Face Recognition using LBP and PCA under Different Lighting Condition

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Abstract – **Face is our primary and first focus of attention in social life which plays an important role in identifying an individual. Though there are variations in face due to aging and distractions like beard, glasses or change of hairstyles we can recognize a number of faces learned throughout our lifespan and identify them at a glance even after years. Face recognition system is a computer application for automatically identifying a person from digital image of a face. Making recognition more reliable under uncontrolled lighting condition is most important challenge in face recognition system. In this project we address this problem by combining the strength of robust illumination normalization, local binary pattern texture descriptor and principal component analysis. Illumination normalization is a simple and efficient pre-processing chain that eliminates most of the effects of changing illumination while still preserving the essential appearance details that are needed for recognition. Local binary pattern texture descriptor which labels the pixels of an image and gives output as a histogram of image is used for feature extraction. And principal component analysis feature dimensionality reduction algorithm is used to improve robustness. The crux of the work lies in obtaining a recognized image of a face. Such image is a recognized face image when Euclidean distance between a test image and training images is minimum.**

Keywords – **Illumination invariance, image preprocessing, local binary patterns, principle component analysis.**

I. Introduction

One of the most important aims of face recognition is to find out efficient and discriminative facial appearance descriptors which can counteract large variations in various illuminations, poses, facial expressions, ageing, partial occlusions and other related changes. Traditional approaches to deal with these issues can broadly be classified into three categories: appearance-based, normalization-based, and feature-based.

In appearance-based approach, training examples are collected under different lighting conditions which are directly used to learn a global model of the possible illumination variations, for example a linear subspace or manifold model [1]. The disadvantage of this method is that it requires large number of training images and an expressive feature set else it is crucial to include a good preprocessor to reduce illumination variations.

Normalization based approach seeks to reduce the image to a more "canonical" form in which illumination variations are suppressed e.g. histogram equalization. This has the merit of easy application to real images and lack of need for comprehensive training data.

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The third approach extracts illumination-insensitive feature sets [1] [2], directly from a given face image. The feature sets may range from geometrical features [3] to image derivative features such as edge maps [2] local binary pattern (LBP) [2], [4], Gabor wavelets, and local autocorrelation filters [5].

In this paper, an integrative framework combines the strengths of all three of the above approaches. Therefore the complete process can be viewed as a pipeline involving image preprocessing, feature extraction, and, feature dimensionality reduction using PCA, classifier, as shown in Fig. 1. Each of the given stage shows increase in resistance to illumination variations and makes the information needed for recognition more evident [2].

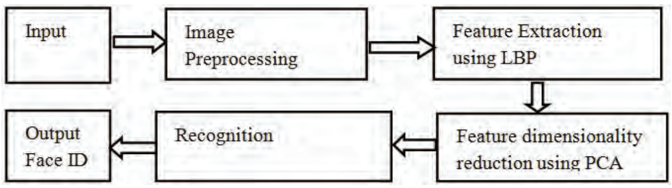

Fig.1. Stages of full face recognition method

The method focuses on robust visual features that are selected to capture as much as possible of the available information. A well-designed image preprocessing pipeline is designed to further enhance robustness.

In this paper, a simple image preprocessing pipeline is used that appears to work well for a wide range of visual feature sets, eliminating many of the effects of changing illumination while still preserving most of the appearance details needed for recognition. Finally the described LBP face descriptor, principle component analysis, measure Euclidean distance for face recognition.

II. Illumination Normalization

Illumination Normalization is an important task in the field of face recognition. It is a preprocessing chain which is applied before feature extraction having a number of stages designed to resist the effects of illumination variation, local shadowing and different highlights. While doing so, it maintains all necessary characteristics of visual appearance. This preprocessing chain consists of following 3stages:

A) Gamma correction;
B) DoG filtering;
C) Contrast equalization.

A. Gamma Correction:

It is a nonlinear operation used to encode or decode luminance value in image. Gamma correction is, in easiest form defined as a power law expression:

$$I_{out} = A I_{in}^{\gamma} \quad (1)$$

where A is a constant and the input and output values are non-negative real values; in the common case of $A = 1$, inputs and outputs are typically in the range of $0-1$. A gamma value $\gamma < 1$ which is often called as an encoding gamma, and the process of encoding with this summarized power-law nonlinearity is called gamma compression; conversely a gamma value $\gamma > 1$ is called a decoding gamma and the application of the expansive power-law nonlinearity is called gamma expansion.

