors of x_j. The constructed nearest neighbor graph is an approximation of the local manifold structure, which will be used by the distance preserving spectral method to add the local manifold structure information to the feature set.
2. **Choosing the weights:** The weight matrix S of graph G models the face manifold structure by preserving local structure. If node i and j are connected, put

$$S_{ij} = e^{\frac{-\left\| x_i - x_j \right\|^2}{t}} \tag{15}$$

where t is a suitable constant. Otherwise, put $S_{ij} = 0$.

3. **Eigen map:** The transformation matrix W_{LPP} that minimizes the objective function is given by the minimum Eigen value solution to the generalized Eigen value problem. The detailed study about LPP and Laplace Beltrami operator is found in [1, 21]. The Eigen vectors and Eigen values for the generalized eigenvector problem are computed using equation 16.

$$XLX^T W_{LPP} = \lambda XDX^T W_{LPP} \tag{16}$$

where D is a diagonal matrix whose entries are column or row sums of S, $D_{ii} = \Sigma_j S_{ji}$, $L = D - S$ is the Laplacian matrix. The i^{th} row of matrix X is x_j. Let $W_{LPP} = w_0, w_1, \ldots, w_{k-1}$ be the solutions of the above equation, ordered according to their Eigen values, $0 \le \lambda_0 \le \lambda_1 \le \ldots \le \lambda_{k-1}$. These Eigen values are equal to or greater than zero because the matrices XLX^T and XDX^T are both symmetric and positive semi-definite. Note that the two matrices XLX^T

and XDX^T are both symmetric and positive semi-definite since the Laplacian matrix L and the diagonal matrix D are both symmetric and positive semi-definite.

By considering the transformation space W_{LDA} and W_{LPP}, the embedding is done as follows:

$$x \to y = W^T x,$$
$$W = W_{LDA} W_{LPP},$$
$$W_{LPP} = [w_0, w_1, ..., w_{k-1}] \qquad (17)$$

where y is a k-dimensional vector, W_{LDA}, W_{LPP} and W are the transformation matrices of LDA, LPP and CGLPF algorithms respectively.

4. EXPERIMENTAL RESULTS AND DISCUSSION

Real world signals usually contain departures from the ideal signal that would be produced by the model of signal production process. Such departures are referred to as noise. Noise arises as a result of unmodeled or unmodelable processes going on in the production and capture of the real signal. It is not part of the ideal signal and may be caused by a wide range of sources, e.g. variations in the detector sensitivity, environmental variations, the discrete nature of radiation, transmission or quantization errors, etc. These noises are the tough challengers in affecting the performance of many biometric techniques. In this work, we introduce different types of noises at varied specifications and analyze the robustness performance of the CGLPF feature set comparing with the conventional existing techniques such as PCA, LDA and LPP.

For our experiments, the facial images from the facial image database ORL are used. The ORL database contains a total of 400 images containing 40 subjects each with 10 images that differ in poses, expressions and lighting conditions. Figure 1 shows the sample images used in our experiments collected from ORL face database. In our experiments, we have used common types of noises namely, Gaussian additive noise, speckle multiplicative noise, quantization noise, and salt and pepper impulsive noise that affect the biometric image processing applications. In order to show the robustness of our CGLPF based face recognition method, these noises are introduced in the ORL database face images before applying the CGLPF algorithm. The ORL face database images with noises are shown in figure 2.

