FACE RECOGNITION USING 2D GABOR FILTER WITH PCA APPROACH

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Abstract- Face recognition is a broadly researched topic by researchers from differing disciplines. Several unsupervised statistical feature extraction strategies have been used in face recognition, out of these in this paper I propose a robust face recognition system using $2D$ Gabor filter with PCA approach. The proposed system was tested on two famous face recognition databases, namely ORL and faces 94 having face recognition rates of 81.72% and 97.30% were obtained respectively. The parameters which we are considered are recognition rate and speed with varying number of training and testing images.

Keywords- Face recognition, Eigen faces, PCA, Preprocessing techniques, $2D$ Gabor filter and feature extraction.

I. INTRODUCTION:

Biometric is a digital analysis using cameras and scanners of biological characteristics such as facial structure, fingerprints, eyes pattern etc. Biometric is accepted to be the successor of established confirmation strategies like passwords, PIN (Personal Identification Number) codes, tokens etc, which may be forgotten, copied or stolen. Biometric elements, for example finger print, palm print, face, iris and voice have encountered an expanded enthusiasm for the most recent two decades by researchers of differing disciplines, for example, neural networks, pattern recognition, image processing, computer vision etc. Amongst these, Face recognition is broadly researched about because of being natural and nonintrusive. The most important advantage of face is that it can be captured at a distance and in a secret manner. Out of the six biometric attributes account by Hietmeyer [1], facial features scored the most noteworthy similarity in a Machine Readable Travel Documents (MRTD) [2] framework in light of various assessment for example enrollment, renewal, machine necessities and open recognition. Face recognition, as one of the major biometric advances, has turned out to be progressively critical inferable from quick advances in image capture gadgets (surveillance cameras, camera in mobile phones), accessibility of tremendous measures of face images on the web and expanded requests for higher security. Takeo Kanade was the first who develop automated face recognition system in his Ph.D. thesis work [3] in 1973. There was a dormant period in automatic face recognition until the work by Sirovich and Kirby [4] on a low dimensional face representation derived using the Karhunen-Loeve transform [5] or Principal Component Analysis (PCA). It is the pioneering work of Turk and Pentland [6] on Eigen face [6, 7] that reinvigorated face recognition research.
Face acknowledgment innovation is presently fundamentally progressed since the Eigen face technique was proposed. In the obliged circumstances, for e.g. where distinctive lighting, posture, remain off, facial wear, and outward appearance can be controlled; automated face recognition can surpass human recognition performance, particularly when the database (gallery) contains countless faces.

An immediate utilization of a (color or gray-level) face image has not been fruitful in expression acknowledgment disregarding standardization procedures to accomplish enlightenment, scale and position variance. The suggestion is that suitable features are needed for facial expression characterization as actually, confirm by the observed human ability to perceive expressions without a reference to facial identity [8, 9]. This gives the inspiration to the present paper to concentrate on specific feature-maps that are extracted from gray-level face image store present facial expressions, thereby reducing the complexity and dimensionality of the problem. We consider just static pictures of expressive human faces(as profit capable in some standard databases),and not their video successions.

In this paper I propose face recognition system using $2D$ Gabor filter with PCA approach. The parameters which we are considered are recognition rate and speed with varying number of training and testing images. The datasets used in our experiments are AT&T's ORL face database [10] and Faces 94 database. Several preprocessing and feature extraction techniques have also been explored for improving the performance of the algorithms.

II. ALGORITHMS AND METHDOLOGIES

2.1 Preprocessing Techniques

Image preprocessing is the technique of upgrading data images prior to computational processing. Preprocessing of images commonly involves removing low frequency background noise, normalizing the intensity of the images, removing reflections and masking portion of images. Preprocessing techniques which I used are following:

2.1.1Image enhancement by median filter:

In face recognition system, it is often desirable to be able to perform some kind of noise reduction on an image so that performance of face recognition improved. Such noise reduction is a typical pre-processing step to enhance the results of later processing (for example, edge detection on an image). The median filter is a nonlinear digital filtering method, often used to remove the unwanted signal that is noise. Median filtering preserves edges while removing noise. The principle thought of the median filter is to run through the flag section by passage, replacing each passage with the median of neighboring entries. The pattern of neighbors is called the "window", which shift entry by entry over the whole signal. For two or higher-dimensional signals for example, pictures or more complex window patterns are possible. When window has an even number of entries, there is more than one possible median and for odd number of entries, all the entries in the window are sorted numerically and then the middle value is median.

