Recognition Based System Using Principal Component Linear Discriminant Analysis

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Abstract--- **A robust face recognition system for large scale data sets taken under uncontrolled illumination variations. The proposed face recognition system consists of a novel illumination insensitive preprocessing method, a hybrid Fourier based facial feature extraction, and a score fusion scheme. First, in the preprocessing stage, a face image is transformed into an illumination insensitive image, called an integral normalized gradient image, by normalizing and integrating the smoothed gradients of a facial image. Then, for feature extraction of complementary classifiers, multiple face models based upon hybrid Fourier features are applied. The hybrid Fourier features are extracted from different Fourier domains in different frequency bandwidths, and then each feature is individually classified by linear discriminant analysis. In addition, multiple face models are generated by Plural normalized face images that have different eye distances. Finally, to combine scores from multiple complementary classifiers, a log likelihood ratio based score fusion scheme is applied. The proposed system using the face recognition grand challenge (FRGC) experimental protocols is evaluated FRGC is a large available data set.**

Index Terms: Face recognition, face recognition grand challenge, feature extraction, preprocessing, score fusion.

I. Introduction

Automatic face recognition is an important vision task with many practical applications such as biometrics, video surveillance, image retrieval, and human computer interaction. One major issue for face recognition is how to ensure recognition accuracy for a large data set captured in various conditions. Several face data sets are collected to compare many different algorithms with the same protocols on the same data set. They include face recognition technology (FERET) face recognition vendor test (FRVT) and face authentication test. Most recently, face recognition grand challenge (RRGC) has been designed to improve the accuracy of recognition systems in a large scale data set, particularly focused on verification of the person rather than identification. The FRGC data set contains face images collected in different settings (controlled studio versus uncontrolled illumination conditions) with two different facial expressions (neutral versus smiling) taken for several months.

In FRGC, 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. to overcome the uncontrolled environmental problems, we introduce a systematic approach that combines multiple classifiers with complementary features instead of improving the accuracy of a single classifier. Illumination insensitive preprocessing and a score fusion technique are incorporated into the proposed face recognition system.

II. Preprocessing

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. That is, a little illumination direction variation can significantly change the appearance based face model. A number of preprocessing algorithms to minimize the effect of illumination changes for face recognition have occurred within the 3-D face model training stages.

III. Feature extraction

Features to be used for person classification are extracted to identify any invariance in the face images against environmental changes. In this application, appearance based subspace representation have been implemented in face recognition. They include principal component analysis (PCA) local feature analysis (LFA) linear discriminant analysis (LDA) and independent component analysis (ICA). Those methods are derived from an ensemble of statistics within the given training images.

The methods are easy to implement for practical applications.
In addition, with these methods it is not necessary to carry out extra high computational burdens except vectors projections, while other structural based schemes, such as dynamic link
architecture and elastic bunch graph matching perform intense template matching on relatively high resolution images to localize fiducial points near eyes, nose, mouth, etc.

IV. Score fusion

In this paper a set of complementary classifiers, we build a unified classifier combining these complementary classifiers. The purpose here is to construct a strong classifier by suitably combinings a set of classifiers. To this end, we want to keep as much information each classifier extracts as possible, and at the same time the combination should be easy to implement. The information each classifier extracts is well summarized in the score each classifier produces. Hence, combining the classifiers can be achieved by processing the set of scores produced by component classifiers and generating a new single score value. This process is called score fusion.

V. Illumination insensitive variation

Compared to the controlled illumination changes in the studio (indoors, same day, overhead), achieving high recognition accuracy in an uncontrolled illumination situation (outdoors, different day) is hard, as mentioned in the FRVT2002 report. The main reason is that the image distortion caused by illumination changes makes images of different persons in the same

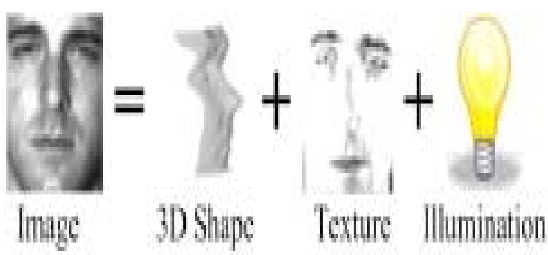


Figure.1. Lambertian reflectance image model

Figure 1 shows that the illumination conditions more similar rather than images of the same person under various illumination changes. Consequently, we propose a novel illumination invariant preprocessing algorithm based upon local analysis as
opposed to global analysis such as histogram equalization to deal with the uncontrolled illumination situation.

V.1 Illumination analysis

Assuming the Lambertian reflectance model, the grayscale intensity image is represented by

$$\chi_{(i,j)} = \rho_{(i,j)}\mathbf{n}^T_{(i,j)}.S \qquad (1)$$

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.