Figure 1: The sample set of images collected from ORL database

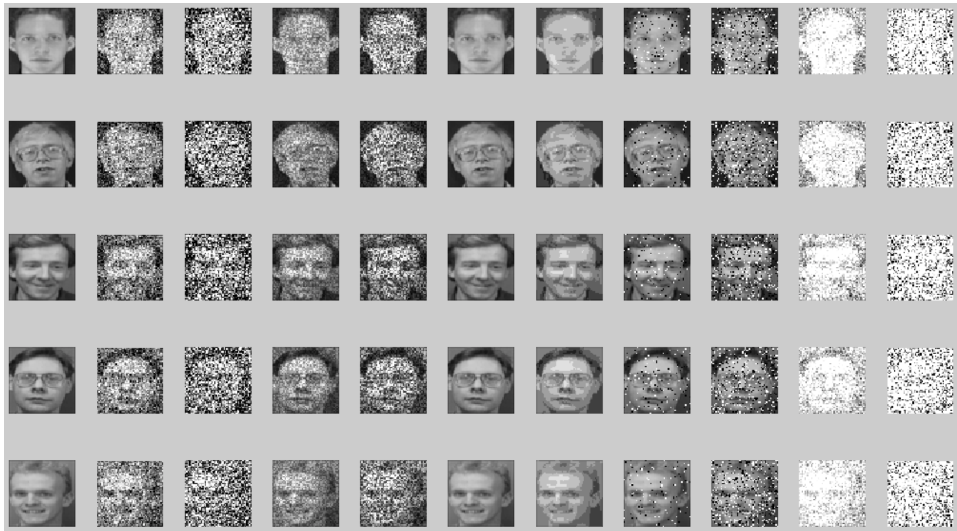

Figure 2: The sample set of noisy images

The first column of figure 2 shows the original image set without noise. The second and third columns show the images affected by Gaussian noise with mean 0.05 variance 0.05, and mean 0.05 variance 0.2 respectively. Similarly fourth and fifth columns show the image with speckle noise with variance 0.05 and 0.2 respectively. Quantization noise image with 1 bit and 6 bit quantization error are shown in column 6 and 7. Column 8 and 9 show the image with salt and pepper noise with variance of 0.05 and 0.2 respectively. Column 10 and 11 indicate the images affected by Gaussian noise with mean 0.5, variance 0.05 and mean 0.75, variance 0.5 respectively. It is evident from the figure that when the noise level increases, the face images get affected more and sometimes is not visible. Hence in our experiments, we have considered mean and variance varying from 0 to 0.2 only.

Any biometric authentication tool has some set of images called as prototype images also known as authenticated images, and another set of images which are given as input for the purpose of probing. The tool has to decide whether the input probe image is accepted or not by verifying the similarities of probe image and any matching prototype image without considering noises present, variations in poses, lighting conditions or illuminations. To start with, the probing image set is formed by applying the Gaussian noise with mean and variance equal to 0.05 on all the 400 images of the ORL face database. All the 400 images in the ORL database without adding any noise are taken as the prototype image set. Hence we got 400 images in prototype set (40 subjects X 10 poses) and 400 images in probe set (40 subjects X 10 poses). The CGLPF feature set is formed by applying the CGLPF technique on both the sets and the signatures are used in experimental phase.

In the experimental phase, we take the first image of the first subject from the prototype image set as the query image and the top matching ten images are found from a set of all 400 probe images. If the top matching images lie in the same row (subject) of the prototype query image, then it is treated as a correct recognition. The number of correct recognized images for each query image in the prototype image set is calculated and the results are shown in figure 3 for Gaussian noise with mean 0.05 and variance 0.05.

The same procedure is repeated by using PCA, LDA and LPP method and the results are depicted in figures 4, 5, and 6 respectively. Figure 7 shows the comparison of overall percentage of recognition using CGLPF, PCA, LDA and LPP. It can be noted from this figure that, the CGLPF outperform the other existing techniques like PCA, LDA and LPP in the Gaussian noisy environment with mean and variance equal to 0.05.

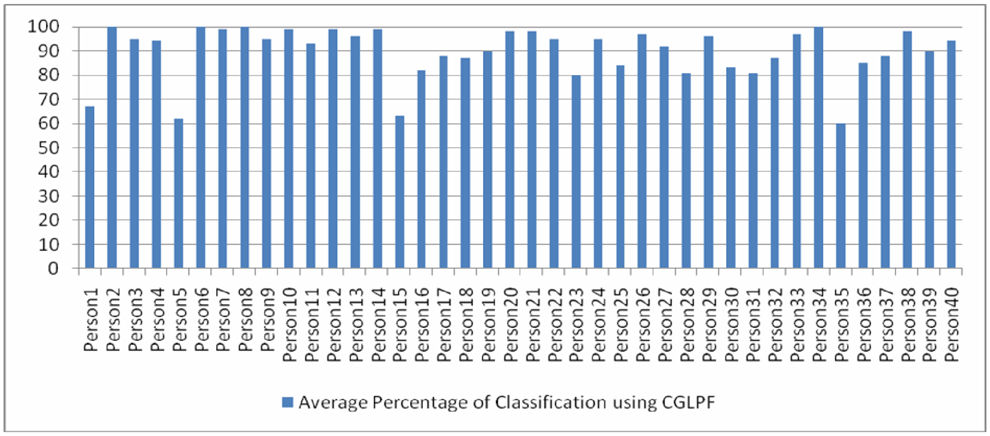

Fig.3.The average percentage of correct recognition obtained using CGLPF with Gaussian noise having mean 0.05 and variance 0.05