2.1.2 Image enhancement by adaptive histogram equalization:

Adaptive histogram equalization (AHE) is a computer image processing technique used to enhance the contrast in images. It varies from normal histogram equalization in the regard that the adaptive histogram equalization computes few histograms, each corresponding to a distinct section of the image, and uses them to redistribute the illumination values of the image. It is therefore suitable for improving the nearby contrast and enhancing the definitions of edges in every area of an image.

Ordinary histogram equalization utilizes a similar change got from the picture histogram to change all pixels. This works well when the distribution of pixel qualities is similar all through the image. However, when the image contains areas that are essentially lighter or darker than the majority of the image, the difference in those areas won't be adequately improved. Adaptive histogram equalization (AHE) enhances this by changing every pixel with a transformation function derived from a neighborhood region.

2.2 Feature extraction Techniques

The input data can be transformed into a reduced set of features (also named a features vector) whenever an algorithm is too large to be processed and it is suspected to be redundant (e.g. the repetitiveness of images presented as pixels). This process is called feature selection. The selected features are expected to have the applicable information from the input data, so that the desired task can be performed by using this reduced information instead of the entire initial data.

2.2.1Principal Component Analysis (PCA):

Principal component analysis is a statistical procedure utilizes an orthogonal transformation to change a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components, i.e. “eigen faces” to reduce the immense redundancies in face pictures. Because of its potency in noise sensitivity compensation these global representations can be superior to the original distorted images [11], which could be blurring, partial occlusion, and background variation. During preparing, PCA catches the difference between preparing tests and makes an arrangement of trademark highlight pictures called principal components, i.e. "eigenfaces" [12]. By taking projection of every face image in dataset on eigen face component we can obtain vectors of weight. These weights become appropriate features for classifiers in much lower dimension. Hence PCA extract the features of face image as well as reduce the dimensions.

2.2.2 2D Gabor filter:

Pictures from a similar face, taken at (almost) a similar posture yet under varying illumination, often lie in a low-dimensional straight subspace known as the harmonic plane or illumination cone [13,14].The Gabor Wavelet (Gabor filter) represents a band-pass linear filter whose impulse response is a harmonic function multiplied by a Gaussian function. Thus, two dimensional Gabor filter constitutes a complex sinusoidal plane of specific frequency and orientation modulated by a Gaussian envelope [15]. It achieves an optimal resolution in both spatial and frequency domains. A bidimensional Gabor filter filters with different frequencies and orientations which are helpful for tracing useful features from an image.

2.2.3 Hybrid approach:

Now we have formulated one hybrid approach by combining 2D Gabor filter and PCA because using 2D Gabor filter is a sound approach to get rid of illumination, poses and facial expression changes [16] and using PCA we can lower the dimensions. Hence by using both together we can find good results.

2.3 Classification

2.3.1 K-Nearest Neighbor(KNN):

The K-nearest neighbor is a supervised learning algorithm where the result of new instance query is classified based on majority of K- nearest neighbor category. The motivation behind this algorithm is to arrange a new object based on attributes and training samples. Given a query image, we find K numbers of objects or training images closest to the query image. K- nearest neighbor algorithm use neighborhood classification as the prediction value of the new query instance.

2.3.2 Euclidean distance:

Euclidean distance is utilized to group unknown image data to classes which minimize the distance between the image information and the class in multi-feature space. The Euclidean distance is expressed as an index of closeness so that the minimum distance is identical to the maximum closeness. The Euclidean distance is hypothetically identical to the similarity closeness.

