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Face Recognition using Local Texture Descriptor

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Abstract **–A face recognition system is a computer application for automatically identifying a person from a digital image. Recognition of face in uncontrolled lightening situations is one of the most important bottlenecks for practical face recognition systems. This paper addresses the problem of illumination effects on Face recognition and work for an approach to reduce their effect on recognition performance. For this following methods are used: (*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*) Local Binary Pattern (LBP) texture descriptor which labels the pixels of an image and gives output as a histogram of image; and (*iii*) principle component analysis (PCA) feature extraction algorithm is used to improve robustness. The proposed method is tested on ORL face database. The crux of the work lies in optimizing Euclidean distance classifier for recognition of face.**

Keywords **– Face recognition, illumination invariance, image preprocessing, local binary patterns, principle component analysis, visual features.**

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 illumination, pose, facial expression, ageing, partial occlusions and other changes. Traditional approaches to deal with these issues can broadly be classified into three categories: appearance-based, normalization-based, and feature-based methods.

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.

The third approach extracts illumination-insensitive feature sets [1] [2], directly from the given image. These feature sets range from geometrical features [3] to image derivative features such as edge maps [2] local binary patterns (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 stage increases resistance to illumination variations and makes the information needed for recognition more evident [2].

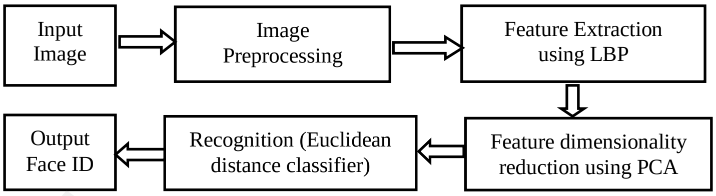


Fig. 1. Stages of full face recognition method.

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. Then described LBP face descriptor, principle component analysis, and finally 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 applied before feature extraction having a number of stages designed to resist the effects of illumination variation, local shadowing and highlights. While doing so, it preserves essential elements of visual appearance. This preprocessing chain consist 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:

$$I_{out} = AI_{in}^{\gamma} \qquad (1)$$

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). 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 reflective stage produces this given stage in a log(I) regardless of a real intensity of an illumination. In actuality a complete log adaptation is often too strong, keeping to more-amplify the noise in dark regions of image, but a power law with exponent γ in the range $[0, 0.6]$ 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. Obscured images are attained by convolving the original grayscale image with Gaussian kernels having differing standard diversions. Obscuring an image by using a Gaussian kernel suppresses only high frequency spatial data. 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 removes 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]:

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

Where the default values of $\sigma_1$and σ_2 are chosen as 1.0 and 2.0 respectively. Since this effect leads to the reduction in the overall contrast produced by the operation and hence the contrast has to be enhanced in the subsequent stages.

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 image intensities. It is important to use a robust estimator because the signal typically contains extreme values produced by highlights, small dark regions such as nostrils, garbage at image edges, chin, forehead etc.

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 consider 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. It can be seen as an integrated technique to the traditionally deviated statistical and structural model of texture evaluation. 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. Second significant characteristic is its computational simplicity, which makes it possible to examine images in worthwhile real-time settings.
An original LBP operator (Ojala et al. 1996) [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]

$$LBP(x_c, y_c) = \sum_{n=0}^{7} 2^n s(i_n - i_c) \qquad (3)$$

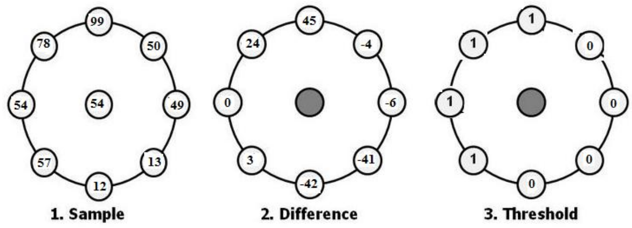


Fig 2. An example of LBP computation

where,

$$s(u) = \begin{cases} 1, & if\ u \geq 0 \\ 0 & Otherwise \end{cases}$$

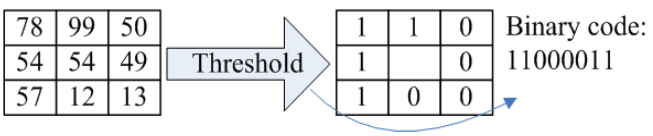


Fig. 3. Illustration of the basic LBP operator for above example

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. 2.

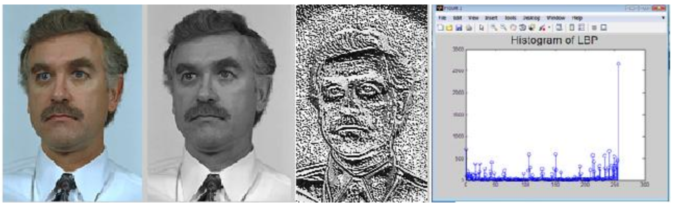


Fig.4. I/P RGB image, Gray image, LBP image, Histogram of LBP

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.3. is uniform. Uniformity is a vital concept in LBP methodology, which represent basic structural instruction such as edges, corners, etc. Ojala et al. noticed that in spite of the fact that only 58 of 256 8-bit patterns are uniform, nearly 90 percent of all noticed image neighborhoods are uniform. 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.4.

