Face Recognition and Verification using Histogram Equalization

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Abstract: - This paper proposes a face recognition and verification algorithm based on histogram equalization to standardize the faces illumination reducing in such way the variations for further features extraction; using the image phase spectrum and principal components analysis, which allow the reduction of the data dimension without much information loss. Evaluation results show the desirable features of proposal scheme reaching recognition rate over 97% and a verification error lower than 0.003%

Key-Words: - Histogram Equalization, Fast Fourier Transform, Principal Component Analysis.

1 Introduction

Face recognition has received significant attention during the last several years [1], [2], because it plays an important role in many application areas, such as human-machine interaction, authentication and surveillance, etc. [3].

Biometrics consists of a set of automated methods for recognition or verification of individuals using physical or behavioral characteristics of such; as face, fingerprint, signature, voice, etc. This technology is based on the fact that each single person is unique and has distinctive features that can be used for identification.

Face recognition has been a topic of active research since the 80's, proposing solutions to several practical problems. Face recognition is probably the biometric method easier to understand, because we identify people by mainly their faces. However the recognition process used by the human brain for identifying faces has not a concrete explanation. Because it is now essential to have a reliable security systems in offices, banks, businesses, shops, etc. several approaches have been developed, among them the face-based identity recognition or verification systems are a good alternative for the development of such security systems [4].

Over the past two decades, the problem of face recognition has attracted substantial attention from various disciplines and has witnessed an impressive growth in basic and applied research, product development, and applications. Several face recognition systems have already been deployed at ports of entry at international airports in Australia and Portugal [5], most of them provides fairly good recognition rates although presents several limitations due to the illumination conditions.

This paper proposes to equalize the histogram of the image to improve the illumination on the images to be evaluated. Once these images are equalized and reduced, we proceed to extract the features of the face under analysis using phase information and the Principal Component Analysis (PCA). Then the matrix obtained using the PCA is used to train a Support Vector Machine method.

2 Background

On this section we present the different techniques used on the system proposed.

2.1 Histogram Equalization

The histogram manipulation, which automatically minimizes the contrast in areas too light or too dark of an image, consists of a nonlinear transformation that it considers the accumulative distribution of the original image; to generate a resulting image whose histogram is approximately uniform. On the ideal case, the contrast of an image would be optimized if all the 256 intensity levels were equally used. Obviously this is not possible due to the discrete nature of digital data of the image. However, an approximation can be achieved by dispersing peaks in the histogram of the image, leaving intact the lower parts. This process is achieved through a transformation function that has a high inclination where the original histogram has a peak and a low inclination in the rest of the histogram.

Consider r to denote the continues intensity values of the image to be processed, which takes vales in the range [0, L-1], with r=0 denoting the black and L-1 the white. For r satisfying these conditions the transform function is given by:

$$s = T(r) \qquad 0 \le r \le 1 \tag{1}$$

This produces a level of *s* for each pixel value *r* in the original image. Assuming that the transformation function *T(r)* satisfies the following conditions:

(a) $T(r)$ is single-valued and monotonically increasing in the interval $0 \leq r \leq 1$; and

(b) $0 \leq T(r) \leq 1$ for $0 \leq r \leq 1$

The gray levels in an image may be viewed as random variables in the interval [0, L-1]. One of the most fundamental descriptors of a random variable is its probability density function (PDF). Let $p_r(r)$ and $p_s(s)$denote the probability density functions of random variables r and s, respectively, where p_r and p_s are, in general, different functions. From a basic probability theory elementary result, it follows that, if $p_r(r)$ and $T(r)$ are known and satisfies condition (a), then the probability density function $p_s(s)$ can be obtained as follows:

$$p_s(s) = (L-1)p_r(r)\left|\frac{dr}{ds}\right| \quad (2)$$

Thus, the probability density function of the transformed variable, s, is determined by the gray-level PDF of the input image and the chosen transformation function, $T(r)$.