III. EXPERIMENTS AND EVALUATION PARAMETERS

3.1 Databases used

3.1.1ORL Databases:

In ORL database (sample shown in fig.1) we use 10 different facial expressions with facial detail (smiling, anger, eyes open, eyes closed, normal face, glasses, no glasses) for 40 different people thus creating 10×40 that is equal to 400 different set of face images. Other than these properties the images were taken at various times and there are varieties in lighting and scale up to 10%. All images are gray scaled images in pgm format with dimension 92×112 pixels. Testing on this database would help us to comprehend whether the algorithms have a decent speculation capacity.

3.1.2 Faces94 Databases:

In Faces94 database (sample shown in fig.2) we use 10 different facial expressions with facial detail (smiling, anger, eyes open, eyes closed, normal face, glasses, no glasses) for 10 different people thus creating 10×10 that is equal to 100 different set of face images. Other than these properties the images were taken at various times and there are varieties in lighting and scale. All images are colored images in jpg format with dimension 180×200 pixels. Testing on this database would help us to comprehend whether the algorithms have a decent speculation capacity.

Fig1: A subject from ORL Database.

Fig2: A subject from Faces94 Database.

3.2 Evaluation parameter

In this experiment we take two evaluation parameters, correct recognition rate and computation rate (CPU time).

3.2.1 Recognition rate:

Recognition rate is calculated by calculating recognition performance rate having different number of training and testing images.

3.2.2 Computational rate:

Computational rate is calculated by calculating total time elapsed by the CPU during whole process of face recognition experiment.

3.3 Experiment

3.3.1 Face recognition using PCA:

3.3.1.1 Training:

Consider a training set containing T images with each image have a dimension $N_1 \times N_2$. Now reshape this matrix into a column matrix also called as column vector i.e. $Y_1, Y_2 ....Y_T$ having dimension $N_1 * N_2 \times 1$. After this all the column vectors are bunch together so that training vector of dimension $N_1 * N_2 \times T$ is formed. Now we have to calculate overall mean of training set images i.e.:

$$\overline{Y} = \frac{1}{T}\sum_{i=1}^{T} Y_i \qquad (1)$$

After this mean center image of each image of training set is calculated as:

$$\varphi_i = Y_i - \overline{Y} \qquad (2)$$

Where $i = 1, 2, \ldots\ldots\ldots T$

For calculating the principal component i.e. eigen vectors and eigen values we must form a covariance matrix of mean centered image.

$$L = \frac{1}{T}\sum_{i=1}^{T} \varphi_i \varphi_i^{'} = AA^{'} \qquad (3)$$

Compute the eigen vectors μ_i of $AA^{'}$. All Eigen-values of matrix L are sorted and those who are less than a specified threshold are eliminated. Eigen-values suppose X having maximum values among all thus we obtain X eigen faces (ε_j for $j = 1, 2, ...k$) are used to find weights by the equation:

$$w_j = \varepsilon_j^T (Y_i - \overline{Y}) \qquad (4)$$

Where $i = 1, 2, \ldots\ldots\ldots T$ and $j = 1, 2, ...k$. These weights give us a vector $\left[\Omega = w_1, w_2 ....w_k\right]$, which depicts the contribution of each eigen face in representing the training face image.

3.3.1.2 Recognition:

Recognition function compares two faces by projecting the images into face-space and measuring the Euclidean distance between them. All centered images are projected into face-space by multiplying in Eigen-face basis.

Projected vector of each face will be its corresponding feature vector. Then it extracts the PCA features from test image calculating Euclidean distances i.e. $\min\left(\left\|\Omega_i - \Omega_k\right\|\right)$ between the projection of all centered training images and the projected test image.

3.3.2 Face recognition using hybrid approach:

In hybrid approach we use 2D Gabor filter for feature extraction with PCA for face recognition because using 2D Gabor filter is a sound approach to get rid of illumination, poses and facial expression changes [10] and using PCA we can lower the dimensions. Hence by using both together we can find good results.