Here, this is a nonlinear gray-level transformation that replaces gray level I with I^{γ} $(for\ \gamma > 0)$or $log(I)$ (for $\gamma = 0$), where $\gamma \in [0,1]$ is a user defined parameter. This enhances the local dynamic range of the image in dark or shadowed regions while compressing it in bright regions and at peaks. An emphasized principle is that an 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). A power law with exponent γ in the range (0 to 0.6) is a good compromise. Here use $(\gamma = 0.3)$ as the default setting [2].

B. Difference of Gaussian(DoG) Filtering:

Gamma correction does not remove the influence of overall intensity gradients such as shading effects. In computer vision, Difference of Gaussians is a grayscale image enhancement algorithm that involves the subtraction of one blurred version of an original grayscale image from one more less obscured variant of actual. Subtracting one image from other image conserves spatial information that lies between the ranges of frequencies that are preserved in the two obscured images. Therefore a difference of Gaussians is a band-pass filter that discards all but a handful of spatial frequencies that are present in the original grayscale image. As an image enhancement algorithm, the Difference of Gaussian (DOG) can be utilized to increase the visibility of edges and other detail present in a digital image. The difference of Gaussians algorithm can remove the high frequency detail that often includes random noise and this approach could be found well suitable for processing images with a high degree of noise.

The DOG impulse response is defined as [9]:

$$DoG(x,y) = \frac{1}{2\pi\sigma_1^2} e^{\frac{x^2+y^2}{2\sigma_1^2}} - \frac{1}{2\pi\sigma_2^2} e^{\frac{x^2+y^2}{2\sigma_2^2}} \quad (2)$$

where the default values of σ_1 and σ_2 are chosen as 1.0 and 2.0 respectively.

C. Contrast Equalization:

Contrast Equalization is also known as histogram equalization. Contrast Equalization is an approach to adjust image intensities to enhance contrast, means rescales the intensities of given image. A robust estimator is important to be used because the signal typically contains extreme values produced by highlights, minute dark regions like that of nostrils, junk on the image edges, chin, forehead etc. Here a simple and rapid approximation is preferred based on a two stage process as follows:

$$I(x,y) = \frac{I(x,y)}{(mean\ (\min\left(\tau\left|I(x',y')\right|^{\alpha}\right))^{1/\alpha}} \quad (3)$$

Here, α is a strongly compressive exponent that reduces the influence of great values, τ is an outset used for shorten large values later than the first phase of normalization, and the mean is over the whole (unmasked part) image. By default $\alpha = 0.1$ and $\tau = 10$ is used.

Fig.2. Output of preprocessing original RGB image, Gray image, Gamma correction image, DoG filter image, HE image.

III. LOCAL BINARY PATTERN

Local Binary Pattern (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by making a threshold on a neighborhood of each pixel and considers result as a binary number or local binary pattern histogram of an image. Due to its discriminative power and calculated clarity, LBP texture operator has become a prevailing modus operandi in various applications. Perhaps the most important characteristic of LBP operator in real-world applications is its robustness to monotonic gray-scale changes rooted, e.g. illumination variations.

An original LBP operator [6] forms labels for image pixels by threshold of 3×3 neighborhood for each pixel with the center value and considering the result as a binary number. The histogram of these $2^8 = 256$ heterogeneous labels can then be used as a texture descriptor. Using a circular neighborhood and bi linearly interpolating values at non-integer pixel coordinates allow any radius and number of pixels in the neighborhood.

Formally, the LBP operator takes the form [2]:

$$LBP(x_c, y_c) = \sum_{n=0}^{7} 2^n s(i_n - i_c) \quad (4)$$

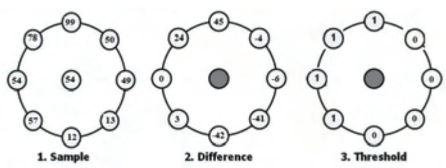

Fig. 3. An example of LBP computation

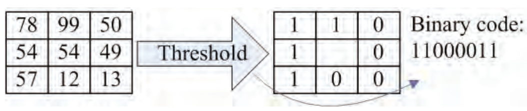

Fig.4. Illustration of the basic LBP operator for above example

Where, in this case n runs over the 8 neighbors of the central pixel c, i_c and i_n are the gray-level values at c and n, and $s(u)$ is 1 if $u \geq 0$ and 0 otherwise. The LBP encoding process is illustrated in Fig. 3.