IV. Principle Component Analysis

Principal Component Analysis (PCA) is one of the most successful techniques that have been used in face recognition. The basic purpose of PCA is to simplify large dimensionality of data space (observed variables) to smaller intrinsic dimensionality of feature space (independent variables), which are needed to describe the data reasonably. It's a case when there is a sound correlation between observed variables. 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 $\times$ columns of image) representing a set of sampled images. p_j's represent the pixel values.

$$x_i = [p_1 \ldots . p_N]\text{\^{}T}, \qquad i = 1, \ldots, M \qquad (4)$$

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

$$m = \frac{1}{M}\sum_{i=1}^{M} x_i \qquad (5)$$

And let w_i be defined as mean centered image

$$w_i = x_i - m \qquad (6)$$

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

$$\lambda_i = \frac{1}{M}\sum_{n=1}^{M} (e_i^T w_n)^2 \qquad (7)$$

is augmented with the orthonormality constraint

$$e_l^T e_k = \delta_{lk} \qquad (8)$$

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

$$C = WW^T \qquad (9)$$

where W is a matrix composed of the column vectors w_i placed side by side. The size of C is $\mathrm{N} \times \mathrm{N}$ 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 $\mathrm{M} \times \mathrm{M}$ matrix $W^T W$. Let d_i and μ_i be the eigenvectors and eigenvalues of $W^T W$, respectively.

$$W^T W d_i = \mu_i d_i \qquad (10)$$

By multiplying left to both sides by W

$$WW^T(Wd_i) = \mu_i(Wd_i) \qquad (11)$$

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 $\mathrm{M} - 1$ (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

$$\Omega = [\mathrm{v}_1 \mathrm{v}_2 \ldots \mathrm{v}_{\mathrm{M}'}]^{\mathrm{T}} \qquad (12)$$

where $v_i = e_i w_i$. v_i is the i$^{\text{th}}$ 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

$$\epsilon_k = \|\Omega - \Omega_k\| \tag{13}$$

where Ω_k is a vector describing the kth face class. If ϵ_k is less than some predefined threshold θ_ϵ, a face is classified as belonging to the class k. Otherwise the face is classified as unknown.

VI. PROCEDURE AND WORKING

1. Preparation of training data set aligns a set of face images as a training set from 1 to N number of faces. In this process it reshapes all 2D images of the training database into 1D column vectors. Afterword, it puts 1D column vectors in a row to construct 2D matrix.
2. Then illumination normalization takes place. It consists of preprocessing chain, which gives result as a balanced intensity image.
3. Then use of local binary pattern (LBP) returns LBP histogram of an image.
4. And finally Principle Component Analysis (PCA) determines the most discriminating features between images of faces. In it first of all mean is calculated then deviation of each image from the mean value is calculated. The next step is to sort and eliminate Eigen values. All Eigen values of matrix A are sorted which are less than a specified threshold are eliminated. Then eigenvectors of covariance matrix C (or so-called "Eigenfaces") are calculated. They can be recovered from A's Eigenvectors. Recognition is done by Projecting centered image vectors into face space. All centered images are projected into face space by multiplying in Eigenface basis. Projected vector of each face would be its corresponding feature vector. Finally Euclidean distance between projected test image and the projection of all centered training images are calculated. If Euclidean distance between a test image and training images is zero then it is a known face image otherwise consider as unknown face image.

V. IMPLEMENTATION AND RESULT

In order to obtain a fair empirical evaluation of face detection methods, it is important to use a standard and representative test set for experiments. To test the proposed method, the ORL Face database has been used. The ORL face database contains a set of faces taken between April 1992 and April 1994 at the Olivetti Research Laboratory in Cambridge, UK. The use of only frontal face views other than lighting, expression and identity may vary.

All images undergo the same geometric normalization prior to analysis conversion to 8 bit gray-scale images; rigid scaling and image rotation to place the centers of the two eyes at fixed positions, and image cropping to 112x92 pixels. The default settings of different parameters are summarized in table I.

TABLE I. DEFAULT PARAMETER SETTING

Procedure	Parameter	Value
Gamma Correction	γ	0.3
DOG Filtering	σ	2
	σ	3
Contrast Equalization	α	0.1

A face image in 2-dimension with size M × N can also be considered as one dimensional vector of dimension MN. For example, 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 30 different subjects. 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.5. shows results of preprocessing chain. Fig. 6.shows histogram output of gray image and DoG filter image. Images of one individual are shown in fig.7.