Our approach designs 2D odd-symmetric Gabor filters for face image recognition, having the following form:

$$G_{\theta_k f_i \sigma_x \sigma_y}(x, y) = \exp\left(-\left[\frac{x_{\theta_k}^2}{\sigma_x^2} + \frac{y_{\theta_k}^2}{\sigma_y^2}\right]\right) . \cos\cos(2\pi f_i x_{\theta_k} + \varphi) \qquad (5)$$

Where $x_{\theta_k} = x\cos\cos\theta_k + y\sin\sin\theta_k$, $y_{\theta_k} = y\cos\cos\theta_k - x\sin\sin\theta_k$, f_i provides the central frequency of the sinusoidal plane wave at an angle θ_k with the x axis, σ_x and σ_y represent the standard deviations of the Gaussian envelope along the two axes, x and y. We set the phase $\varphi = \pi / 2$ and compute each orientation as:

$$\theta_k = \frac{k\pi}{n} \ \ where \ \ k = \{1, \ldots, n\} \qquad (6)$$

The $2D$ filters $G_{\theta_k f_i \sigma_x \sigma_y}$ given by relation (5) represent optimally captures both local orientation and frequency information from a digital image. Each face image is filtered with $G_{\theta_k f_i \sigma_x \sigma_y}$ at different orientations, frequencies and standard deviations. So, the design of Gabor filters for facial recognition requires an appropriated choice of those filter parameters. Therefore, we think of some proper variance values, a set of radial frequencies and a sequence of orientations.

3.3.2.1 Training:

3.3.2.1.1 Load the training images.

3.3.2.1.2 Apply the 2D Gabor filter on different scales and orientations. Here we consider four orientations $\left(0^0, \frac{\pi}{2}, \pi, \frac{3\pi}{2}\right)$ and four scales.

3.3.2.1.3 Map each image in column vector $Y_1, Y_2 ....Y_T$.

3.3.2.1.4 Calculate overall mean of face images.

3.3.2.1.5 Calculate mean center image.

3.3.2.1.6 Calculate the T images covariance matrix.

3.3.2.1.7 Calculate the eigen vectors and eigen values of covariance matrix.

3.3.2.1.8 Calculate X eigen vectors corresponding to X largest eigen values.

3.3.2.1.9 Calculate the weights $w_j = \varepsilon_j^T (Y_i - \overline{Y})$, where $i = 1, 2, \ldots\ldots\ldots T$ and $j = 1, 2, ...k$ to get a vector $\left[\Omega = w_1, w_2 ....w_k\right]$.

3.3.2.2 Recognition:

3.3.2.2.1 Normalize the Ψ test image $\left(\varphi_T = \psi - \overline{Y}\right)$

3.3.2.2.2 Project to eigen space $\left(\Omega_T = \varepsilon_j^T - \varphi_T\right)$

3.3.2.2.3 Calculate the Euclidean distances i.e. $\min\left(\left\|\Omega_i - \Omega_k\right\|\right)$ for $i = 1, 2, \ldots\ldots\ldots T$

3.3.2.2.4 The index of this minimum gives the closest match of the test image to the training image.

3.4 Result

All the experiments have been done using MATLAB 7.8.0. To covers all conditions of human face recognition, images with variation in size, pose and expression has been taken. Table 1 and 2 shows the result taking different number of testing and training images using different databases ORL and face 94 databases.

Table 1: Recognition rate and CPU time using different number of testing & training images of ORL Database.

Algorithm	No. of training samples/class	9	8	7	6	5	4	3	2	1
PCA	Recognition rate (%)	95.00	95.00	95.00	93.75	82.50	81.67	79.28	75.62	65.27
	CPU time(sec)	.7325	.6234	.5112	.4605	.4360	.4377	.3330	.2284	.2363
2D Gabor filter and PCA	Recognition rate (%)	92.00	92.00	90.83	86.25	84.50	78.75	77.14	70.94	63.06
	CPU time(sec)	.6927	.5715	.5210	.4868	.4466	.4217	.4058	.3869	.3816

Table 2: Success rate and CPU time using different number of testing and training images of face94 Database.