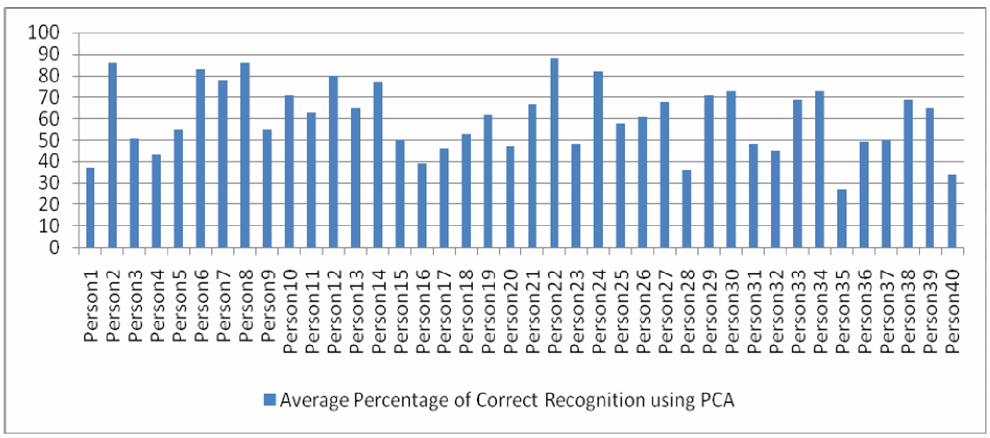

Fig.4.The average percentage of correct recognition obtained using PCA with Gaussian noise having mean 0.05 and variance 0.05

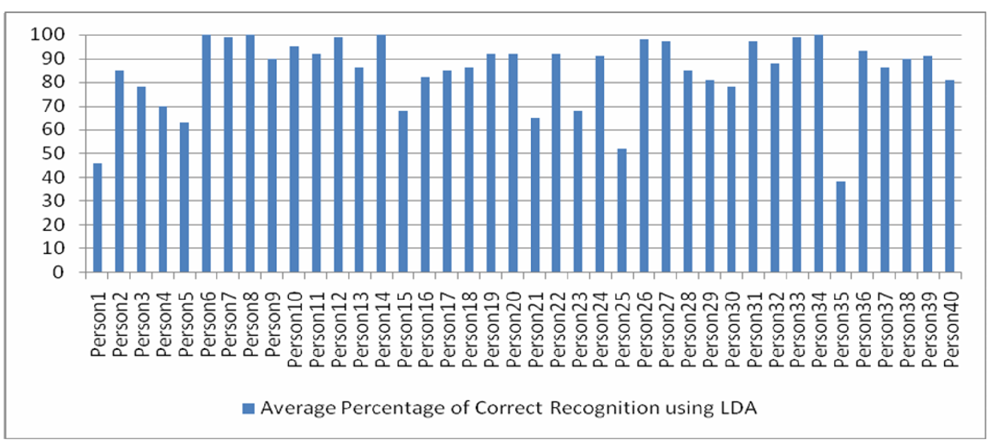

Fig.5.The average percentage of correct recognition obtained using LDA with Gaussian noise having mean 0.05 and variance 0.05