VI. Integral Normalized Gradient Image (INGI)

This paper can make the following assumptions: 1) most of the intrinsic factors is in the high spatial frequency domain, and 2) most of the extrinsic factor is in the low spatial frequency domain. Considering the first assumption, one intrinsic factor, but it has been proved that this kind of filter is not robust to illumination variations. In addition, a high pass filtering operation may have a risk of might use a high pass filter to extract the removing some of the useful intrinsic factor. Hence, we propose an alternative approach, namely, employing a gradient operation. The
gradient operation is written as

$$\begin{aligned}\nabla\chi &= \nabla\left(\rho\sum_i \mathbf{n}^T\cdot\mathbf{s}_i\right)\\ &= (\nabla\rho)\sum_i \mathbf{n}^T\cdot\mathbf{s}_i + \rho\nabla\left(\sum_i \mathbf{n}^T\cdot\mathbf{s}_i\right)\\ &\approx (\nabla\rho)\sum_i \mathbf{n}^T\cdot\mathbf{s}_i = (\nabla\rho)W\end{aligned}$$

(2)
where the approximation comes from the assumptions that both the surface normal direction (shape) n and the light source direction s vary slowly across the image, whereas the surface the surface texture p varies fast. The scaling factor W is Σ n^T s the extrinsic factor of our imaging model.

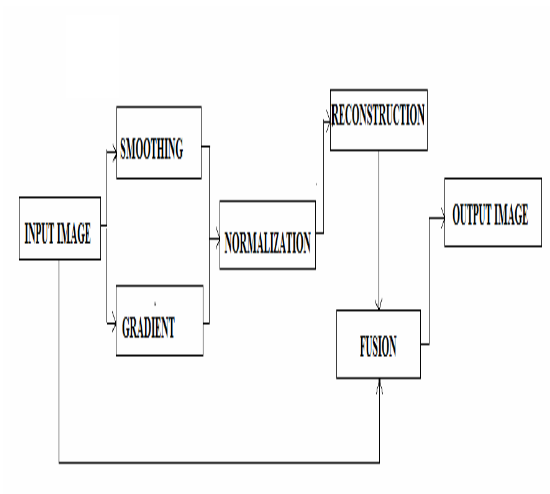


Figure 2. Block Diagram Of Preprocessing Image

Figure 2 shows a grayscale image from grayscale value of one point (i, j) in an image, we can normalized gradient maps. If given an initial estimate the grayscale of any point by an integration method, such as an interactive isotropic diffusion method, such as an interative isotropic diffusion method. However this isotropic method has one shortcoming. It blurs the step edge regions of an image.

VII. LINEAR DISCRIMINANT ANALYSIS

LDA is a supervised learning method that finds the linear projection in subspaces; it maximizes the between class scatter while minimizing the within class scatter of the projected data. According to this objective, two scatter matrices the between class scatter matrix S_B and the within class scatter matrices S_W are defined as

$$S_B = \Sigma \; M_c (m_c - m)(m_c - m)^T \qquad (3)$$

$$S_W = \Sigma \; \Sigma M_c (x - m_c)(x - m_c)^T \qquad (4)$$

In face recognition, when dealing with high dimensional image data, the class scatter matrix SW is often singular. To overcome this problem, PCA is first used with the sample data to reduce its dimensionality. Hence we will call it PCLDA.

VIII. Hybrid fourier feature for face recognition

This have three different Fourier feature domains, namely, the real and imaginary component (RI) domain,
Fourier spectrum (Γ) domain, and phase angle (Φ) domain. Now present how its apply the three frequency band selections B_1, B_2, and B_3 to the three Fourier features domains. The RI domain has more powerful descriptions to distinguish faces than other domains,

so we apply $RI_{B1} \sim RI_{B2}$ to it. On the other hand, the Γ and Φ domains do not make use of the highest frequency regions because the discriminating power of the highest frequency parts in these Fourier domains are small. Figure 3 is the higher frequency information of the phase angle is sensitive to small spatial changes and, thus, only Φ_{B1} is adopted.