A transformation function of particular importance in image processing has the form

$$s = T(r) = (L-1)\int_0^r p_r(w)dw \quad (3)$$

For discrete values we deal with probabilities and summations instead of probability density functions and integrals. Thus the probability of occurrence of gray level r_k in an image is approximated by

$$P_r(r_k) = \frac{n_k}{n} \qquad k = 0,1,2,\ldots,L-1 \quad (4)$$

where, n is the total number of pixels in the image, $n_k$is the number of pixels that have gray level r_k, and L is the total number of possible gray levels in the image. Thus the discrete version of eq. (3) becomes

$$S_k = T(r_k) = (L-1)\sum_{j=(r_j)0}^{k} p_r \quad (5)$$

$$S_k = (L-1)\sum_{j=0}^{k}\frac{n_j}{n} \quad (6)$$

for $k = 0,1,2,\ldots,L-1$. Thus, a processed (output) image is obtained by mapping each pixel with level r_k in the input image to a corresponding pixel with level s_k in the output image via Eq. (6). As indicated earlier, a plot of $p_r(r_k)$ versus r_k is called a *histogram*. The transformation (mapping) given in Eq. (6) is called *histogram equalization* or *histogram linearization*.[6]

2.2 Principal Component Analysis

Principal component analysis (PCA) is a standard tool in modern data analysis, widely used in diverse fields from neuroscience to computer graphics, because it is a efficient, non-parametric method for extracting relevant information from confusing data sets. [7]

To develop a PCA analysis of input images, firstly consider that each image is stored in a vector of size N

$$x^i = \left[x_1^i \ldots x_N^i\right]^T \quad (7)$$

Next, subtract from each training images the average image is follows that

$$\bar{\boldsymbol{x}}^i = \boldsymbol{x^i} - \boldsymbol{m} \quad (8)$$

Where

$$\boldsymbol{m} = \frac{1}{P}\sum_{I=1}^{p}\boldsymbol{x}^i \quad (9)$$

Next, using the training images given by (9), and combining them into a data matrix of size NxP, where P is the number of training images and N is the image size. Here each column is a single image, that is

$$\bar{X} = \lfloor \bar{x}^1 \mid \bar{x}^2 \mid \ldots \mid \bar{x}^P \rfloor \quad (10)$$

Next, the covariance matrix is estimated as

$$\Omega = \overline{XX}^T \quad (11)$$

This covariance matrix has up to P eigenvectors associated with non-zero eigenvalues, assuming P<N. The eigenvectors are sorted, from high to low, according to their associated eigenvalues. The eigenvector associated with the largest eigenvalue is the eigenvector that finds the greatest variance in the images. The eigenvector associated with the second largest eigenvalue is the eigenvector that finds the second most variance in the images. This trend continues until the smallest eigenvalue is associated with the eigenvector that finds the least variance in the images. Then the eigenvalues and corresponding eigenvectors must be computed for the covariance matrix. Thus

$$\Omega\mathrm{V} = \Lambda\mathrm{V} \quad (12)$$

where V is the set of eigenvectors associated with the L eigenvalues. Once the eigenvalues are estimated, the eigenvectors $v_i \in V$ are sorted according to their corresponding eigenvalues $\lambda_i \in V$ from the higher to the lower value, keeping only the eigenvectors associated with the P larger eigenvalues. This matrix of eigenvectors is the eigenspace **V,** where each column of **V** is an eigenvector of Ω [8] , That is

$$\mathbf{V} = \lfloor \boldsymbol{v}_1 | \;\; \boldsymbol{v}_2 | \ldots | \boldsymbol{v}_P \rfloor \quad (13)$$

Thus, finally the reduced space is obtained as

$$\boldsymbol{Y} = \boldsymbol{V}^{\boldsymbol{T}} \overline{\boldsymbol{X}} \quad (14)$$

2.3 Feature Extraction

The Discrete Fourier Transform (DFT) is a specific form of Fourier analysis to convert one function in the spatial domain, into another frequency domain. The DFT decomposes an image into its real and imaginary components, or into magnitude and phase components. which is a representation of the image in the frequency domain.