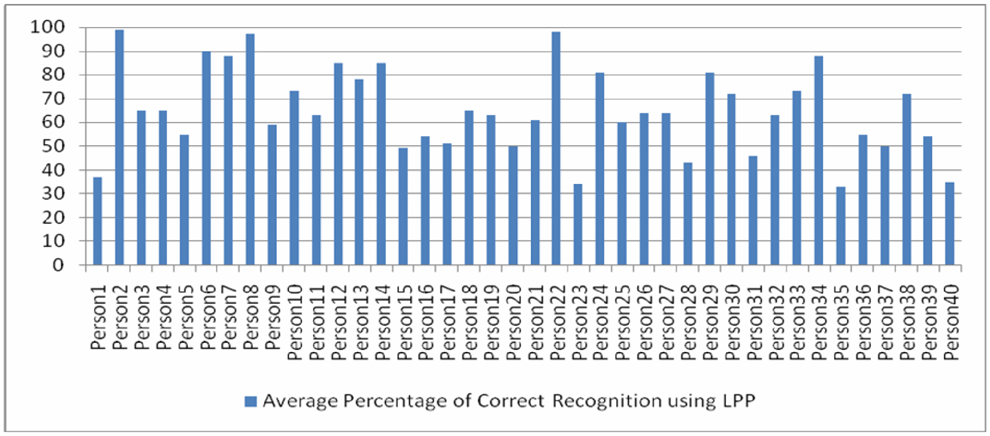

Fig.6.The average percentage of correct recognition obtained using LPP with Gaussian noise having mean 0.05 and variance 0.05

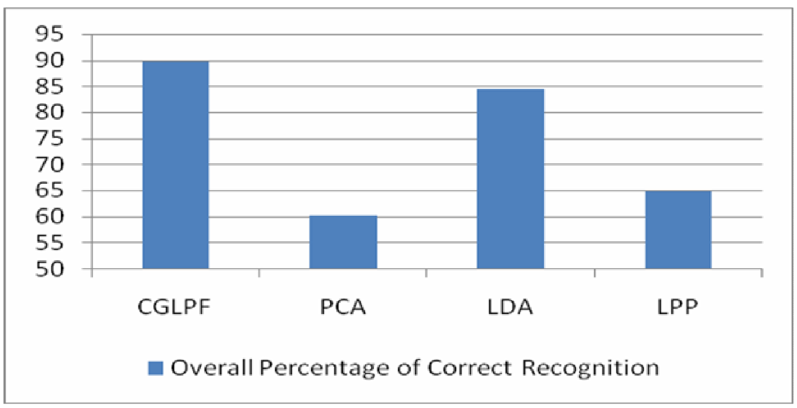

Fig.7. Comparison of overall percentage of correct recognition using CGLPF, PCA, LDA and LPP with Gaussian noise having mean 0.05 and variance 0.05

In the second part of our experiments, various other noises such as speckle, quantization and salt and pepper noises are applied by varying their respective parameters like mean and / or variance or quantization bits, in the probe images and various features of CGLPF, PCA, LDA and LPP algorithms are extracted. During the testing phase, the prototype images are taken one by one and the same features are extracted from it. The top ten matching images are taken and the numbers of correct matching images are counted. The overall percentage of correct recognition results obtained are tabulated in Table 1 for various noises with mean ranging from 0.05 to 0.2 and variance from 0.05 to 0.2. For most of the cases, our CGLPF algorithm performs better than other conventional techniques and it shows the high robustness of our proposed algorithm. For some cases, the LDA algorithm shows slightly improved results and it is observed that such cases use low variance value noises. In general, the high variance among the pixels increases the discrimination features among the local neighborhood pixels. Also the low variance exhibits the discrimination features among the global structure of the image. Hence when the variance becomes high, the added local features in the CGLPF method gives better results than the LDA which uses only the global structure information. Further, if the variance is low i.e., when the images possess high discrimination information in its global structure than local neighborhood, our CGLPF algorithm utilizes the global information preserved in it to produce good results.

