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Gamma Correction Technique Based Feature Extraction for Face Recognition System

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***Abstract*-One of the most important challenges for practical face recognition systems is to make recognition more reliable under uncontrolled lighting conditions. We tackle this by using novel illumination-insensitive preprocessing method. The proposed face recognition system consists of a gamma correction, a preprocessing stage, a hybrid Fourier-based facial feature extraction, and Principal Component Linear Discriminant Analysis (PCLDA). Gamma Correction is a nonlinear gray-level transformation that replaces gray-level I with Iγ (for γ > 0), where γ is a user-defined parameter. In the preprocessing stage, an "Integral Normalized Gradient Image", (INGI) is obtained by transform a face image into an illumination-insensitive image. The effect of illumination gets reduced in the INGI by normalizing and integrating the smoothed gradients of a facial image. Using frequency band model selection the hybrid Fourier features are extracted from three different Fourier domains in different frequency bandwidths and further by adding PCLDA the robustness of the system gets improved. In face recognition, it is not possible to process with the entire extracted features, hence the dimension of the feature vectors has to be reduced. In this paper, this is done by using the linear method called PCLDA. The proposed system using the Yale B data set which is having a 2-D face images under various environmental variations such as illumination changes and expression changes.**

Keywords-Gamma Correction, Preprocessing, Feature extraction, PCLDA and Yale B data set

I. INTRODUCTION

Face recognition is an active research topic in the areas of pattern recognition, computer vision, and machine learning. Face recognition has received a great deal of attention from the scientific and industrial communities over the past several decades owing to its wide range of applications in information security and access control, law enforcement and surveillance. Our review focuses on the related work based on subspace learning to improve the accuracy of 2-D recognition algorithms and it mainly depends on two groups, i.e., the linear and nonlinear methods.

Linear methods are the most traditional subspace analysis methods and its various algorithms are Principal Component Analysis (PCA) [9] and Linear Discriminant Analysis (LDA) [6]. PCA and LDA are the two classic tools widely used in the appearance-based approaches for data reduction and feature extraction. LDA-based algorithms outperform PCA-based ones in low-dimensional representation of the objects. In high-dimensional pattern recognition tasks many LDA-based algorithms suffer from the problem called "Small Sample Size problem" (SSS), where the number of available samples is smaller than the dimensionality of the samples. The traditional solution to the SSS problem is to utilize PCA concepts in conjunction with LDA (PCA+LDA) called PCLDA. In both these methods we assume that the data obey Gaussian distribution and then the 2D-PCA and 2D-LDA uses 2-D matrices instead of image vectors to construct the basis matrix of subspace analysis.

However, the linear method is bound to ignore the nonlinearity in many faces. This is a bottleneck for achieving a high-performance recognition system, so the nonlinear methods called the kernel-based methods, e.g., Kernel PCA (KPCA) and Kernel LDA (KLDA) map face images into the high-dimensional feature space to linearly separate the nonlinear distributions in the image space. In this method instead of processing with the whole matrix the kernel value is computed and it is used for further processing.

A number of preprocessing algorithms [7], [8] to minimize the effect of illumination changes for face recognition have been developed, and many developments and advantages have occurred within the 3-D face model training stages. Illumination variation is the main obstacle for face recognition since face image appearances of the same person change under different illuminations. Sometimes, the changes in terms of different illuminations among the same person are greater than those of different persons among the same illumination. This problem is serious in face recognition, especially when appearance-based methods are applied.

Features to be used for person classification are extracted to identify any invariance in the face images against environmental changes. In this paper, the Fourier features extracted from three different types of domains are concatenated real and imaginary components domain, Fourier spectrums domain, and the phase angle domain. Three different frequency bandwidths are also designed to extract more complementary frequency features for these three domains.

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In Yale B, the main issue is how to match two face images of the same person under different conditions. One is taken in a controlled studio setting while the other is captured in uncontrolled illumination conditions such as hallways, atria, or outdoors. Yale B has provided high resolution images together with four ground truth locations of the four fiducial points, namely two eyes, nose, and mouth points, to give more chances to improve the recognition performance.