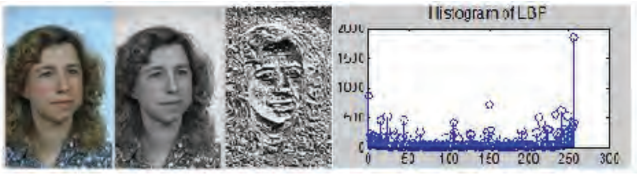

Fig.5. I/P RGB image, Gray image, LBP image, Histogram of LBP

Two extensions of original operator were made in [7]. The first described LBP is for neighborhoods of various sizes, hence this makes it feasible to manage with textures of different scales. Other defined LBP uniform patterns are uniform if they contain at most one 0-1 and one 1-0 transition when viewed as a circular bit string. For example, the LBP code in Fig.4. is uniform. Uniformity is a vital concept in LBP methodology, which represent basic structural instruction such as edges, corners, etc. In these methods that histogram LBP is, a number of bins which can thus be considerably reduced by assigning all non-uniform patterns to a bin, constantly without dropping too much information.LBP image and their histogram image is shown in Fig.5.

IV. Principle Component Analysis

Principal Component Analysis (PCA) is one of the most successful techniques that have been used in face recognition. The functions which PCA does are prediction, redundancy removal, feature extraction, data compression, etc [8]. The main idea of using PCA for face recognition is to express the large 1-D vector of pixels constructed from 2-D facial image into the compact principal components of the feature space. It is known as eigenspace projection. Eigenspace is calculated by specifying the eigenvectors of the covariance matrix derived from a set of facial images (vectors).

Mathematics of PCA [8] - a 2-D facial image can be represented as 1-D vector by concatenating each row (or column) into a stretched narrow vector. Suppose there is M vectors of size N (=rows of image ×columns of image) representing a set of sampled images. p_j 's represent the pixel values.

$$x_i = [p_1 \ldots . p_N]^{\mathrm{T}}, \quad i = 1, \ldots, M \tag{5}$$

The images are mean centered by subtracting the mean image from each image vector. Mean image m is represented as:

$$m = \frac{1}{M}\sum_{i=1}^{M} x_i \tag{6}$$

And let w_i be defined as mean centered image

$$w_i = x_i - m \tag{7}$$

A goal is to find a set of e_i 's which have the largest possible projection onto each of the w_i 's. To find a set of M orthonormal vectors e_i for which the quantity

$$\lambda_i = \frac{1}{M}\sum_{n=1}^{M}(e_i^T w_n)^2 \tag{8}$$

is augmented with the orthonormality constraint

$$e_l^T e_k = \delta_{lk} \tag{9}$$

It has been shown that the e_i 's and λ_i 's are given by the eigenvectors and eigenvalues of the covariance matrix

$$C = WW^T \tag{10}$$

where W is a matrix composed of the column vectors w_i placed side by side. The size of C is $N \times N$ which could be enormous. For example, images of size 64×64 create the covariance of size 4096×4096. It is not practical to solve for the eigenvectors of C directly. A conventional theorem in linear algebra states that the vectors e_i and scalars λ_i can be obtained by solving for the eigenvectors and eigenvalues of the $M \times M$ matrix $W^T W$. Let d_i and μ_i be the eigenvectors and eigenvalues of $W^T W$, respectively.

$$W^T W d_i = \mu_i d_i \tag{11}$$

By multiplying left to both sides by W :

$$WW^T (Wd_i) = \mu_i (Wd_i) \tag{12}$$

which means that the first $M-1$ eigenvectors e_i and eigenvalues λ_i of WW^T are given by Wd_i and μ_i, respectively. Wd_i needs to be normalized in order to be equal to e_i. Since we only sum up a finite number of image vectors, M, the rank of the covariance matrix unable to exceed $M-1$ (The -1 come from the subtraction of the mean vector m).