Noise Details	Techniques			
	CGLPF	PCA	LDA	LPP
Gaussian Mean = 0, Variance = 0.05	90.9	64.75	90.875	68.45
Gaussian Mean = 0, Variance = 0.1	80.4	56.075	65.625	56.325
Gaussian Mean = 0, Variance = 0.15	76.7	44.05	63.35	40.675
Gaussian Mean = 0, Variance = 0.2	74.175	39.05	45.075	27.975
Gaussian Mean = 0.05, Variance = 0	92.6	65.575	93.1	74.55
Gaussian Mean = 0.05, Variance = 0.05	89.675	60.2	84.45	64.95
Gaussian Mean = 0.05, Variance = 0.1	74.325	51.725	67.5	48.75
Gaussian Mean = 0.05, Variance = 0.15	68.15	42.425	62.8	41
Gaussian Mean = 0.05, Variance = 0.2	60.175	37.525	44.625	30.7
Gaussian Mean = 0.1, Variance = 0	83.05	51.35	79.2	62.55
Gaussian Mean = 0.1, Variance = 0.05	80.075	49	76.15	52
Gaussian Mean = 0.1, Variance = 0.1	59.225	44.75	55.575	39.125
Gaussian Mean = 0.1, Variance = 0.15	58.275	39.875	51.675	33.775
Gaussian Mean = 0.1, Variance = 0.2	58.025	33.925	39.35	25.7
Gaussian Mean = 0.15, Variance = 0	59.05	30.725	55.5	41.725
Gaussian Mean = 0.15, Variance = 0.05	48.15	34.2	46.625	38.8
Gaussian Mean = 0.15, Variance = 0.1	46.95	34.775	46.45	30.2
Gaussian Mean = 0.15, Variance = 0.15	51.125	34.375	43	26.175
Gaussian Mean = 0.15, Variance = 0.2	50.775	27.925	34.975	23.525
Gaussian Mean = 0.2, Variance = 0	35.375	12.9	27.1	25.925
Gaussian Mean = 0.2, Variance = 0.05	44.475	21.75	37.65	23.3
Gaussian Mean = 0.2, Variance = 0.1	46.7	26.575	33.75	18.05
Gaussian Mean = 0.2, Variance = 0.15	41.35	26.675	30.4	23.025
Gaussian Mean = 0.2, Variance = 0.2	32.975	22.625	26.95	16.9
Speckle Variance = 0.05	95.875	68.5	96.925	74.5
Speckle Variance = 0.1	94	66.125	94.175	71.75
Speckle Variance = 0.15	93.425	63.725	90.2	70.175
Speckle Variance = 0.2	85.3	61.575	83.625	68.125
Quantization Bits Quantized = 1	96.925	69.35	93.05	77.3
Quantization Bits Quantized = 2	95.875	69.225	92.9	77.025
Quantization Bits Quantized = 3	94.25	68.825	92.825	77.025
Quantization Bits Quantized = 4	94	67.9	91.85	76.15
Salt & Pepper Variance = 0.05	95.8	66.9	94.725	74.525
Salt & Pepper Variance = 0.1	94.275	64.775	90.7	71.3
Salt & Pepper Variance = 0.15	92.825	60.075	80.125	67.275
Salt & Pepper Variance = 0.2	87.725	56.775	76.725	60.6

TABLE 1: Comparison of overall percentage of correct recognition obtained using CGLPF, PCA, LDA, and LPP under different noises with mean and variance ranging from 0 to 0.2 or quantization bits from 1 to 4.

Related to time complexity, it is the nature that the time complexity is increasing when using the combined schemes compared to using the techniques individually. But in our proposed method, the training is done offline and the testing is done in the real time or online. In the online phase, it is only going to project the testing image into the CGLPF feature set which is having only lower dimensions compared to the cases when the techniques are used individually. Hence when we employ our method in real time applications, there is no delay in the online and the offline delay does not cause any considerations in the real time image processing.

5. CONCLUSIONS

The robustness of CGLPF algorithm that combines the global and local information preserving features has been analyzed under various noisy environments such as Gaussian, speckle, quantization, and salt and pepper noise using ORL facial image database. In the feature set created using Laplacian faces in earlier papers, they use the PCA algorithm, only for reducing the dimension of the input image space whereas we use LDA algorithm for preserving the discriminating features in the global structure. Thus CGLPF feature set created using the combined approach retains both the global information and local information, in order to make the face recognition insensitive to most of the noises.

It is also observed that our proposed CGLPF algorithm shows the good robustness under different types of noisy conditions with respect to the percentage of correct recognition and in general it is superior to the conventional algorithms such as PCA, LDA and LPP. In our combined feature set, the preserved global features help to provide better robustness when the variance among the pixel intensities is high, while local feature preserved algorithm LDA shows better robustness when the variance is low. Therefore, the CGLPF feature set obtained through the combined approach would be an attractive choice for many facial related image applications under noiseless as well as noisy environments.

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