II. ILLUMINATION ANALYSIS

Assuming the Lambertian reflectance model, the grayscale intensity image of a 3-D object is represented by

$$X_{(i,j)} = \rho_{(i,j)} n^{T}_{(i,j)}.S \quad (1)$$

Where $\rho_{(i,j)}$ is the surface texture associated with point (i,j) in the image, $n_{(i,j)}$ is the surface normal direction (shape) associated with point (i,j) in the image, and S is the light source direction whose magnitude is the light source intensity [1].

Here $\rho_{(i,j)}$ is the intrinsic factor and $n^{T}_{(i,j)}.S$ is the extrinsic factor for face recognition. The intrinsic factor is illumination free and represents the identity of a face image, whereas the extrinsic factor is very sensitive to illumination variations, and only partial identity information is included in the 3-D shape. The definitions of intrinsic and extrinsic factors are also based upon the Lambertian reflectance model with point lighting sources. In this paper, illumination-insensitive image is obtained by enhancing the intrinsic factor and depressing the extrinsic factor in the input image [2].

Gamma Correction is a nonlinear gray-level transformation that replaces gray-level I with Iγ (for $\gamma > 0$), where γ is a user-defined parameter.

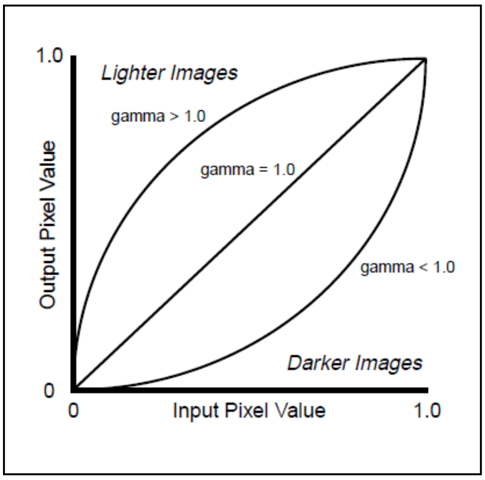


Figure 1. Gamma Curves

This enhances the local dynamic range of the image in dark or shadowed regions while compressing it in bright regions and at highlights. The underlying principle is that the intensity of the light reflected from an object is the product of the incoming illumination 'L' (which is piecewise smooth for the most part) and the local surface reflectance 'R' (which carries detailed object-level appearance information). We want to recover object-level information independent of illumination, and taking logs makes the task easier by converting the product into a sum: for constant local illumination, a given reflectance step produces a given step in log(I) irrespective of the actual intensity of the illumination.

The shape of the gamma curve is determined by a number ranging from 0.0 to 10.0 (user defined) known as the "gamma value". Figure 1 shows several gamma curves demonstrating the effect that the gamma value has on the shape of the gamma curve.

III. INTEGRAL NORMALIZED GRADIENT IMAGE

Smoothing is a filtering technique which is used to remove the unwanted information from the image. To perform a smoothing operation we apply a filter to our image. The most common types of filters are low pass, Gaussian, median, bilateral etc. Most of the extrinsic factors are in the low spatial frequency domain. In this paper smoothing operation is done by low pass filter in order to extract the extrinsic factors. To overcome the illumination sensitivity, we further normalized the gradient map. Normalization is the process of dividing the gradient operation by smoothing.

Image reconstruction is to recover a grayscale image from normalized gradient maps. If given an initial grayscale value of one point (i,j) in an image, the grayscale of any point can be estimated by an integration method, such as an iterative isotropic diffusion method [3]. It blurs the step-edge regions of an image, so an alternative approach called anisotropic approach can be used.

As complete removal of the illumination variations can lead to loss of useful information for face recognition, we fuse the reconstructed image with the original input image. For fusing size of the reconstructed image and size of the input image should be same. Finally the ultimate preprocessed image is obtained and the entire process for the INGI image is illustrated in Figure 2.

