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A Comparative Dimensionality Reduction Approach For Face Recognitionunder Uncontrolled Illumination Variations

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Abstract*— Most of the method developed for face recognition with face images collected under relatively well controlled conditions have difficulty in dealing with the range of appearance variations that commonly occur in unconstrained natural images due to different factors. A simple, efficient image processing chain is used whose practical recognition performance is comparable to or better than current methods, a rich descriptor for local texture called Local Binary Pattern(LBP), is used for feature extraction, dimensionality reduction is performed using Principal Component Analysis(PCA) and Linear Discriminant Analysis (LDA). To demonstrate the effectiveness of the proposed method, we give results on the Extended Yale-B dataset which contains images of 38 subjects under 64 illumination and 9 poses.

Index Terms*—Face recognition, Feature extraction, illumination normalization, linear discriminant analysis, local binary patterns, principal component analysis.

I. INTRODUCTION

Face recognition is a difficult problem because of the generally similar shape of faces combined with the numerous variations between images of the same face. The image of a face changes with facial features, age, viewpoint, illumination conditions, noise etc. The task of a face recognition system is to recognize a face in a manner that is as independent as possible of these image variations. Digital image processing is the use of computer algorithms to perform image processing on digital images.

Biometrics is the process by which a person's unique physical and other trait are detected and recorded by an electronic device or system. Face recognition has recently received extensive attention as one of the most significant applications of image understanding. Lighting variations are one of the most difficult problems of face recognition and has received much attention in recent years. In computer science, in particular, biometrics is used as a form for identification, access control and verification. In this paper, it presents a simple and efficient pre-processing chain which includes four methods Gamma correction, DoG filtering, Masking and Equalization that eliminates most of the effects of changing illumination that will still preserve the essential appearance details that are needed for recognition. Here first collect the images which will later undergo pre-processing steps which will result in a normalized output and local binary pattern for feature extraction.

The robustness here are improved by using Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). After performing the dimensionality reduction, classification is done using equidistant classification. This provides new ways to recognize the face under difficult lighting conditions.

To demonstrate the effectiveness of the proposed method, we give results on the Extended Yale-B dataset to test recognition under difficult illumination conditions. Extended Yale-B, includes images of 38 subjects under 9 different poses and 64 illumination conditions.

The rest of the paper is organized as follows. Section II presents related works, Section III describes proposed work, Section IV reports experimental results and Section V concludes.

II. RELATED WORKS

This section describes the existing work. The input image is given to the feature extraction processes such as LBP, Gabor and in combination of LBP and Gabor and the output of these has undergone the classification process and checks the performance of each feature extraction process based on classification. Fig. 2.1 illustrates existing work.

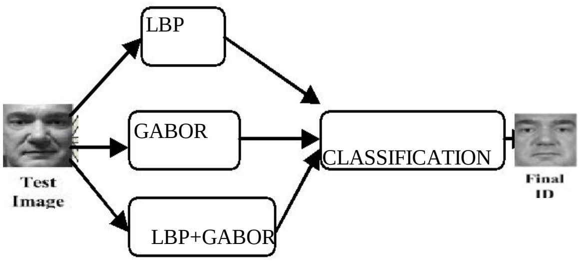

Fig. 2.1. Block diagram of existing system

2.1. Local Binary Pattern

The LBP operator was originally designed for describing the texture of a particular image. The operator assigns a label to each pel(pixel) of a picture by thresholding the 3×3-neighborhood of every pel with the middle pel price and considering the result as a binary range as illustrated in fig. 2.2. Then, the histogram of the labels can be used as a texture descriptor. Another equally vital is its procedure simplicity that makes it potential to research pictures in a difficult period of time settings.

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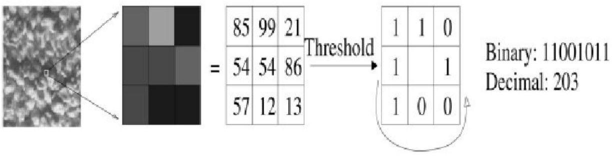

Fig. 2.2. Local Binary patterns

The LBP methodology and its variants have already been employed in an oversized range of applications everywhere all over the world.

2.2 Gabor Feature Extraction

It is the convolution of an image with a family of Gabor kernels. Let I(x,y) be an image, the convolution of the image I and a Gabor kernel is defined as follows:

$O_{\mu,v}(z)=I(z)*\psi_{\mu,v}(z)$

Where z=(x,y), convolution operator is denoted by , $O_{\mu,v}(z)$ is the convolution result corresponding to the Gabor kernel at orientation μ and scale v.

III. PROPOSED WORK

In proposed work, an input image is given to preprocessing steps such as Gamma Correction, DoG filtering, Masking and Equalization variations and then to LBP, Gabor, LBP+Gabor and output of these feature extraction are given to PCA and similarly to LDA, final classification is done. Fig. 3.1 illustrates the proposed work.