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

TABLE II. RECOGNITION RATE USING LBP AND PCA

Method	Face Recognized	False Recognition	Recognition%
PP + LBP	278	22	94.66
PP+LBP+PCA	290	10	98.78

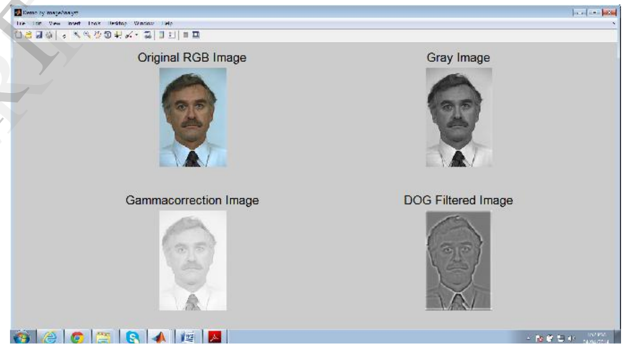


Fig.5. The stages of image preprocessing pipeline I/P RGB image, Gray image, Gamma correction image, DoG filter Image

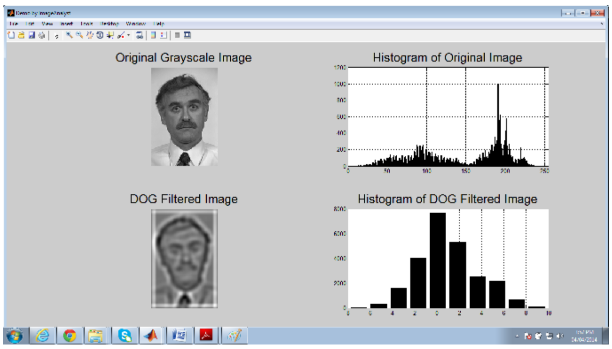
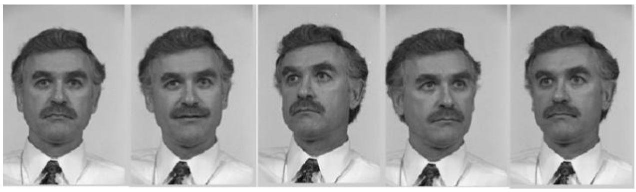
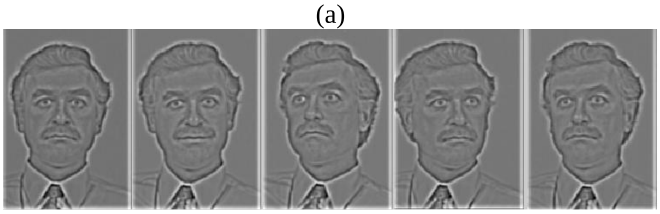


Fig. 6. Histograms of gray image and DoG filter image



(a)



(b)

Fig.7.Examples of images of one person from the training database. The columns respectively give images from subsets 1 to 5. (a) original images. (b) the corresponding illumination normalized images obtained with the praposed preprocessing chain.

VI. Conclusion

This paper presented new methods for face recognition under uncontrolled lighting based on robust preprocessing and the LBP local texture descriptor. The crux of the work lies in making three main contributions: (*i*) a simple and efficient preprocessing chain; (*ii*) a rich local texture descriptor called Local Binary Pattern (LBP) and (*iii*) use of principle component analysis (PCA) feature extraction. Finally recognition of face is done using an Euclidean distance classifier. If Euclidean distance between a test image and training images is zero or minimum then it is a known face image otherwise it is consider as a unknown face image. Thus the main advantage of this method is simplicity, computational efficiency. Face recognition using LBP and PCA gives better results and improve accuracy.

References

[1] Y. Adini, Y. Moses, and S. Ullman, “Face recognition: The problem of compensating for changes in illumination direction,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 19, no. 7, pp. 721–732, Jul. 1997.

[2] X.Tan and Bill Triggs “Face Recognition under difficult lighting condition” IEEE Transaction on Image processing vol.19. no.7. June2010.

[3] R. Brunelli and T. Poggio, “Face recognition: Features versus Templates,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 15, no. 10, pp.1042–1052, Oct. 1993.

[4] T. Ahonen, A. Hadid, and M. Pietikainen, “Face description with local binary patterns: Application to face recognition,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 12, pp. 2037–2041, Dec. 2006.

[5] F. Guodail, E. Lange, and T. Iwamoto, “Face recognition system using local autocorrelations and multiscale integration,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 18, no. 10, pp. 1024–1028, Oct. 1996.

[6] T. Ojala, M. Pietikainen, and D. Harwood, “A comparative study of texture measures with classification based on feature distributions,” *Pattern Recognition*, vol. 29, no. 1, pp. 51–59, 1996.

[7] T. Ojala, M. Pietikainen, and T. Maenpaa, “Multiresolution gray-scale and rotation invarianat texture classification with local binary patterns,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 7, pp. 971–987, Jul. 2002.

[8] K. Kim “Face Recognition using Principle Component Analysis” Department of computer science, University of Maryland.MD 20742,USA.

[9] S .Anila and Dr. N. Devrajan “Processing Technique for Face Recognition under varying illumination condition”. Globle Journal of computer science and technology graphics and vision vol.12.ver.1.0,2012.