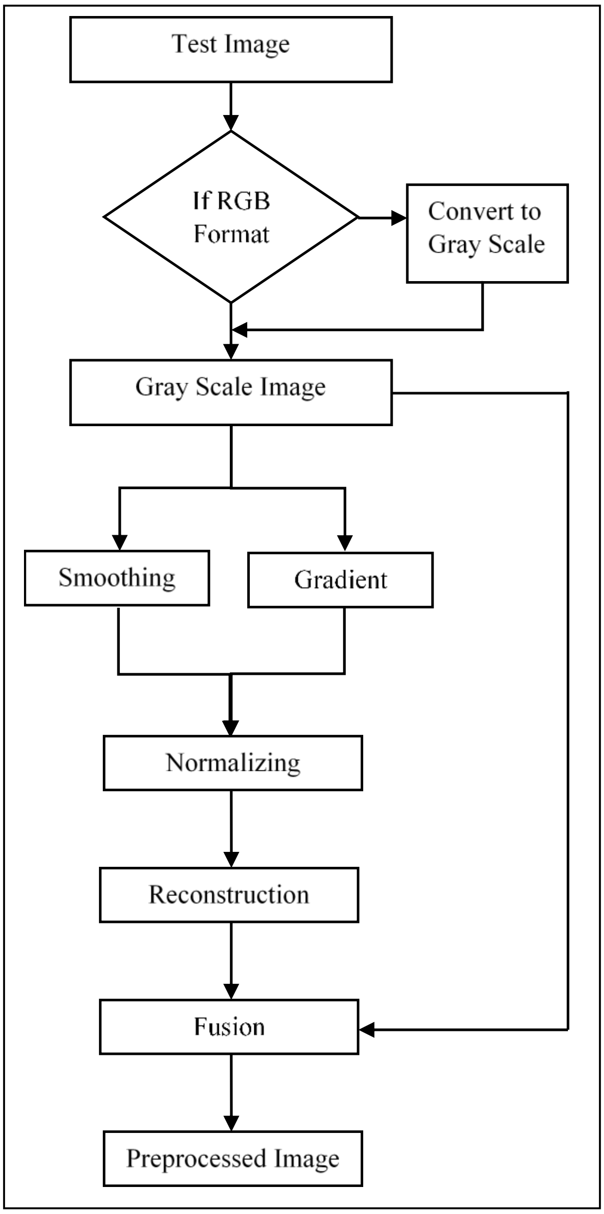


Figure 2. Flow Chart for Integral Normalized Gradient Image.

A. 2-D Discrete Fourier features for face recognition

The Fourier transform is applied to a spatial face image to analyze facial features in the Fourier domain [4]. The Fourier transform of a real function is generally complex and it is given by

$$F_{(u,v)} = R_{(u,v)} + jI_{(u,v)} \tag{2}$$

where $R_{(u,v)}$ is real component of $F_{(u,v)}$ and $I_{(u,v)}$ is imaginary components of $F_{(u,v)}$. The magnitude function called the Fourier spectrum is defined as

$$\left|F_{(u,v)}\right| = \left[R^2_{(u,v)} + I^2_{(u,v)}\right]^{1/2} \tag{3}$$

and the phase function is defined as

$$\emptyset_{(u,v)} = \tan^{-1}\left[I_{(u,v)}/R_{(u,v)}\right] \quad (4)$$

Three different Fourier features extracted from the domains are Real and Imaginary component (RI) domain, Fourier spectrum (Γ) domain and Phase angle (Φ) domain.

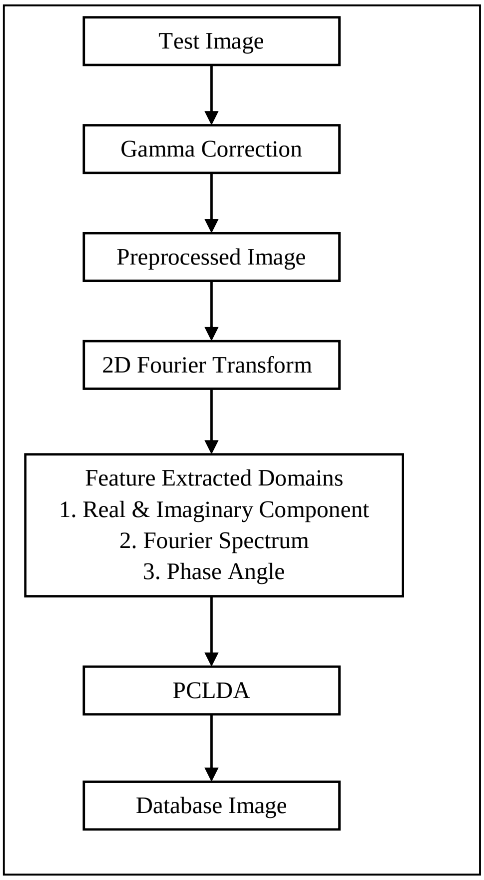


Figure 3. Overall Flow Diagram

The overall flow is shown in Figure 3, To represent the image as a feature vector, the magnitude coefficients are widely used. This is because a little spatial displacement in an image will change the phase values drastically while the magnitude varies smoothly when there is no compensator for the phase shift [5]. In face recognition system, this displacement often occurs when an eye detector finds imprecise eye positions and causes a little misalignment of a face image at the normalization stage.