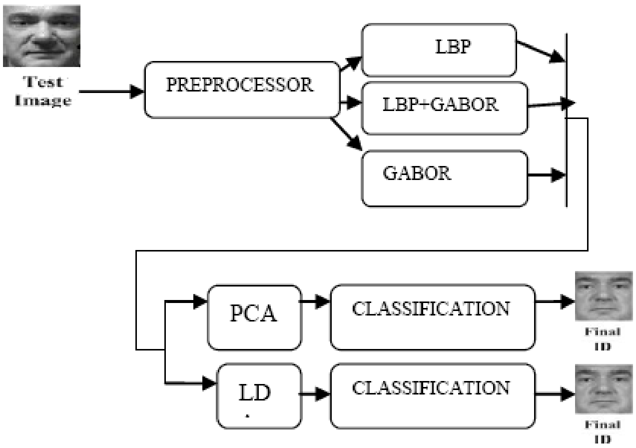

Fig. 3.1. An input image is given to preprocessing and then to LBP, Gabor, LBP+Gabor and this result are given to PCA and similarly LDA, final classification is done

3.1. Illumination Normalization

This section describes about the illumination normalization method.

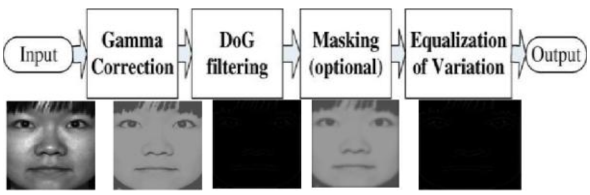

Fig. 3.2. (Top) the stages of our image pre-processing pipeline, and (bottom) an example of the effect of the three stages— from left to right: input image; image after Gamma correction; image after DoG filtering; image after robust contrast normalization.

This is a pre-processing chain run before feature extraction that incorporates a series of stages designed to counter the consequences of illumination variations, native shadowing, and highlights whereas conserving the essential components of visual look. Fig. 3.2 illustrates the three main stages and their effect on a typical face image. In detail, the stages are as follows.

Gamma correction: Gamma correction enhances the local dynamic range of the image in dark or shadowed regions while compressing it in bright regions and at highlights. Gamma correction is, within the simplest cases, outlined by the following,

Power law expression:

$V_{out} = A\, V_{in}^{\gamma}$

Where *A* is a constant and also the input and output values square measure non-negative real values; within the common case of A = one, inputs and outputs square measure usually within the range 0–1. A gamma price γ < one is usually referred to as a cryptography gamma, and also the method of cryptography with this compressive power-law nonlinearity is called gamma compression conversely a gamma price γ > one is referred to a coding gamma and also the application of the expansive power-law nonlinearity is named gamma enlargement.

Difference of Gaussian Filtering (DoG) : DoG is the next step after gamma correction**.** High-pass filtering removes each the helpful and also the incidental information, so simplifying the popularity drawback and so the incidental knowledge, so simplifying the popularity drawback in many cases increasing the overall system performance.

Masking: If facial regions (hair style, beard) that area unit felt to be moot or too variable got to be cloaked out, the mask ought to be applied at this time, either strong artificial gray-level edges are introduced into the DoG convolution, or invisible regions are taken into account during contrast equalization.

Equalization Variation: The final stage of pre-processing chain rescales the image intensities standardize a robust measure of overall contrast or intensity variation. It is necessary to use a strong reckoner as a result of the signal usually contains extreme values created by highlights, tiny dark regions like nostrils, garbage at the image borders, etc.

3.2. Principal Component Analysis (PCA)

PCA is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables called principal components. The number of principal elements is a smaller amount than or adequately the quantity of original variables.PCA is sensitive to the relative scaling of the original variables.

TABLE I PARAMETER REPRESENTATIONS

Notations	Description
M	The number of data points For training
n	Total number of features
M	Total number of classes
mk	Total number of data Points in k-the class
Xi	The i-the data point
Sb	The between-class scatter matrix
Sw	the within-class scatter Matrix
St	The total scatter matrix
A	The transformation vector
C	covariance
C	Covariance Matrix

Algorithm

The notations used in the algorithm are given in TABLE I

1. Consider ‘m’ classes containing ‘n’ images
2. Compute mean for all classes

$$x' = \frac{1}{m}\sum_{i=1}^{m} x_i \qquad (3.1)$$

3. Subtract mean from each image of all classes.

$$y = \sum_{i=1}^{m} x_i - x' \qquad (3.2)$$

4. Compute the covariance matrix of the result obtained in above step3

$$c = \frac{1}{m}\sum_{i=1}^{m} y_i y_i^T \qquad (3.3)$$

5. From covariance matrix, corresponding Eigenvector and Eigenvalues are obtained

$$CV = \lambda V \qquad (3.4)$$

Where C is covariance matrix, λ is Eigenvalue and V is Eigenvector

6. For Eigen value≠0, choose corresponding, Eigenvector and thus obtained reduced dimension

7. Projecting the data by multiplying image which subtracted mean images and Eigenvector to obtain Eigen faces

$$d = y \times V \qquad (3.5)$$

After the PCA operation is done the next step is to do the classification. Here classification is done using equi- distant classification.