Algorithm	No. of training samples/class	9	8	7	6	5	4	3	2	1
PCA	Recognition rate (%)	100	95	96.67	97.50	98	98.33	98.57	96.25	98.88
	CPU time(sec)	.6110	.2289	.2799	.2550	.2355	.3106	.2913	.2779	.4074
2D Gabor filter and PCA	Recognition rate (%)	100	95.00	96.67	97.50	98.00	98.33	98.57	95.00	96.67
	CPU time(sec)	1.134	.3921	.3922	.3840	.3838	.3860	.3778	.3804	.3742

IV. CONCLUSION

PCA with 2D Gabor filter is a valuable process in face recognition with more information. The 2D Gabor filter is well suited to manage different image resolution and allow the image decomposition in different kinds of coefficients without any loss in the image information. We have presented here two algorithms; recognition rate of PCA is comparable to the recognition rate of PCA with 2D Gabor filter.

REFRENCES

[1] R. Hietmeyer. Biometric identification promises fast and secure processing of airline passengers. The International Civil Aviation Organization Journal, 55(9):10–11, 2000.
[2] Machine Readable Travel Documents (MRTD), http://www.icao.int/mrtd/overview/overview.cfm.
[3] Kanade T. (1973), Picture Processing System by Computer & Recognition of Human face. A PhD thesis, Department of Information Science, Kyoto University.
[4] M.Kirby and L.Sirovich, Application of the KL Procedure for the Characterization of Human Faces, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 12, no. I, pp. 103-108, Jan. 1990.
[5] Stark, Henry, Woods , John W. (1986). "Probability, Random Processes, and Estimation Theory for Engineers".
[6] M.Turk and A.Pentland, Eigenfaces for Recognition, J.Cognitive Neuroscience, voU, no. l , pp.71-86, 1991.
[7] A.Pentland, B.Moghaddam, T.Starner, "View-Based and Modular Eigenspaces for Face Recognition;' IEEE conference on computer vision and pattern recognition, Seattle, WA (Seattle WA), 1994.
[8] N. Costen, T.F. Cootes, G.J. Edwards, C.J. Taylor, Automatic extraction of the face identity-subspace, Image Vision Computing 20 (2002) 319–329.
[9] A. Samal, P.A. Iyengar, Automatic recognition and analysis of human faces and facial expressions: a survey, Pattern Recognition 25 (1) (1992) 65–77.
[10] ORL, "The ORL face database" at the AT&T (Olivetti) Research Laboratory, 1992. Available from: http://www.uk.research.att.com/facedatabase.html.
[11] W. Zhao, R. Chellapa, "Face processing advanced modeling and methods", Elsevier, 2006.
[12] Georgios Goudelis, Stefanos Zafeiriou, Anastasios Tefas, Ioannis Pitas, "Class-specific kernel-discriminant analysis for face verification," IEEE Trans. on Information Forensics and Security, vol. 2, no. 3, Sept. 2007.
[13] R. Basri, D. Jacobs, Lambertian reflectance and linear subspaces, IEEE Transac- tions on Pattern Analysis and Machine Intelligence 25 (2) (2003) 218–233.
[14] A. Georghiades, P. Belhumeur, D. Kriegman, From few to many: illumination cone models for face recognition under variable lighting and pose, IEEE Transactions on Pattern Analysis and Machine Intelligence 23 (6) (2001) 643–660.
[15] J. R. MOVELLAN, Tutorial on Gabor filters, http://mplab.ucsd.edu/tutorials/gabor.pdf.
[16] S. Marcelja. 1980. Mathematical description of the responses of simple cortical cells. Journal Opt. Soc. America, vol. 70, pp.1297–130