B. LDA

Headings, or heads, are organizational devices that guide the reader through your paper. There are two types: component heads and text heads. LDA [6] is widely used in the appearance-based approaches for data reduction and feature extraction. It maximizes the between-class scatter while minimizing the within-class scatter of the projected data. The between-class scatter matrix S_B and the within-class scatter matrices S_w are defined as

$$S_B = \sum_{i=1}^{C} N_i(\mu_i - \mu)(\mu_i - \mu)^T \quad (5)$$

$$S_W = \sum_{i=1}^{C} \sum_{x_k \in X_i} (X_k - \mu_i)(X_k - \mu_i)^T \quad (6)$$

Where μ_i is the mean image of class X_i, μ is the sample mean for the entire data set and N_i is the number of samples in class X_i. If S_W is non-singular, the optimal projection W_{opt} is chosen as the matrix with orthonormal columns which maximizes the ratio of the determinant of the between-class scatter matrix of the projected samples to the determinant of the within-class scatter matrix of the projected samples, i.e.,

$$W_{opt} = \arg\max_{W} |W^T S_B W| / |W^T S_W W| = [W_1 W_2 \dots W_n] \quad (7)$$

Where W is matrix with orthonormal columns, W^T is Linear Transformation of W, W_i is set of n dimensional Eigen vectors of S_B and S_W.

IV. RESULTS AND DISCUSSION

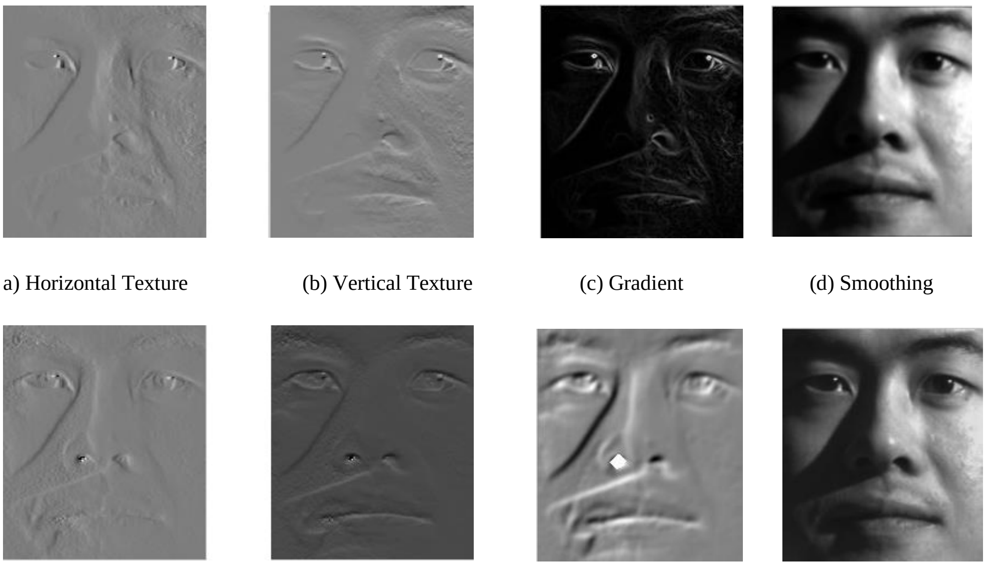
The input image is taken from the Yale B database called test image is shown in Figure 4 and this image has to be recognized in database image called as train image.