3.3. Linear Discriminant Analysis (LDA)

The objective of LDA is to perform dimensionality reduction whereas conserving the maximum amount of the category discriminatory data as potential. It seeks to search out directions on that the categories square measure best separated. It will therefore by taking into thought the scatter within-classes however conjointly the scatter between-classes.

Algorithm

The notations used in the algorithm is given in TABLE I

1. Formulate dataset
2. Compute mean of each dataset and mean of entire data

$$\mu_i = \frac{1}{n_i}\sum_{x \in class_i} x \qquad (3.6)$$

$$\mu = \frac{1}{n_i}\sum_{x_i} x_i \qquad (3.7)$$

where μ_i the mean of ith class and μ is the entire mean

3. Calculate within class scatter Sw and between class scatter Sb.

$$S_b = \sum_{i=1}^{c} n_i(\mu_i - \mu)(\mu_i - \mu)^t \qquad (3.8)$$

$$S_w = \sum_{i=1}^{c} \sum_{x \in class_i} (x_k - \mu_i)(x_k - \mu_i)^t \qquad (3.9)$$

4. Solve the Eigen value problem

$$S_w V = \lambda S_b V \qquad (3.10)$$

$$S_b v - \lambda S_w v = 0$$
$$(S_b - S_w)v = 0 \qquad (3.11)$$
$$Sv = 0$$
$$Sv = 0 \Rightarrow [v, ev] = eig(S)$$

5. Project each sample x_i to a linear subspace Y_i i.e.

$$Y_i = V^t \ x_i$$

where V^t is the projection metrics.

6. Thus the classes are well separated.

IV. EXPERIMENTAL RESULTS

We illustrate the effectiveness of our methods by presenting experiments on one large-scale face data sets with difficult lighting conditions-Extended Yale B. We divide the results into 3 sections, the first focusing on pre-processing steps and then on LBP and then on PCA and LDA.

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Fig. 4.1 Examples of the effect of different pre-processing methods. Column 1 shows the original image, 2 shows the output of gamma correction, 3 shows output of DoG filtering, 4 shows output of equalization of 2 subjects from Yale-B dataset.

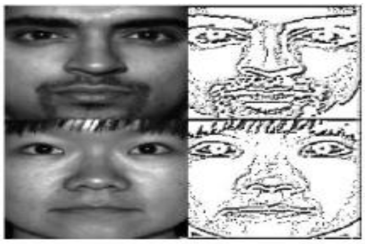

Fig. 4.2. Examples above show the output of LBP feature Extraction and the histogram below shows the original image and the extracted image.

TABLE II PARAMETER SETTINGS FOR OUR METHOD

TRAINING PERCENT	CLASSIFICATION ACCURACY				
	LBP	GABOR	LBP+GABOR	GABOR+PCA	GABOR+LDA
10	83.3	63.3	63.3	63.3	64
20	80	66.25	66.25	68.7	69
30	82.8	67.14	67.14	70	71
40	85	71.66	71.66	76.6	77
50	84	82	82	90	90
60	87.5	87.5	87.5	90	90
70	83.3	96.6	96.6	100	100
80	90	95	95	100	100
90	90	100	100	100	100
100	90	100	100	100	100

From the measurement results, it is analyzed that LDA is having classificationaccuracy 71 for training percent 30; PCA with 70 for training percent 30; Gabor with 67.14 for training percent 30; and LBP with 82.8 for 30 training percent and performance measure is shown in Fig. 4.3

Fig. 4.3 Comparative performance of LBP, GABOR, LBP+GABOR, GABOR+PCA, GABOR+LDA

From above graph we can measure the corresponding classification accuracy for different training percents.

V. CONCLUSION

This work represents an efficient system that is resistant to varying lighting condition and efficiently recognizing the face under difficult conditions. The main contributions are as follows: efficient image pre-processing chain whose practical recognition performance is adored or higher than current illumination standardization ways, an upscale descriptor for native texture known as LBP and dimensionality reduction is done using LDA.Thus presenting a new system which is resistant to varying illumination conditions. Future work can be done by considering the local components rather than considering the global components.

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AUTHORS PROFILE

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