$$YRI_{B1} = W^T_{RIB1} (RI_{B1} - m_{RIB1}) \qquad (6)$$

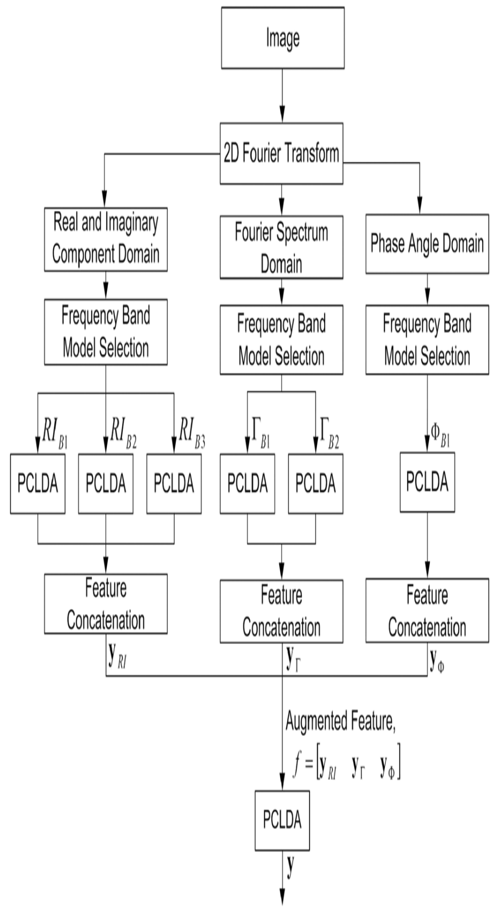
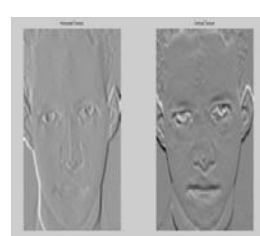


Figure 3. Structure of hybrid Fourier based upon PCLD

X. Simulation result:



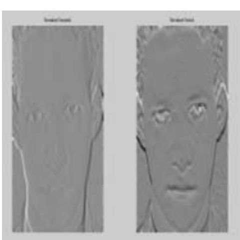
Result1:Input image   Result2:Horizontal & Vertical texture

Result1&2 shows input and textures of an image

METHOD	PSNR	PREPROCESSING TIME (sec)
EXISTING METHOD(LDA)	46.8132	50
PROPOSED METHOD(PCLDA)	10	4

Result3:Gradient image   Result4:Smoothing image

Result3&4 shows gradient and smoothing image



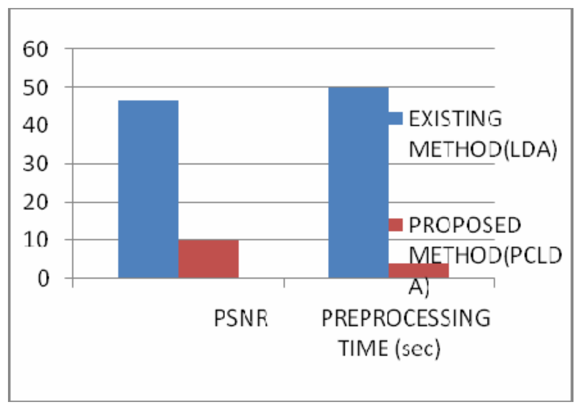
Result5:Normalized image   Result6:Reconstruction image

Result5&6 shows normalized and reconstruction image

Result7: Preprocessed image

Result7 shows preprocessed image

TABLE I. COMPARISON BETWEEN EXISTING AND PROPOSED METHOD



Graph 1. Comparison between Existing and Proposed method

In this preprocessing method it as been proved that our method is better than the existing method.

X. Conclusion

In this paper an normal input image with various environmental condition like illumination, intensity ,noise as removed by this pre processing stage and an standard input image is obtained with a standard illumination in the image. A pre processing method based upon the analysis of the face imaging model withdefinitions of intrinsic and extrinsic factors of a human face and proposed the INGI method as an illumination insensitive representation for face recognition.

REFERENCE

[1] P. J. Phillips, H. Moon, S. A. Rizvi, and P. J. Rauss, "The FERET evaluation methodology for face recognition algorithms," IEEE Trans. Pattern Anal. Mach. Intell., vol. 22, no. 10, pp. 1090–1104, Oct. 2000.

[2] D. Blackburn, E. Tabassi, and M. Bone, "Face recognition vendor test 2002: evaluation report,"2003 Available: http://www.frvt.org/

[3] K. Messer, J. Kittler, M. Sadeghi, M. Hamouz, and A. Kostin et al.,"Face authentication test on the BANCA database," in Proc. Int.

[4] P. J. Phillips, H. Moon, S. A. Rizvi, and P. J. Rauss, "The FERET evaluation methodology for face recognition algorithms," IEEE Trans. Pattern Anal. Mach. Intell., vol. 22, no. 10, pp. 1090–1104, Oct. 2000.

[5] D. Blackburn, E. Tabassi, and M. Bone, "Face recognition vendor test 2002: evaluation report,"2003 Available: http://www.frvt.org/

[6] K. Messer, J. Kittler, M. Sadeghi, M. Hamouz, and A. Kostin et al.,"Face authentication test on the BANCA database," in Proc. Int.