Figure 4. Test Image

(a) γ=2.0 (b) γ=0.5 (c) γ=1.0

Figure 5. Outputs of Gamma Correction

The outputs of gamma correction technique with different gamma values are shown in Figure 5. As the Figure 1 shows, gamma values of less than 1.0 darken an image. Gamma values greater than 1.0 lighten an image and a gamma equal to 1.0 produces no effect on an image.



a) Horizontal Texture (b) Vertical Texture (c) Gradient (d) Smoothing

(e) Normalized Horizontal (f) Normalized Vertical (g) Reconstructed Image (h) Preprocessed Image

Figure 6. Various Steps in Image Processing Techniques

Figure 6(a) and Figure 6(b) shows the horizontal and vertical textures respectively and this texture informations are very sensitive to illumination variations. In gradient operation the entire texture information of the test image extracted is shown in Figure 6(c). In smoothing the illumination sensitivity is further reduced by using low pass filter and the smoothed image is shown in Figure 6(d). The normalized horizontal and vertical textures obtained by the division operation of gradient by smoothing are shown in Figure 6(e) and Figure 6(f) respectively.

To recover the rich texture and remove the noise at the same time, we integrate the normalized horizontal and vertical with the anisotropic diffusion method called reconstructed image shown in Figure 6(g) and the final preprocessed image called INGI image obtained is shown in Figure 6(h) and this preprocessed image is used for extracting the Fourier features from three different domains.

TABLE I. REDUCED FEATURE VECTOR FROM THREE DIFFERENT DOMAINS

Domains	Optimal projection
Real and Imaginary component domain	0.0898
Fourier spectrum domain	0.0898
Phase angle domain	0.0898

TABLE II. MSE and PSNR from Three Different Domains

Domains	MSE	PSNR
Real and Imaginary component domain	1	-54.7151 - 0.0011i
Fourier spectrum domain	1	-57.6716
Phase angle domain	1	-54.7151 - 0.0011i

From this preprocessed image the reduced feature vector, Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) from three different domains are calculated and the values are shown in Table I and Table II respectively.

Figure 7. Database Image

The verification performance is characterized by two statistics: the verification rate (VR) and false acceptance rate (FAR). The FAR is computed from comparisons of faces of different people, defined as “non-match.” On the other hand, the VR is computed from comparisons of two facial images of the same person, defined as “match.” The database image recognized is shown in Figure 7 which is same as the test image shown in Figure 4. The comparison between proposed and existing methods is shown in Figure 8. The proposed method needs only one classifier to achieve high verification rate. Also the recognition time is reduced in this method.

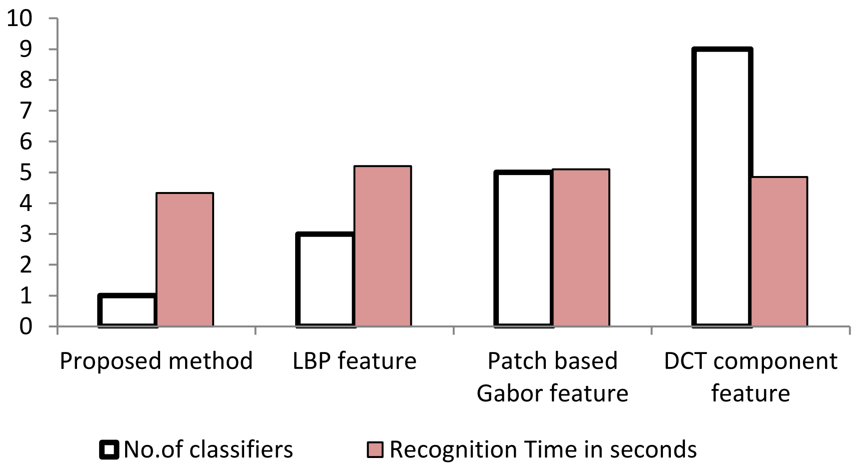


Figure 8. Comparison between Proposed and Existing Methods

V. CONCLUSION

We have presented new method for face recognition under uncontrolled lighting conditions based on robust preprocessing, hybrid Fourier features and PCLDA. The effect of illumination gets reduced in the INGI image at the preprocessing stage. The Fourier features are extracted from each domain within its own proper frequency bands, and to gain the maximum discriminant power of the classes, each feature is projected into the linear discriminative subspace. The dimensionality of the feature vectors are reduced by using PCLDA. Another advantage of the proposed face representation and extraction is that it supports multiple face model to improve accuracy. As a result, it has a potential application for real-time video surveillance systems. Compared with the other global feature-based algorithms, the proposed system demonstrated successful accuracy in face recognition under uncontrolled illumination situations.

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