The eigenvectors equivalent to nonzero eigenvalues of the covariance matrix produce an orthonormal basis for the subspace within which most image data can be represented with a small flaw. The eigenvectors are classified from high to low according to their correlating eigenvalues. The eigenvector associated with the highest eigenvalue is one that reflects the greatest variance in an image. It means lowest eigenvalue is related with the eigenvector that finds the least variance. A facial image can be projected onto $M'(<< M)$ dimensions by computing:

$$\Omega = [\mathrm{v}_1 \mathrm{v}_2 \ldots \mathrm{v}_{M'}]^{\mathrm{T}} \tag{13}$$

where $v_i = e_i w_i$. v_i is the i^{th} coordinate of the facial image in a new space, came as a main component. The vectors e_i are also images, so called, *eigenimages*, or *eigenfaces* in this case. They can be viewed as images and indeed seem as faces. So, Ω describe contribution of each eigenface in representing the facial image by treating eigenfaces as a core set for facial images. An easiest way to determine which face class provides the best description of an input facial image is to find the face class k that minimizes the Euclidean distance:

$$\epsilon_k = \Omega - \Omega_k \tag{14}$$

Where, Ω_k is a vector describing the k^{th} face class.

V. Implementation And Result

The proposed method is tested on two different databases. One is available face database for different set of conditions and other is ORL face database. The use of only frontal face views other than lighting, expression and identity may vary.

Regarding the image size, cropping, and alignment of the datasets:Face database for different set of conditions image cropping to 192×128 pixels.

For AT&T-ORL used the original images at 112×92.The default settings of different parameters are summarized in table I.

Table I
DEFAULT PARAMETER SETTING

Procedure	Parameter	Value for available face database	Value for ORL face database
Gamma Correction	γ	0.2	0.4
DOG Filtering	σ_0	1	2
	σ_1	2	3
Contrast Equalization	α	0.1	0.1
	τ	10	10

A face image in 2-dimension with size $M\times N$ can also be considered as one dimensional vector of dimension MN. For example, face image from trained database with size 192×128 can be considered as a vector of dimension 24,576 or equivalently a point in a 24,576 dimensional space. Similarly face image from ORL (Olivetti Research Labs) database with size 112×92 can be considered as a vector of dimension 10,304 or equivalently a point in a 10,304 dimensional space.

An ensemble of images maps to a collection of points in it takes huge space. Images of faces, being similar in overall configuration, will not be unspecific distribution in this huge image space and thus can be described by a relatively low dimensional subspace.

There are 10 different images of 10 different subjects for face database different set of conditions. And there are 10 different images of 30 different subjects for ORL face database. For some of the subjects, the images were taken at different times, varying lighting condition, facial expressions (open/closed eyes, smiling/non smiling) and facial details. Fig.6. shows results of preprocessing chain. Fig.7. shows histogram output of gray image and DoG filter image.

Computed recognition rate using face database for different set of conditions for 10 different subjects face images with10 images of each person, is shown in table II. And for ORL database for 30 different subjects face images with10 images of each person, is shown in table III.

Table II
RECOGNITION RATE USING LBP AND PCA

Method	Recognition%
PP+LBP+PCA	94

TABLE III
RECOGNITION RATE USING LBP AND PCA FOR ORL FACE DATABASE

Method	Recognition%
PP+LBP+PCA	92

VI.Conclusion

A face recognition system is a computer application for automatically identifying a person from a digital image of face. This Project throws light on new methods for face recognition under different lighting conditions based on robust preprocessing, LBP local texture descriptor and PCA. The crux of the work lies in making three main contributions: (i) simple and efficient preprocessing chain, that eliminates most of the effects of changing illumination while still preserving the essential appearance details that are needed for recognition; (ii) a rich local texture descriptor called Local

Binary Pattern which labels the pixels of an image and gives output as a histogram of an image and (iii) Principle Component Analysis feature extraction algorithm is used to improve robustness. The crux of the work lies in obtaining a known face image. An image is a known face image when Euclidean distance between a test image and training images is minimum. And if this distance is not attained, it is an unknown face image.

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