The feature extraction plays a very important role in the any pattern recognition system. To this end, the proposed algorithm is based in the Normalization and the Phase Spectrum of local regions of an Image. To obtain local equalized image, the local regions of *M x M* pixels where *M* = 3*;M* = 6 and *M = all* are equalized and then the phase spectrum is computed. By equalizing the images and obtaining the phase spectrum of the local regions, it becomes robust to partial variation such as illumination changes or occlusion. All the training images must be equalized before training. In the test, we need to apply the same process before extracting the phase spectrum. In this paper we consider the equalization and phase spectrum extraction of local region of an image to improve the classification and robustness accuracy to partial variations. After the image equalization, we extract the phase spectrum of the same local region, which can be computed through of the Fourier Transform as follows:

$$\theta(\omega) = \tan^{-1} \frac{I(\omega)}{R(\omega)} \quad (15)$$

Where *I(ω)* and *R(ω)* are the imaginary and real components of input image Fourier transform. θ(ω) is the phase extracted from image spectrum of both training and testing images. Oppenheim et. al. [13, 14] have shown that phase information of an image retains the most of the intelligibility of an image.

2.4 Support Vector Machine (SVM)

Support vector machines are basically a binary patterns classification algorithm, whose objective is to assign each pattern to a class. [9],[10]

Consider the problem of separating the training set of vectors $(x_1, y_1), \ldots, (x_l, y_l), \epsilon\, R^n$which belong to two separate classes ($y_i = \{1, -1\}$). Here the goal is to separate the training vectors into two classes by a hyperplane.

$$(\vec{w} \cdot \vec{x}) + b = 0 \,, w \,\epsilon\, R^n \; y \; b \,\epsilon\, R \quad (9)$$

The hyperplane $(wx) + b = 0$ satisfies the conditions:

$$(\vec{w} \cdot \vec{x}) + \; b \; > 0 \;\; if \;\; y_i = 1$$

$$(\vec{w} \cdot \vec{x}) + \; b \; < 0 \;\; if \; y_i = -1 \quad (10)$$

Combining the last two conditions, we obtain:

$$y_i[(\vec{w} \cdot \vec{x}) + b] \geq 1, i = 1,2, .., l \quad (11)$$

Where *w* is a normal vector to the separation hyperplane and *b* is a constant. The separation hyperplane represented by *w* is the one that maximizes the distance, *m*, between the two classes; or the minimization of the functional.

$$\Phi(w) = \frac{\|w\|^2}{2} \quad (12)$$

Therefore, the optimization problem can be reformulated as an unconstrained optimization problem using Langrange multipliers and its solution would be given by the identification of saddle points of the Lagrange functional. [11]

3 Proposed System

On this paper we propose a recognition and verification system that uses the histogram equalization to minimize the contrast in the image of the faces, and then we extract their features applying the Principal Component Analysis (PCA) and phase spectrum to later classify the faces using the Support Vector Machine (SVM). On Fig. 1 we present the general diagram of the proposed system.

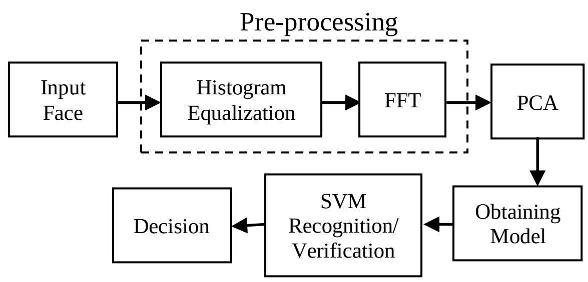

Fig. 1 Block Diagram of the Recognition/Verification System.

First we have the image input which is entered to the pre-processing phase; on this stage we apply the Histogram Equalization combined with the Fast Fourier Transform (FFT) to convert the image from the image (spatial) domain to the frequency domain. Once the image is converted we extract the features using the Principal Component Analysis, where a matrix containing the feature vectors of each face is obtained; with this matrix of PCA a model of each face is found which later will be used on the Recognition or Verification stage of the system, to take a decision. There are variants of the diagram presented above, respecting the pre-processing phase, where the way of applying the histogram equalization and the FFT varies. The first variation is describe on the following diagram on Fig.2

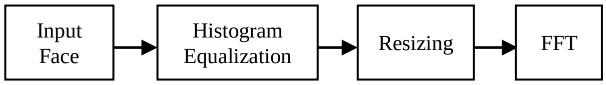

Fig. 2 First Pre-processing Variation

On this first variation we first equalize the face histogram and then resize the image to later estimate the image phase by using the Fourier Transform.

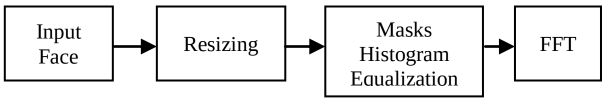

Fig. 3 Second Pre-processing Variation

In the second variation, firstly the image is resized; and a mask is applied to the image. The size of the masks applied is 3x3 and 6x6. Next the histogram equalization is applied to each mask; and then the image is reconstructed using each equalized image block. Finally the Fourier Transform is applied to the whole image.

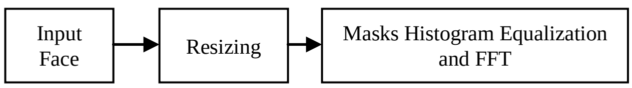

Fig. 3 Third Pre-processing variation

In the third and last variation, the original image is resized and equalized using masks of 3x3 and 6x6. Next the Fast Fourier Transform is applied to estimate the phase image. Finally a reconstructed matrix is obtained using the estimated phase of each block.

After the pre-processing is performed, a Principal Components Analysis is applied to obtain a reduced feature matrix, containing the Features Vectors of the faces under analysis. To get the feature matrix to different groups are created with ten faces each one, the first group containing faces without occlusion and the second one includes faces with and without occlusion. With each one of these groups a different matrix of Principal Components is obtained. Subsequently these matrixes are used to obtain a SVM Model, which later will be used to perform the Recognition or Verification task.

4 Results

On the following tables we present the recognition results for the different test realized with the pre-processing variation.

			Rec. (%)	Ver.		
				%FA	%FR	%E
With equalization	Known faces	w/occlusion	96.27	0.13	5.38	0.18
		w/o occlusion	80.21	0.02	28.29	0.26
	Not known faces	w/occlusion	95.75	0.15	6.17	0.2
		w/o occlusion	77.3	0.03	32.45	0.3
Without equalization	Known faces	w/occlusion	96.41	0.007	14.72	0.12
		w/o occlusion	80.86	0.005	33.87	0.28
	Not known faces	w/occlusion	95.88	0.008	16.88	0.14
		w/o occlusion	78.05	0.0067	38.86	0.33

Table 1. Recognition results with and without equalization

			Rec. (%)	Ver.		
				%FA	%FR	%E
Equalization 3x3	Known faces	w/occlusion	96.58	0.029	9.51	0.10
		w/o occlusion	81.58	0.003	37.61	0.31
	Not known faces	w/occlusion	96.07	0.03	10.91	0.12
		w/o occlusion	78.87	0.003	37.12	0.31
Equalization 6x6	Known faces	w/occlusion	95.95	0.02	11.34	0.11
		w/o occlusion	81.04	0.02	28.89	0.26
	Not known faces	w/occlusion	95.35	0.02	11.34	0,11
		w/o occlusion	78.25	0.02	28.89	0.26

Table 2. Recognition results using mask equalization

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			Rec. (%)	Ver.		
				%FA	%FR	%E
Equalization 3x3 FFT	Known faces	w/occlusion	97.57	0.72	0.73	2.00
		w/o occlusion	85.67	1.51	11.85	1.59
	Not known faces	w/occlusion	97.75	0.83	2.30	0.84
		w/o occlusion	83.56	0.83	14.96	0.95
Equalization 6x6 FFT	Known faces	w/occlusion	97.37	1.53	1.14	1.53
		w/o occlusion	84.4	0.72	13.04	0.82
	Not known faces	w/occlusion	96.98	1.76	1.31	1.75
		w/o occlusion	82.1	1.73	13.60	1.83

Table 3. Recognition results using mask equalization with FFT

4 Conclusion

In this paper, we have presented a face recognition and verification algorithm based on histogram equalization, with different ways to preprocess the face before getting the feature vector using Principal Components Analysis. On the results presented in the past section we can observe that in recognition the best percentages are those where the faces with occlusion were used to obtain the model. Also we can observe that the highest percentage of recognition is with mask equalization with FFT of 3x3 size and with occlusion, with known faces the recognition was of 97.57% and with the not known faces was of 97.75%.

On verification results we can see that the lowest percentage on false acceptance, are those where the mask equalization was applied, where the lowest percentage is for the mask of 3x3 with 0.003% on the cases where occlusion was not used to obtain the SVM Model.

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